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Proximity to Children: A Geospatial Approach to Understanding the Relationship between Fast Food and Schools

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Abstract

In a time when Americans are waking up to the health consequences of consuming fast food, researchers have discovered that fast food restaurants seem to be located in greater concentrations near primary or secondary schools. While this phenomenon affects the food environments of some children and carries implications as to their short term and long term health (which has also been well researched), this paper focuses primarily on fast food restaurants that are within walking distance of schools. Using Geographic Information Systems (GIS) to integrate geospatial, business, demographic, and food quality data, I use linear regressions to examine whether and which fast food restaurants achieve greater sales by being closer to schools. By including an interaction term in my regressions, I find that low-quality, unhealthy fast food restaurants are rewarded with higher sales when in proximity to schools than identical restaurants that are farther away. Conversely, higher-quality fast food establishments actually earn lower sales when in proximity to schools. This paper adds to the existing literature by using fast food sales near schools to infer the dietary choices of children, evaluate the success of location strategies employed by the fast food industry, and offer new insights to public health professionals.

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Dedication

To my Mom, who taught me to notice, and my Dad, who inspired me to care.

Introduction

Since its birth in the 1950s, fast food has become a ubiquitous staple of American consumerism and an icon of the developed world. The fast food of today, which is most simply defined as "mass-produced food that is prepared and served very quickly" (Wikipedia contributors, 2016), has taken many forms and is offered at varying levels of price and nutritional value, but in most cases combines budget prices, lower-quality food ingredients, and quick preparation. In this paper, I define fast food restaurants to be any quick-service chain—from Burger King to Chipotle, Pizza Hut to Subway. Fast food is associated with large national or international brands that have engineered each menu item to the core. From their color schemes (Chang, Lin, 2010) to their carefully designed menu offerings (Horovitz, 2015), fast food chains make calculated strategic decisions in order to survive in their competitive industry.

Despite their seeming ubiquity, one of these strategic decisions relates to where they decide to locate. While there are many factors that help fast food executives decide where to open and close restaurants, these decisions boil down to which markets are the most promising and sustainable. Prior research has found that fast food restaurants appear more frequently when within walking distance (half a mile) of primary and secondary schools than when not within walking distance of schools (Austin et, al., 2005). In the context of growing childhood and adolescent obesity concerns in the United States, this phenomenon has serious implications for children's health by influencing their diets and eating habits (Davis, Carpenter, 2009).

While previous researchers have investigated the issue of fast food restaurants locating near schools and considered its effects on children's health, the aim of this paper

is to consider the proximity relationship between fast food restaurants and schools with a focus on how it affects the restaurants' sales. First, I theorize that fast food restaurants can be interested in locating in the vicinity of schools in order to achieve greater sales. Second, I investigate *which* types of restaurant chains are most incentivized (by higher relative sales) to locate near schools. From this information, I infer what kinds of fast food children and adolescents may be choosing, and how this information can inform child health professionals and the fast food industry.

Using Geographic Information Systems (GIS) I process restaurant location data with school data, local demographic data, and food quality data to generate proximity variables and integrate them into my main dataset. In a similar method used by researchers before me, I consider which types of restaurants tend to be located closer to schools. I then use a multiple linear regression to determine what effect school proximity, in general, has on the typical fast food restaurant's sales.[1] Then I evaluate whether sales performance of restaurants near schools differs between restaurants of different quality, healthiness or value by interacting the quality variable with a school proximity variable.

I find that fast food restaurants generally tend to earn higher sales when within walking distance of schools than when not. However, I also find that low-quality, unhealthy, and low-value fast food restaurants in particular tend to have higher sales when located near schools than when not. Conversely, higher quality, healthier, and better value fast food restaurants have lower sales when in proximity to schools than when not.

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[1] "Types" refers to the cuisine type of the restaurant. Cuisine types include American, chicken, dessert, Mexican, pizza, and sandwiches.

In the rest of this paper I first discuss the relevant past literature on topics of store location, school proximity to fast food, and childhood obesity stemming from fast food proximity to schools. Then I develop and explain my two main hypotheses behind my research in Section 3. In Section 4, I discuss my geographic study area, detailing my rationale behind choosing my sample regions and what fast food restaurants and schools I include in my data. In Section 5, I review my methods. Then I discuss my data sources, results, and limitations in Sections 6, 7, and 8 respectively. Lastly, I discuss the results of my models in Section 9 before concluding with a few possible explanations for my findings, suggesting future areas of related research, and providing a summary in Sections 10, 11 and 12.

Literature Review

Economic geography is a study that involves location and spatial measurements in studying economic activities. Numerous academics as well as industry professionals have examined the importance of location in business, particularly in the retail, hospitality and restaurant industries. In 1929, Harold Hotelling built upon economic theories related to duopolies (Hotelling, 1929). He used a simple model that considered the market between two identical commodity-selling businesses situated along a straight line, denoting Main Street or a railway of length *L*, along which consumers are uniformly distributed. He found that if these shops were "movable" and could position themselves at any point along *L*, the socially optimal location would be for the stores to position themselves at positions of ¼*L* and ¾*L*, such that customers would at most only have to travel ¼*L* to get to the store, assuming that they always chose the nearest store. However, the *profit-maximizing* positioning of these stores would be to cluster next to each other as close to the ½*L* as possible, which insures that each business captures at least half of the market share. In other words, Store A would capture the business of all customers that would have to walk a few steps farther to get to Store B along the line, and Store B would attract all customers on the other side. If a third player were to join the market, it would also situate itself as close to the existing businesses as possible, thus lending to the formation of business clusters. This component of Hotelling's Law, otherwise known as the "Principle of Minimum Differentiation," is a simple economic model that explains why rational competing businesses can be inclined to set up shop near each other (Hotelling, 1929).

Exhibit 1 displays a modern example of Hotelling's Law in practice. Here, competing restaurants, Burger King and McDonald's, are situated side by side along a road in Palatine, Illinois. They were strategically placed in a high-traffic area across the street from the Arlington International Racecourse.

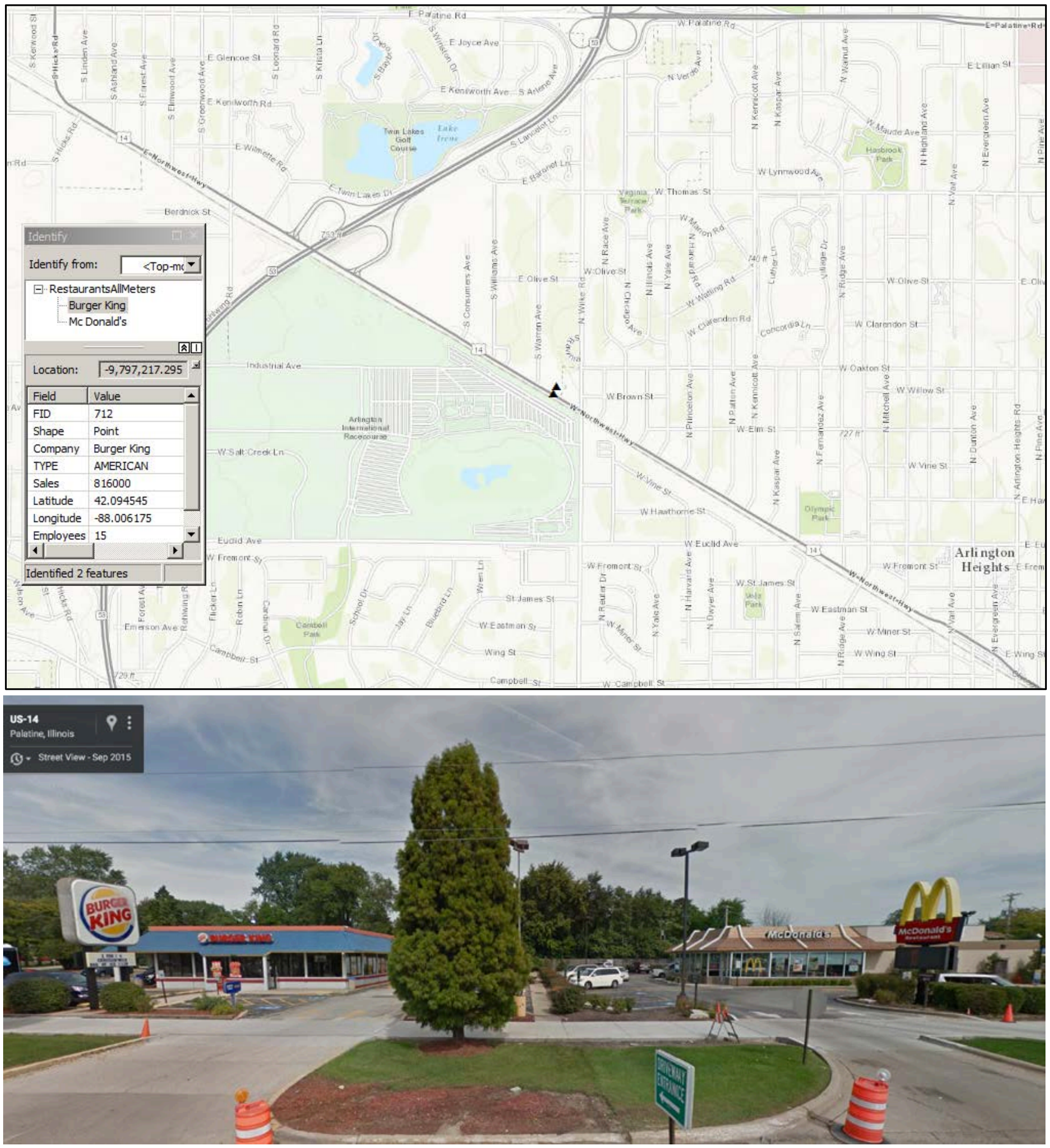

Exhibit 1: A Burger King next to a McDonald's in an ideal location across the street from the Arlington International Racetrack in Cook County, IL

But Hotelling also recognized that in studying competing firms with similar prices and products, there are many other variables to be considered including unquantifiable consumer preferences, slight differences in supplementary products, and proximity of storefronts to consumers and distributors (which affects transportation costs). Furthermore, Hotelling recognized that his model only considered the market between identical businesses situated along a straight line. Hotelling's model is an oversimplification that fails to recognize the effects of differing transportation costs and traffic, relative population densities, property values, other vendors nearby, human behavioral preferences regarding transportation distance, branding, marketing, parking and (if only he had known) innovations like free food delivery and Amazon.com (Hotelling, 1929).

In short, there are many variables that could be considered to help understand the effects that geography and proximity have on businesses. Mathematicians, statisticians, geographers, economists, sociologists, policy analysts, industry professionals and others have used mapping tools like Geographic Information Systems (GIS) to develop a stronger understanding of geography's effect on the economy and society. ArcGIS[2] is a popular GIS software that can be used to aggregate, store, display, and analyze geospatial data. It allows for researchers to take into account factors such as regional and local population characteristics, climate and weather data, and proximity to landmarks and natural resources (Dell, 2009). While there is promise in the potential of GIS as a tool for economists, the movement of adopting GIS as a new technology to inform the study of

[2] More information at: www.arcgis.com/features

economics has also been met with some skepticism (Taupier, Willis, 1994) and relatively little academic research has used geospatial tools. GIS has been applied to natural resource and land use planning, ibid environmental assessment, infrastructure management, transportation planning, public health, social services delivery, economic development, and marketing among others uses (Taupier, Willis, 1994).

Because GIS has the power to measure short distances, it can be used to answer important questions regarding the implications of fast food restaurants within walking distance of schools. Since fast food can be less healthy, it is important from a societal health perspective to better understand this issue and the effects that it can have on youth.

S. Bryn Austin et al. (2008), studied the phenomenon of fast food restaurant clustering around schools. Using geocoded databases, they determined that the concentration of fast food restaurants increases in areas within a short walking distance (400 or 800 meters) of kindergarten, primary and secondary schools in Chicago. They found that 78% of schools were located within half a mile of at least one fast food restaurant and that there was an estimated three to four times more fast food restaurants within 1.5 kilometers from schools than would be expected if the restaurants were distributed in a way that was unrelated to school locations. They concluded that the higher concentration of fast food restaurants within walking distance of schools "expos[e] children to poor-quality food environments in their school neighborhoods" (Austin et al., 2005).

Building on Austin's research, Paul Simon et al. (2008) investigated the proximity of fast food restaurants to public schools, taking into account neighborhood incomes and school level (elementary, middle, and high school) in Los Angeles County, California. In

addition to finding that 23.3% and 64.8% of public schools had at least one fast food restaurant within 400 meters and 800 meters, respectively, they also found that fast food restaurant proximity to schools is inversely related to neighborhood income. When they split schools by local income quartiles, they found that 37.7% of schools in the lowest neighborhood income quartile had a fast food restaurant within 400 meters of campus, while for schools in the highest quartile, the rate of this occurrence was 12.1%. Simon also considered population density and developed a (proxy) variable for commercialization, which they factored into their models. In their discussion, they mentioned the implications of fast food restaurants on childhood diet and obesity, citing the concern that, despite recent efforts to improve nutrition environments in schools, this fast food agglomeration phenomenon exists, particularly in low income communities (Simon et al., 2008).

A study by Davis and Carpenter found that students who had fast-food restaurants located within one half mile of their schools consumed fewer servings of fruits and vegetables, more servings of soda, and were more likely to be overweight or obese than youths from schools that were not within that radius of fast food restaurants (Davis, Carpenter, 2009).

To date, prior research has evaluated the extent to which fast food restaurants position themselves near schools, considering how this might affect children's diets and health outcomes. However, prior research has not addressed whether certain types of restaurants sell more when located close to schools compared to other types of restaurants.

Hypothesis Development

Based on the findings of Austin et al., who found that the incidence of fast food restaurants is higher around schools, I theorize that there exists a strong financial incentive for fast food chains to place stores in school-dense areas. Therefore, my first hypothesis is:

H1: *Fast food restaurants that locate in close proximity to schools achieve higher revenues than other restaurants of the same chain.*

Taking into account Carpenter and Davis' finding that children at schools in close proximity to fast food restaurants are more likely to be overweight or obese, I expect that restaurants that serve "fattening" or otherwise unhealthy or low-quality food achieve higher sales when operating near schools than their healthier counterparts do. Therefore, my second hypothesis is:

H2: *Relatively unhealthy fast food restaurants experience a greater increase in revenues when in proximity to schools than healthier fast food restaurants that are close to schools.*

Geographical Study Area

I focus on proximity relationships between restaurants and schools in the 20 most populous counties in the United States as listed in the 2010 Census. These counties represent a sample of thirteen of the most populated metropolitan areas in the United States.[3] Exhibit 2 displays a map representing 24,506 fast food restaurants in the thirteen metropolitan areas in my sample. The reason for focusing on more population-dense regions is because in more rural areas, town centers naturally lend themselves to a greater incidence of both schools and businesses, which would automatically decrease the distance between restaurants and schools.

Exhibit 2: Map of all fast food restaurants in sample split across 20 counties

[3] See Table 6, in Appendix, for complete list of counties.

My sample consists of 61 national and regional restaurant chains that fall under the categories of fast food or fast casual dining.[4] Fast food is generally associated with low-cost and lower quality quick-service dining. Fast casual restaurants provide a similar short wait time but typically charge a small premium for some combination of better quality food, customer service, cleanliness, and ambiance. Because these restaurants are more likely to fit the schedules and budgets of school children, students are most likely to frequently patronize these establishments over sit-down restaurants, supermarkets, or toy stores. Fast food and fast casual establishments maintain high sales volumes and compete in a relatively saturated market with similar competitors, allowing them to serve as virtually identical data points across communities and regions. In this paper, I refer to both traditional fast food and fast casual as “fast food.”

In my data, I consider schools to include pre-school through high school. Due to data limitations, I only include public schools. Exhibit 3 is a representation of a sample of the geospatial coordinates on a map. The black triangles signify fast food restaurant locations and the red squares signify public schools, which I refer to generally as “schools.”

[4] See Table 7, in Appendix, for complete list of chain restaurants in sample.

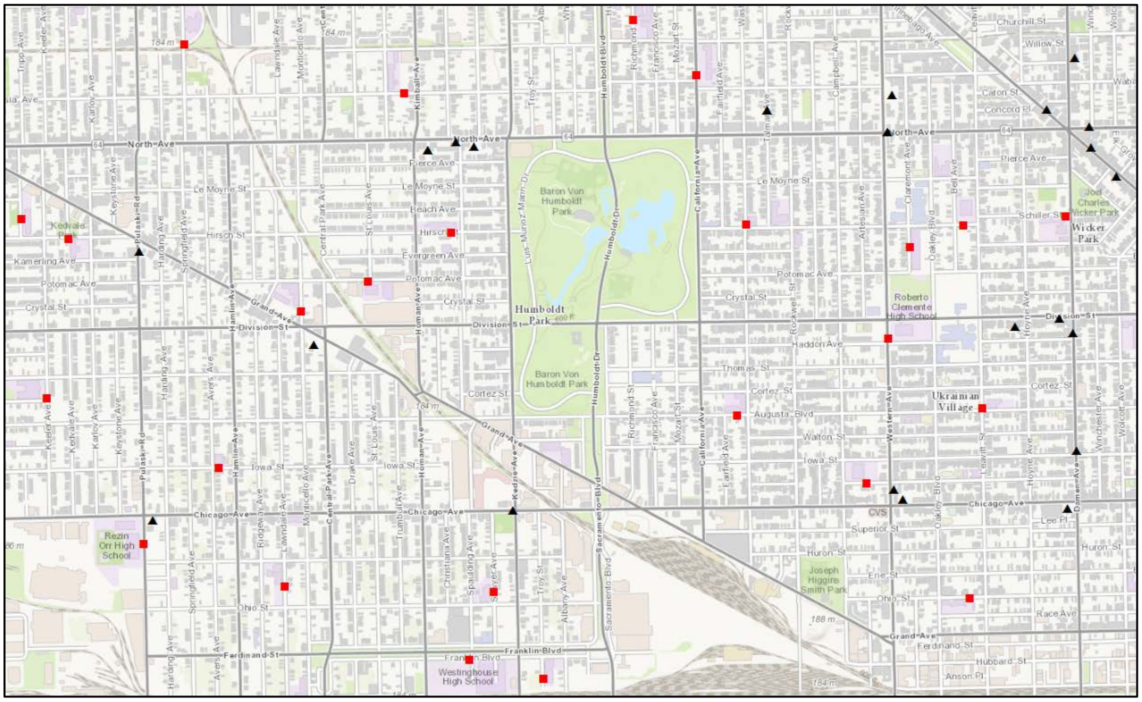

Exhibit 3: Map of Humboldt Park Neighborhood in Chicago, IL with fast food restaurants and schools

Methods

I consider three separate dependent variables that are intended to capture restaurant performance of individual restaurant locations. Sales volume (*sales*) is the simplest performance proxy that is provided for each restaurant in the ReferenceUSA database. While profit is a variable that captures the varying costs of different locations, I do not use profit as the independent variable because this study is more focused on determining the number of customers rather than determining the business viability. I create another dependent variable called *salestoavgratio* which is generated by dividing a given restaurant location's revenue by the average revenue of all locations in the same chain. I create a third dependent variable called *salestoregionalavgratio* by dividing sales by the average sales of restaurants of the same chain in the same state.

The main independent variable is intended to capture the proximity of schools to restaurants. Using ArcGIS, this can be measured two main ways—by finding the distance from a restaurant to its nearest school, or by determining the number of schools within a certain radius. By using the Near tool in ArcGis, I take each restaurant point on a restaurant layer and calculate the distance to its nearest school on a school layer. With each of these distances associated with each restaurant, ArcGIS outputs a variable called *distancetonearestschool*, which gives the distance to a restaurant's nearest school. Following the conventions of the studies done by Austin et al. and Simon et al., who looked at the number of restaurants within 400 meters (quarter-mile) and 800 meters (half a mile) of a given school, I find the number of *schools* within a 400 meter radius and 800 meter radius of a given *restaurant*. I create this variable by creating 400 and 800 meter

circular buffers[5] around each restaurant in my restaurant layer and determining how many schools fall into each of these buffers. These 400 and 800 meter buffers are represented as concentric circles on a map to signify a reasonable walking distance (see Exhibit 4), as 400 meters equates to about five minutes of walk time, and 800 meters, ten.[6] These variables are coded as *schct400* ("School Count within 400m") and *schct800* respectively.

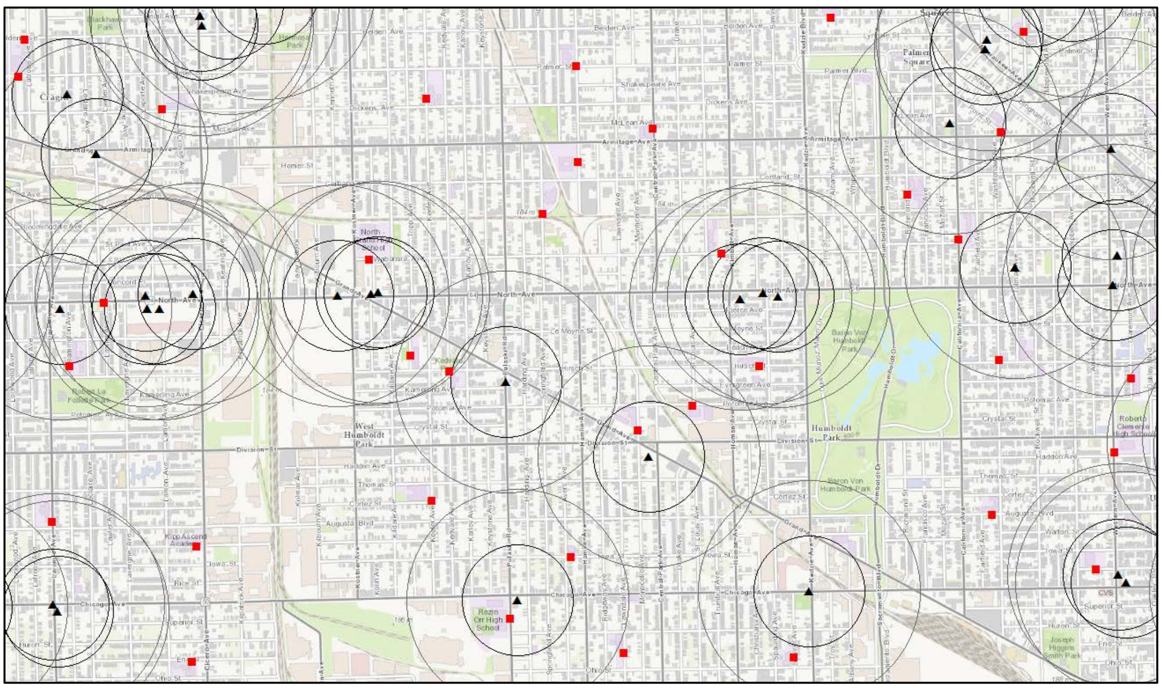

Exhibit 4: Humboldt Park neighborhood in Chicago, IL with 400m and 800m buffers around fast food restaurants

I first mirror the basic analysis done by Austin et al. and Simon et al. However, instead of focusing on schools, I focus on restaurants. I compute the average distance that

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[5] In spatial analysis, a *buffer* is a zone around a map feature measured in units of distance or time. A buffer is used in proximity analysis.

[6] Time estimation based on the assumption that standard walking speed is 3 miles per hour and 400 meters is equivalent to one quarter mile (400 m = 0.249 mi.).

a restaurant is from its nearest school, the average number of schools within 400 meters and 800 meters of a restaurant, and the percent of restaurants that have at least one school within 400 meters and 800 meters or "walking distance." I then determine which types of restaurants are more likely to have schools within 400 and 800 meter radii. I verify these results using a one-way ANOVA model to ensure that the differences between results for each restaurant type are statistically significant.

Since this study focuses on the effect of school proximity on fast food restaurants, one of the three variables for school proximity is used in each regression (but never more than one to avoid multicollinearity). The dependent variable is always one of the three variables relating to restaurant sales. The rest of the variables relate to elements of the restaurant location itself, data related to the nearest school, data on proximity to nearby fast food restaurants, and local demographic characteristics such as income. These data are matched with each restaurant location (in this case, each observation) using a spatial join function in ArcGIS.

Restaurant data include the three dependent variables discussed earlier, the type of cuisine served (*type_id*), the square footage (*squarefootage*), the number of operating hours in a week (*hoursopenperweek*), a healthiness rating (*grellingrade*[7]), a food quality and freshness rating (*r_quality*[8]), and a value rating (*r_value*[9]). To correct for the effects of pricing, reputation, and branding specific to each chain, I include a categorical variable for each company (*company_id*). Local demographic variables consist of the average

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[7] Grellin.org is a restaurant rating website that uses publicly available data on restaurant food to determine which restaurants have the healthiest menus. "Grellin Grade" is the name of their rating.
[8] The Food Quality and Freshness rating comes from Consumer Reports (consumerreports.org). Accessing these data requires a paid subscription.
[9] The Value rating comes from Consumer Reports.

adjusted gross income (*adjgrossincome*) and percent of black residents (*pctblack*) in the census tract of the restaurant.[10] To correct for the regional effects that may come from varying salaries and cost of living across the country, I include a categorical variable denoting county (*county_id*). School data include the percentage of students on a free lunch program (*pctfreelunch*) at the school nearest to the fast food restaurant. Merging the influences of Hotelling's law regarding retail agglomeration and proximity buffers used to determine school proximity, I consider the number of other fast food restaurants within 400 and 800 meter radii (*rstct400* and *rstct800*).

The first regression focuses on determining whether school proximity is correlated with restaurant sales.

$$sales_i = \beta_0 + \beta_1 schct800_i + \beta_2 rstct800_i + \beta_3 adjgrossincome_i + \beta_4 squarefootage_i + \beta_5 company\_id_i + \mu_i$$

Here I use raw sales volume per store (*sales*) as my dependent variable, which makes it easiest to interpret coefficients.[11] I use the number of schools within 800 meters as a measure of school proximity and correct for various restaurant location-specific factors including the square footage and the chain itself (*company_id*). I include average adjusted gross income of the restaurant's census tract to correct for the consumer preferences of likely customers from the area. Taking into account local incomes also means that, due to multicollinearity, I do not adjust for variables such as the percent of

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[10] A study by Jason Block et. al., found that fast food restaurants are more commonly located in black and low-income neighborhoods, suggesting that environmental exposure to fast food is a contributor to the prevalence of obesity among black and low-income populations (Block, Scribner, DeSalvo, 2004).
[11] I also used the other dependent variables I generated (*salestoavgratio* and *salestoregionalavgratio*) in regressions similar to this one. The results of those were similar (*salestoavgratio*) or lacked significance (*salestoregionalavgratio*).

students on the free lunch program or the percentage of black residents in the tract group, as those factors are correlated. Following the theories of restaurant agglomeration by Hotelling, I also take into account the number of other fast food restaurants within 800 meters.[12]

In my next set of regressions I look at whether a chain's food quality, healthiness, or value[13] has an effect on revenues by adding a categorical variable.

$$sales_i = \beta_0 + \beta_1 schct800_i + \beta_2 rstct800_i + \beta_3 adjgrossincome_i + \beta_4 squarefootage_i + \boldsymbol{\beta_5 r\_quality_i} + \mu_i$$

$$sales_i = \beta_0 + \beta_1 schct800_i + \beta_2 rstct800_i + \beta_3 adjgrossincome_i + \beta_4 squarefootage_i + \boldsymbol{\beta_5 grellinquartile_i} + \mu_i$$

$$sales_i = \beta_0 + \beta_1 schct800_i + \beta_2 rstct800_i + \beta_3 adjgrossincome_i + \beta_4 squarefootage_i + \boldsymbol{\beta_5 r\_value_i} + \mu_i$$

Because the quality, healthiness, and value of restaurants are correlated with the restaurant chains, I omit the *company_id* variable from the previous regression so as to avoid multicollinearity.[14]

Following my second hypothesis, I determine whether higher quality (and healthier and greater value) fast food restaurants have higher revenues when in proximity to schools. (If I find that relatively healthier restaurants earn higher revenues near schools, this could be good news for children's health advocates.) My last set of regressions include an interaction term between the school proximity variable and the (one of the) quality, healthiness, or value variables.

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[12] I also ran other regressions in which I swapped in other collinear variables.
[13] While value is not directly related to my hypothesis, I include it in one of my regressions because it may have significance.

$$sales_i = \beta_0 + \beta_1 schct800_{\mathrm{i}} + \beta_2 rstct800_{\mathrm{i}} + \beta_3 adjgrossincome_{\mathrm{i}} + \beta_4 squarefootage_{\mathrm{i}} + \beta_5 r\_quality_{\mathrm{i}} + \boldsymbol{\beta_6 schct800_{\mathrm{i}} \times r\_quality_{\mathrm{i}}} + \mu_{\mathrm{i}}$$

$$sales_i = \beta_0 + \beta_1 schct800_{\mathrm{i}} + \beta_2 rstct800_{\mathrm{i}} + \beta_3 adjgrossincome_{\mathrm{i}} + \beta_4 squarefootage_{\mathrm{i}} + \boldsymbol{\beta_5\, grellinquartile_{\mathrm{i}} + \beta_6 schct800_{\mathrm{i}} \times grellinquartile_{\mathrm{i}}} + \mu_{\mathrm{i}}$$

$$sales_i = \beta_0 + \beta_1 schct800_{\mathrm{i}} + \beta_2 rstct800_{\mathrm{i}} + \beta_3 adjgrossincome_{\mathrm{i}} + \beta_4 squarefootage_{\mathrm{i}} + \boldsymbol{\beta_5\, r\_value_{\mathrm{i}} + \beta_6 schct800_{\mathrm{i}} \times r\_value_{\mathrm{i}}} + \mu_{\mathrm{i}}$$

By including an interaction term in these regressions, I determine whether the sales revenue response to the proximity to schools differs at different levels of quality, healthiness or value of the restaurants. This regression may give insights into what kinds of restaurants students prefer as well as what kinds of restaurant chains would be incentivized to open new locations in the proximity of schools.[15]

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[15] I also ran this interaction regression with quartile groupings of the Grellin fast food healthiness grading system (*grellinquartile*) and food value (*r_value*) instead of *r_quality*.

Data Sources

The restaurant data are compiled from the ReferenceUSA database, which maintains business and residential data aggregated from 5,000 public sources.[16] The queried ReferenceUSA data include information on individual locations of chain stores. Relevant location-specific variables included the company name, address, latitude and longitude (used for processing in ArcGIS), annual revenues, square footage and daily operating hours. The ReferenceUSA data used in this study include 24,506 unique restaurant locations in the counties listed previously. In addition to the restaurant data provided by ReferenceUSA, I use data relating to healthiness and value. I use the Grellin Grade from the fast food healthiness rating website, Grellin.org[17], and use a *Food Quality and Freshness* rating and a *Value* rating from Consumer Reports[18].

The school data come from two sources. Because of the increased geospatial accuracy of GIS data that is available for California schools, California public school data are compiled from the UCLA Geoportal of California Public Schools. All school data from outside California are compiled through the National Center for Education Statistics school search feature. Demographic data are acquired from the American FactFinder database (a service of the U.S. Census Bureau) by tract group in each of the 20 counties used in the study. Local income data (average adjusted gross income), from the Statistics of Income tax statistics provided by the IRS, are matched with each of the restaurants by zip code.

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[16] http://www.referenceusa.com/Static/DataQuality
[17] See Table 8, in Appendix, for complete list of Grellin Grades and quartiles.
[18] See Table 9, in Appendix, for complete list of Consumer Reports ratings.

ArcGIS is used to combine the restaurant, school, and census data by geospatial proximity. Using a spatial join function, I take the latitude and longitude coordinates provided by ReferenceUSA and the UCLA Geoportal, the addresses of school locations provided by the National Center for Education Statistics, and the census tract data provided by American Factfinder, and combine all the data into a usable dataset. In the final dataset, each restaurant location serves as an individual observation.

Table 1 displays the summary statistics of the variables in my final dataset.

Table 1: Summary Statistics

VARIABLES[19]	(1) N	(2) mean	(3) sd	(4) min	(5) max
company_id*	24,496			1	61
sales	24,496	1.146×10^{06}	777,900	42,000	1.185×10^{06}
natlavgsales	24,496	1.175×10^{06}	648,002	246,962	3.539×10^{06}
regionalavgsales	24,496	1.175×10^{06}	951,116	54,000	1.794×10^{07}
salestoavgratio	24,496	0.990	0.426	0.0143	15.28
salestoregionalavgratio	24,496	0.998	0.360	0.00541	13.93
schct400	24,496	0.261	0.727	0	10
schct800	24,496	1.068	1.93	0	25
distancetonearestschool	24,496	1,019	1,241	0.626	42,193
type_id*	24,496			1	6
grellingrade*	20,013	21.29	17.89	0	55
r_quality*	20,661	2.876	0.706	1	5
r_value*	20,661	2.881	0.493	1	4
adjgrossincome	24,267	102,513	63,539	363	392,605
county_id*	24,496			1	20
squarefootage	24,475	19,503	12,504	1,250	40,000
hoursopenperweek	10,302	84.69	23.30	1	135.1
pctblack	24,067	0.122	0.189	0	1
rstct400	24,496	2.808	2.804	0	26
rstct800	24,496	5.425	6.828	0	85
pctfreelunch	15,578	0.549	0.285	0	0.998

[19] Variables marked with an asterisk (*) are categorical variables and are regressed as such in the following regressions.

Results

Table 2 shows that 16.7% and 47.8% of restaurants in the sample are within 400 meters and 800 meters of one or more public schools, respectively. Restaurants that specialize in desserts, such as ice cream and doughnut chains, have the highest average percentage of schools within 400 meters and 800 meters of their locations at 22.2% and 57.0%, respectively.

Table 2: Summary of school proximity variables and restaurant proximity variables by cuisine type.

Type	**Count**	**Average Distance to Nearest School (meters)**	**Average number of schools within 400m**	**Average number of schools within 800m**	**% of restaurants with 1 or more schools within 400m**	**% of restaurants with 1 or more schools within 800m**
AMERICAN	7768	1089***	0.22***	0.94***	14.56***	44.25***
CHICKEN	2892	929***	0.25***	1.07***	17.63***	51.70***
DESSERT	2304	881***	0.39***	1.54***	22.18***	56.94***
MEXICAN	2404	1076***	0.20***	0.88***	12.85***	44.18***
PIZZA	3325	906***	0.29***	1.20***	19.52***	53.74***
SANDWICHES	5803	1065***	0.25***	1.02***	16.58***	45.22***
Overall	**24496**	**1019**	**0.25**	**1.06**	**16.62**	**47.82**

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In Table 3, I use four continuous and one categorical variable to determine whether restaurant sales vary with the number of schools within walking distance. Based on this model, for every additional school within 800 meters of a fast food restaurant, sales volume increases by $14,254. Each additional fast food restaurant within 800 meters is associated with an increase in revenues of $2990. The adjusted gross income of the local census tract expectedly has a small but highly significant coefficient, which

makes sense considering that fast food consumers can come from almost any economic background. [20] The square footage also is positively correlated with revenues as expected. The categorical variables of 49 of the 61 companies are significant to the 5 percent level. If this regression is run without the *company_id* variable, the R-squared drops from 0.68 to 0.30, so a lot of the variation in a given restaurant's revenue is explained by the restaurant chain it belongs to.

Table 3: Multiple linear regression of sales on school count within 800m, restaurant count within 800 meters, tract group adjusted gross income, and restaurant square footage. The county categorical variable *county_id* was also uses as an explanatory variable. However, this variable has 61 levels and is excluded from this table in the interest of brevity. All but 12 of these 61 levels were significant at the 5 percent level, suggesting that company affiliation affected sales in each case significantly. See Table 10 (in Appendix) for complete results.

VARIABLES	Sales
schct800	15,290***
	(1,545)
rstct800	2,927***
	(786.0)
adjgrossincome	0.582***
	(0.0469)
squarefootage	15.87***
	(0.360)
Constant	484,338***
	(45,136)
Observations	24,246
R-squared	0.680

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

In Table 4, I include a food quality categorical variable and remove the *company-_id* variable to avoid multicollinearity. In doing so, I find that restaurants with the highest and lowest quality ratings earned greater revenues than companies with mid-level food

[20] See Table 11, in Appendix, for regression with interacted adjusted gross income term.

quality ratings. When I run the same regression with the Grellin healthiness rating quartiles instead of the quality variable, I find that companies in lower quartiles (i.e. less healthy restaurants) have higher sales than healthier restaurants. When I use Consumer Reports' Value ratings, it is clear that higher value restaurants on average earn higher revenues per store than lower value restaurants.

Table 4: Three multiple linear regression of sales on school count within 800m, restaurant count within 800m, tract group adjusted gross income, and restaurant square footage with a quality, healthiness, and value variable (all categorical), respectively.

VARIABLES	(Quality & Freshness) Sales	(Grellin) Sales	(Value) Sales
schct800	17,340***	19,080***	18,170***
	(2,473)	(2,231)	(2,652)
rstct800	1,984*	2,200*	2,601**
	(1,142)	(1,215)	(1,198)
adjgrossincome	0.563***	0.656***	0.747***
	(0.0709)	(0.0686)	(0.0781)
squarefootage	29.93***	29.92***	35.47***
	(0.355)	(0.396)	(0.383)
2.r_quality	1.025×10^{06}***		
	(62,042)		
3.r_quality	504,755***		
	(61,144)		
4.r_quality	682,621***		
	(61,597)		
5.r_quality	1.779×10^{06}***		
	(89,216)		
2.grellinquartile		717,279***	
		(15,380)	
3.grellinquartile		215,944***	
		(9,620)	
4.grellinquartile		29,711***	
		(10,185)	
2.r_value			646,641***
			(64,834)
3.r_value			761,398***
			(64,770)
4.r_value			889,202***
			(69,168)
Constant	-168,322***	257,426***	-349,486***
	(63,105)	(14,117)	(66,895)
Observations	20,452	19,829	20,452
R-squared	0.412	0.439	0.312

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

In Tables 4 and 5, the continuous explanatory variables remain mostly consistent in terms of their significance and reasonable in their coefficients. For each additional surrounding restaurant there is an increase in sales of about $2000, though the variables become less significant with the introduction of the quality and Grellin variables. Adjusted gross income still has a small, highly significant coefficient, and sales still has a similar coefficient, consistent with the first regression as shown in Table 3.

Table 5: Three multiple linear regressions of sales on school count within 800m, restaurant count within 800m, tract group adjusted gross income, and restaurant square footage with an interaction term between school count within 800 meters and quality, healthiness, and value dummy variables, separately.

VARIABLES	(Quality & Freshness) Sales	(Grellin) Sales	(Value) Sales
schct800	163,649**	16,947***	181,007**
	(75,652)	(3,699)	(74,147)
rstct800	2,014*	2,271*	2,252*
	(1,147)	(1,205)	(1,200)
adjgrossincome	0.551***	0.648***	0.752***
	(0.0709)	(0.0681)	(0.0780)
squarefootage	29.93***	29.79***	35.51***
	(0.355)	(0.395)	(0.383)
2.r_quality	1.125×10^{06}***		
	(70,549)		
3.r_quality	629,275***		
	(69,752)		
4.r_quality	805,512***		
	(70,588)		
5.r_quality	1.806×10^{06}***		
	(103,271)		
2.r_quality * schct800	-132,404*		
	(75,959)		
3.r_quality * schct800	-154,671**		
	(75,640)		
4.r_quality * schct800	-156,022**		
	(75,933)		
5.r_quality * schct800	-6,746		
	(92,045)		
2.grellinquartile		663,314***	
		(17,475)	
3.grellinquartile		230,573***	

		(11,163)	
4.grellinquartile		44,958***	
		(11,863)	
2.grellinquartile * schct800		54,636***	
		(9,441)	
3.grellinquartile * schct800		-13,900***	
		(4,519)	
4.grellinquartile * schct800		-15,166***	
		(4,428)	
2.r_value			782,823***
			(73,488)
3.r_value			879,058***
			(73,360)
4.r_value			1.076×10^{06}***
			(78,411)
2.r_value * schct800			-172,784**
			(74,183)
3.r_value * schct800			-155,201**
			(74,200)
4.r_value * schct800			-219,402***
			(74,652)
Constant	-282,919***	262,767***	-473,737***
	(71,278)	(14,380)	(75,039)
Observations	20,452	19,829	20,452
R-squared	0.414	0.444	0.314

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

Table 5 introduces interaction terms to the regressions. The first of the regressions include an interaction between food quality and the number of schools within 800 meters of a given fast food restaurant in the sample. The second regression in Table 5 replaces the food quality variable in the interaction with the Grellin grade quartile, which measures healthiness. The third regression includes the Value variable in the interaction term.

The results of the first regression in Table 5 indicate that the sales lower quality fast food restaurants increase more with school proximity than do the sales of higher

quality fast food restaurants. In the regression using Grellin grade quartiles instead of the food quality rating, the significance is greater. Additionally, the R-squared term increases from 0.41 to 0.44. However, when looking at the Grellin quartile interactions, the relationship between healthiness and the advantage of school proximity is less clear. Based on the coefficients, restaurants in the lower two quartiles (by healthiness) have increasingly higher revenues as the number of schools within 800 meters increases whereas restaurants in the higher two quartiles have lower and lower revenues as the number of schools within walking distance increases. In the same regression with value as the interaction term, R-squared term decreases to 0.31 but every variable is significant to the 5 percent level. The coefficients of the interaction between value and the number of schools within 800 meters do not show a clear trend, but suggested that fast food restaurants considered to have good "value for the money" tend to do worse in the proximity of schools than restaurants that are considered to have "less value" in their offerings.

Limitations

The datasets used only include primary and secondary level public schools, so while 90 percent of K-12 students attend public schools, there is still a key portion of the population that is not represented (CAPE, 2015). This study also omits college-age students. The data combines ages and grade levels together such that it does not consider whether effects are greater among different school levels.

The restaurant data has a few shortcomings as well. The data used in this study look only at a single snapshot in time. Future studies could study the effect of school closures or openings on nearby restaurants' revenues or analyze the changes in revenue during the summer quarter when school is (presumably) not in session. Secondly, the restaurant data only include large restaurant chains as observations, overlooking independent restaurants and local chains.

The GIS tool with which I construct my buffers to find schools within a given radius employ Euclidean distance, or straight-line, "as the crow flies" distance, instead of using Manhattan distance, which considers walking-time distances. While none of the previous studies I encountered use Manhattan distance, the results may be more accurate if walk-times, rather than straight-line distances, are used to generate my school proximity variables.[21]

This study does not consider the price of typical foods at the restaurants in the sample. It is probable that the price of a meal would affect any consumer's decision to eat at a restaurant, especially a child with a limited allowance.

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[21] The reason why I do not use walk-time buffers is because generating walk-time buffers for over 24,000 observations requires too much computing power for my available resources.

Discussion

When I interact the school proximity variable with ratings of healthiness, food quality & freshness, and value, the results show that certain restaurants that are nearer to schools, namely the unhealthy, low-quality, and low-value fast food restaurants, tend to perform better than others. Perhaps more disturbingly, fast food restaurants that have higher healthiness, quality, and value seem to fare worse in the vicinity of schools than when they are farther away from them.

The results of the models are by and large consistent. Across all of the regressions local adjusted gross income as an explanatory variable, despite being significant, always maintains a coefficient between 0 and 1. This finding challenges the assumption that people from poorer communities consume more fast food than others. In fact, in regressions that interact adjusted gross income (quartiles) with *SchCt800*, there is no significance.[22] This lack of strong correlation is supported by research done by Vikraman et al., who find in their study that there is no significant difference in fast food consumption by poverty status among children and adolescents (Vikraman et al., 2015).

Consistent with Hotelling's somewhat counter-intuitive game theory research on the advantages of store clustering, the models showed that being near other fast food restaurants indeed has its advangates. In fact, all of my regressions indicated a positive and significant correlation (at least to the 10 percent level). While Hotelling's Law suggests a correlation with sales, its effect pales in comparison to that of schools. In each of the non-interacted models, the advantage of proximity to one additional school is

[22] For interacted terms, $p>0.1$. See Table 11 in Appendix.

equivalent to that of over four additional fast food restaurants, perhaps implying that it would be equally advantageous for a fast food restaurant to be located in a strip mall as it would be to set up shop next to a school.

Surprisingly, the Dessert category of ‘restaurants’ (as displayed in Table 2) is on average nearest to and more frequently found around schools than the other categories. Considering that ice cream and doughnut shops are tempting and convenient delicacies for children, a heightened demand for such products is understandable. Considering that compared to the other cuisine types, the Dessert cuisine type category has the fewest restaurants (amounting to just 2,304 of the observations), it is remarkable that it has the highest percentage of restaurants with one or more schools within 400 and 800 meters. (One would expect that larger cuisine type categories, like American, which has 7,768 of the sample, would have a higher percentage of restaurants within walking distance of a school.) Unfortunately, many of Grellin’s graded restaurants and all of the Consumer Reports data omit the “Dessert” restaurants, so many are not included in samples where I include Grellin or Consumer Reports data.

Conclusion

These findings complement a growing body of research on the relationships between school-aged children, fast food, and childhood obesity. The problem with fast food restaurant proximity to schools is that it is ultimately a driver for child and adolescent fast food consumption. As mentioned earlier, a study found that students who have fast-food restaurants located within one half mile of their schools consume less fruits and vegetables, more soda, and are more likely to be overweight or obese than students from schools that are not within that distance of fast food restaurants (Davis, Carpenter, 2009). Previous research has found that about 3 in 10 children in the U.S. consume food from at least one fast food establishment on a typical day and that children on average get 12.4% of their daily calories from fast food restaurants alone (Vikraman et al., 2015). When broken up by age, the data show that about 17% of adolescents' daily caloric intake is from fast food (Vikraman et al., 2015).[23] When compared to the average among adults, who consume about 11% of their calories from fast food, it is clear that there is a market for fast food restaurants near schools (Fryar, Ervin, 2013).[24]

The findings of this study begin to explain another side of the relationships between school children and fast food restaurants, and by extension, children and health. While studies show that, indeed, fast food restaurants are more likely to be in proximity of schools than not, and that school children have appetites for fast food, my research has begun to uncover (a) what revenue incentives (or disincentives) exist for fast food

[23] Note: Data collected in 2011-2012
[24] Note: Data collected in 2007-2010

restaurants to locate near schools and (b) what types of fast food school children are opting to eat.

In a time when Americans are becoming increasingly cognizant of and prudent in their health decisions (USDA Office of Communications, 2014), it makes sense that the typical media-attuned (Cleland et al., 2002), slightly-overweight American adult may be driving the extra mile, or spending the extra dollar to eat at Rubio's rather than at Del Taco. Assuming that popularity corresponds with greater demand, and thus higher revenues, the findings of my regressions show that an almost opposite environment exists in proximity to schools. Whereas in the adult world, it may be trendy to eat at Shake Shack over Burger King, children simply don't have the means, desire, or information to choose to eat at healthier quick-service restaurants. This scenario could indicate the existence of a long term trend that would push unhealthy fast food restaurants closer and closer to schools and children who (a) are not attuned to weight-loss trends in society, (b) do not make personal health decisions, (c) do not have the means of driving, and (d) do not have "the extra dollar." Furthermore, by the time the typical child has become educated of the benefits of a better diet or consumed enough fast food to feel its health consequences, he has probably graduated only to be replaced by another naïve child.

My results, when placed in the context of previous research, also imply that there could be a reciprocal cause and effect relationship that could lead to a vicious cycle (in Exhibit 5) between low-quality fast food proximity to schools and children's health. Because that my data represent a snapshot in time, I cannot meaningfully investigate the longitudinal hypotheses inherent in Exhibit 5. While the vicious cycle is theoretical, the notion that there is a self-perpetuating relationship between low-quality fast food and

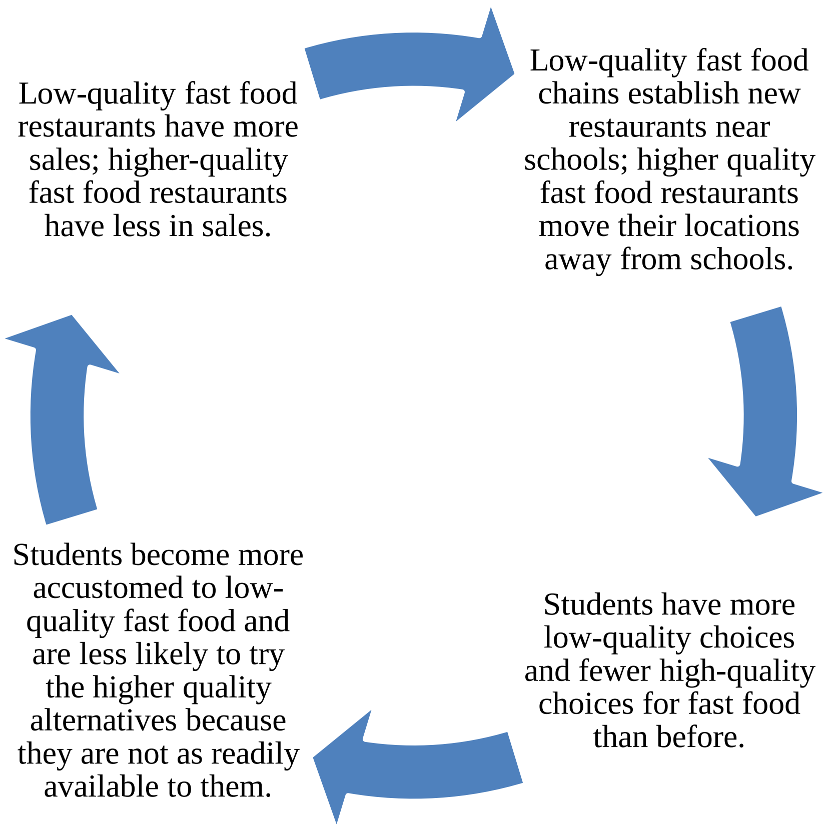

Exhibit 5: A theoretical vicious cycle whereby student habits adversely affect their school's local food environment, and vice versa.

school children suggests *intent*, both from the consumers in the transaction as well as the producers—suggesting one more possible explanation: Marketing.

A quick Google search of "fast food advertising" will return the standard ten search results on the first page. One of them is a Wikipedia page dedicated to the practice, and eight of them talk specifically about children as recipients of fast food advertising.[25] Fast food advertising strategies are at the crux of every well-known fast food operation. A 2006 study estimated that the fast food industry spent $1.6 billion

[25] Google search results for "fast food advertising."

marketing directly to children ages 2-17, which represented 17 percent of the total marketing budgets of the reporting fast food brands (Marr, 2008). Another report states that during the year 2012, the average preschooler (2 to 5 years) saw 1,000 ads from fast food restaurants, while children (6 to 11 years) saw 1,200 and teens (12 to 17 years) saw 1,750 ads (Harris et al., 2013). Given the efforts of some fast food companies to target children as consumers, it is no surprise that children often crave particular fast food. For example, a report found that "40% of parents report that their children ask them to go to McDonald's at least once a week [and] 15% of preschoolers ask to go every day" (Harris et al., 2010). These facts make it clear that, not only are some fast food restaurants targeting children, but their efforts are working quite effectively. While my models cannot confirm this hypothesis, it is very possible that a major determinant of fast food restaurant sales near schools is the amount and 'quality' of targeted marketing campaigns aimed at the child and teen demographics.

Future Research

Further research extending from this paper could combine the methodologies of this study with the wealth of information that has been collected on targeted fast food advertising to children. By interacting variables on restaurant advertising spending, TV advertisement viewership, and other marketing metrics with my school proximity variables in this study, researchers and marketers could potentially uncover a strong metric that measures the success of targeted youth advertising campaigns. Researchers could consider Norway, Sweden and Quebec (Canada)—places that have banned targeted junk food advertising to children—as experimental groups (Alkharfy, 2011).

Researchers should also consider how these results would change based on the level of the school as well as the academic performance of their students. While high schools are likely to generate greater sales for nearby fast food restaurants (Zenk, Powell, 2008), students may also be more prudent in their restaurant habits and choose healthier options. There may also be a correlation between student test performances and their fast food restaurant preferences.

Another area of research could investigate how school cafeterias affect the fast food dining habits of students. Given that many school cafeterias struggle to provide healthy or desirable food to its students, evaluating whether healthy cafeterias lead to greater unhealthy fast food consumption from nearby restaurants could add to the literature on school nutrition programs.

An extension of this study should also consider the role that price has to play in children’s fast food preferences. It is possible that a major driver of the increased sales of low-quality fast food restaurants near schools is due to pricing of menu items. Similarly,

integrating data on children’s perception of food taste could increase the explanatory power of the models used in this study (Caine-Bish, Scheule, 2009).

Lastly, research should be conducted on what kinds of policies or measures can be taken by schools and communities to disincentivize fast food restaurants from locating near schools. An example of a policy that should be researched first is New York’s 200 foot rule which prevents liquor vendors from being within 200 feet of a school or place of worship (Governor, 2008). While implementing a ban on certain unhealthy fast food restaurants within a certain radius of schools may not be possible, the benefits and consequences of levying a tax could be investigated.

Summary

Inspired by the research of public health professionals, who previously found that fast food restaurants appeared more frequently around schools than would otherwise be expected, I set out to understand the incentives of the players involved. By regressing fast food sales volume on measures of school proximity, food quality, and other relevant explanatory variables, I confirm the intuitive notion that school kids frequent fast food joints, leading those restaurant locations to have higher sales. My results also suggest that fast food restaurants that serve “junk” food are more likely to achieve higher revenues when within walking distance of schools and that fast food restaurants serving higher-quality food are penalized in their sales when they do the same. While this suggests that children are opting to eat less healthy food when given the choice, leading to numerous serious health implications, I focused on how fast food restaurants, as providers of this food, are incentivized to perpetuate these children’s diet choices and may continue do so at greater costs to society.

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Appendix

Table 6: List of 20 most populous counties in the United States, in order from most populous to least populous[26]

County	State	Metropolitan Area
Los Angeles	CA	Los Angeles
Cook	IL	Chicago
Harris	TX	Houston
Maricopa	AZ	Phoenix
San Diego	CA	San Diego
Orange	CA	Los Angeles
Miami-Dade	FL	Miami
Kings	NY	New York City
Dallas	TX	Dallas-Fort Worth
Riverside	CA	Los Angeles
Queens	NY	New York City
San Bernardino	CA	Los Angeles
King	WA	Seattle
Clark	NV	Las Vegas
Tarrant	TX	Dallas-Fort Worth
Santa Clara	CA	San Francisco Bay Area
Broward	FL	Miami
Bexar	TX	San Antonio
Wayne	MI	Detroit
New York	NY	New York City

[26] Source: http://www.census.gov/popest/data/counties/totals/2011/tables/CO-EST2011-07.csv

Table 7: List of all 61 fast food restaurants in alphabetical order[27]

Restaurant Name	Type	Count	Average Sales
A&W Restaurants	American	44	831681.8
Arby's	Sandwiches	238	961647.1
Baja Fresh Mexican Grill	Mexican	79	1121051
Baskin-Robbins	Dessert	710	527525.4
Ben & Jerry's	Dessert	66	550212.1
Blimpie Subs & Salads	Sandwiches	53	246962.3
Braum's Ice Cream & Dairy	American	50	1274720
Burger King	American	1046	1339047
Burger Street	American	12	327916.7
Carl's Jr	American	569	1280861
Carvel Ice Cream & Bakery	Dessert	49	256285.7
Charley's Grilled Subs	Sandwiches	22	571590.9
Checkers Drive-In Restaurant	American	83	1227205
Chick-Fil-A	Chicken	254	2143008
Chipotle Mexican Grill	Mexican	545	1257541
Chronic Tacos	Mexican	25	560800
Church's Chicken	Chicken	338	631787
Cinnabon	Dessert	67	525029.9
Cold Stone Creamery	Dessert	266	780744.4
Culver's	American	37	2053541
Dairy Queen	American	320	660521.9
Del Taco	Mexican	363	1453052
Domino's	Pizza	900	983965.6
Dunkin' Donuts	Dessert	1002	689340.3
El Pollo Loco	Chicken	375	1370528
Farmer Boys	American	73	1543644
Fatburger	American	63	843079.4
Firehouse Subs	Sandwiches	124	833491.9
Five Guys Burgers & Fries	American	212	1123344
In-N-Out Burger	American	200	3538810
Jack In The Box	American	1142	1433140
Jersey Mike's Subs	Sandwiches	245	627367.3
Jimmy John's	Sandwiches	377	997055.7
Johnny Rockets	American	81	1888469
KFC	Chicken	772	1131635
Krispy Kreme Doughnuts	Dessert	62	1488694

[27] Data Source: ReferenceUSA U.S. Businesses Database
Link: http://www.referenceusa.com/Home/Home

Little Caesars Pizza	Pizza	781	841768.2
Mc Donald's	American	2317	2435911
Moe's Southwest Grill	Mexican	32	891312.5
Mrs Field's Cookies	Dessert	82	312109.8
Panera Bread	Sandwiches	269	2004591
Papa John's Pizza	Pizza	531	1100908
Pizza Hut	Pizza	1032	1266585
Popeye's Louisiana Kitchen	Chicken	413	992433.4
Qdoba Mexican Grill	Mexican	77	843311.7
Rubio's Coastal Grill	Mexican	149	1236383
Sbarro	Pizza	81	753148.1
Shake Shack	American	22	873454.5
Sonic Drive-In	American	407	1300914
Steak 'n Shake	American	36	2441722
Subway	Sandwiches	4475	453779.7
Taco Bell	Mexican	1006	1222666
Taco Bueno	Mexican	55	896200
Taco Del Mar	Mexican	31	328193.5
Taco Time	Mexican	42	1029571
Umami Burger	American	23	1704391
Wendy's	American	677	1513994
Whataburger	American	269	1643320
White Castle	American	85	1539812
Wing Street	Chicken	390	1139087
Wingstop	Chicken	350	775600
Totals:		24496	1145767

Table 8: Grellin Grade and Quartile[28]

	Restaurant Name	Grellin Grade (*grellingrade*)	Grellin Quartile (*grellingquartile*)
1	Chipotle Mexican Grill	55	4
2	Subway	48	4
3	Rubio's Coastal Grill	43	4
4	Jersey Mike's Subs	33	4
5	El Pollo Loco	31	4
6	In-N-Out Burger	30	4
7	Taco Bell	28	4
8	Del Taco	22	4
9	Jack In The Box	19	3
10	Popeye's Louisiana Kitchen	19	3
11	Little Caesars Pizza	16	3
12	Carl's Jr	14	3
13	Church's Chicken	13	3
14	Whataburger	13	3
15	Burger King	12	3
16	KFC	11	3
17	Arby's	10	2
18	White Castle	10	2
19	Johnny Rockets	9	2
20	Mc Donald's	8	2
21	Culver's	7	2
22	Sonic Drive-In	7	2
23	A&W Restaurants	6	2
24	Dairy Queen	5	2
25	Pizza Hut	5	1
26	Baskin-Robbins	1	1
27	Checkers Drive-In Restaurant	1	1
28	Papa John's Pizza	1	1
29	Cold Stone Creamery	0	1
30	Domino's	0	1
31	Five Guys Burgers & Fries	0	1
32	Krispy Kreme Doughnuts	0	1

[28] Missing from data: Baja Fresh Mexican Grill, Ben & Jerry's, Blimpie Subs & Salads, Braum's Ice Cream & Dairy, Burger Street, Carvel Ice Cream & Bakery, Charley's Grilled Subs, Chick-Fil-A, Chronic Tacos, Cinnabon, Dunkin' Donuts, Farmer Boys, Fatburger, Firehouse Subs, Jimmy John's, Moe's Southwest Grill, Mrs Field's Cookies, Panera Bread, Qdoba Mexican Grill, Sbarro, Shake Shack, Steak 'n Shake, Taco Bueno, Taco Del Mar, Taco Time, Umami Burger, Wendy's, Wing Street, Wingstop
Source: www.grellin.org
Methodology: http://www.grellin.org/about

Table 9: Consumer Reports Fast Food Restaurant Data[29]

	Restaurant Name	**Food Quality & Freshness (*r_quality*)**	**Value (*r_value*)**
1	Rubio's Coastal Grill	[redacted] [30]	[redacted]
2	In-N-Out Burger	[redacted]	[redacted]
3	Chipotle Mexican Grill	[redacted]	[redacted]
4	Jersey Mike's Subs	[redacted]	[redacted]
5	El Pollo Loco	[redacted]	[redacted]
6	Whataburger	[redacted]	[redacted]
7	Culver's	[redacted]	[redacted]
8	Five Guys Burgers & Fries	[redacted]	[redacted]
9	Baja Fresh Mexican Grill	[redacted]	[redacted]
10	Chick-Fil-A	[redacted]	[redacted]
11	Firehouse Subs	[redacted]	[redacted]
12	Jimmy John's	[redacted]	[redacted]
13	Panera Bread	[redacted]	[redacted]
14	Qdoba Mexican Grill	[redacted]	[redacted]
15	Steak 'n Shake	[redacted]	[redacted]
16	Subway	[redacted]	[redacted]
17	Del Taco	[redacted]	[redacted]
18	Jack In The Box	[redacted]	[redacted]
19	Popeye's Louisiana Kitchen	[redacted]	[redacted]
20	Carl's Jr	[redacted]	[redacted]
21	Church's Chicken	[redacted]	[redacted]
22	Arby's	[redacted]	[redacted]
23	White Castle	[redacted]	[redacted]
24	Johnny Rockets	[redacted]	[redacted]
25	Sonic Drive-In	[redacted]	[redacted]
26	A&W Restaurants	[redacted]	[redacted]
27	Pizza Hut	[redacted]	[redacted]
28	Papa John's Pizza	[redacted]	[redacted]
29	Domino's	[redacted]	[redacted]
30	Moe's Southwest Grill	[redacted]	[redacted]

[29] Missing from data: Dairy Queen, Baskin-Robbins, Cold Stone Creamery, Krispy Kreme Doughnuts, Ben & Jerry's, Blimpie Subs & Salads, Braum's Ice Cream & Dairy, Burger Street, Carvel Ice Cream & Bakery, Charley's Grilled Subs, Chronic Tacos, Cinnabon, Dunkin' Donuts, Farmer Boys, Fatburger, Mrs. Field's Cookies, Shake Shack, Taco Bueno, Taco Del Mar, Taco Time, Umami Burger, Wing Street, Wingstop
Source: www.consumerreports.org
Methodology: http://www.consumerreports.org/cro/about-us/whats-behind-the-ratings/research/index.htm
[30] Note: The Consumer Reports ratings data is redacted in the online publication due to copyright restrictions. The data can be accessed with a paid subscription to Consumer Reports and log in credentials at: http://www.consumerreports.org/cro/health/food/fast-food-restaurants/fast-food-restaurant-ratings/ratings-overview.htm

31	Wendy's		
32	Taco Bell		
33	Little Caesars Pizza		
34	Burger King		
35	KFC		
36	Mc Donald's		
37	Checkers Drive-In Restaurant		
38	Sbarro		

Table 10 (Complete version of Table 3): Multiple linear regression of sales on school count within 800m, restaurant count within 800 meters, tract group adjusted gross income, and restaurant square footage with a county categorical variable.

VARIABLES	Sales
schct800	15,290***
	(1,545)
rstct800	2,927***
	(786.0)
adjgrossincome	0.582***
	(0.0469)
squarefootage	15.87***
	(0.360)
2.company_id	117,238**
	(48,991)
3.company_id	150,711***
	(54,864)
4.company_id	-194,644***
	(45,251)
5.company_id	-286,754***
	(54,614)
6.company_id	-439,998***
	(48,348)
7.company_id	334,209***
	(63,684)
8.company_id	400,060***
	(46,120)
9.company_id	-356,232***
	(54,105)
10.company_id	336,626***
	(46,541)
11.company_id	-397,176***
	(48,633)
12.company_id	-472,196***
	(58,297)
13.company_id	253,154***
	(63,145)
14.company_id	1.156×10^{06}***
	(67,340)
15.company_id	224,435***
	(46,702)
16.company_id	-202,107***
	(53,448)
17.company_id	-104,762**
	(45,786)
18.company_id	-478,420***
	(47,907)

19.company_id	-41,712
	(53,498)
20.company_id	1.218×10^{06}***
	(89,958)
21.company_id	-91,161*
	(47,640)
22.company_id	498,711***
	(49,057)
23.company_id	112,921**
	(45,418)
24.company_id	-203,470***
	(45,064)
25.company_id	425,076***
	(53,185)
26.company_id	618,687***
	(59,839)
27.company_id	71,245
	(59,697)
28.company_id	-43,103
	(51,037)
29.company_id	87,805*
	(52,488)
30.company_id	2.496×10^{06}***
	(59,249)
31.company_id	483,084***
	(45,605)
32.company_id	-203,733***
	(46,703)
33.company_id	56,560
	(47,954)
34.company_id	837,337***
	(110,639)
35.company_id	232,566***
	(45,848)
36.company_id	486,309***
	(107,203)
37.company_id	-27,918
	(45,180)
38.company_id	1.418×10^{06}***
	(47,812)
39.company_id	-30,142
	(64,914)
40.company_id	-534,574***
	(46,976)
41.company_id	961,353***
	(52,280)
42.company_id	128,596***
	(46,377)
43.company_id	256,711***
	(45,744)

44.company_id	159,277***
	(47,019)
45.company_id	-43,537
	(52,503)
46.company_id	211,343***
	(49,300)
47.company_id	-267,631***
	(71,342)
48.company_id	24,155
	(290,260)
49.company_id	386,027***
	(49,625)
50.company_id	1.436×10^{06}***
	(115,653)
51.company_id	-256,812***
	(44,310)
52.company_id	296,702***
	(45,428)
53.company_id	69,618
	(51,594)
54.company_id	-344,564***
	(57,242)
55.company_id	197,376***
	(60,543)
56.company_id	719,988***
	(107,764)
57.company_id	540,509***
	(47,452)
58.company_id	648,200***
	(52,660)
59.company_id	667,592***
	(80,323)
60.company_id	80,620*
	(46,510)
61.company_id	999.5
	(62,848)
Constant	484,338***
	(45,136)
Observations	24,246
R-squared	0.680

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

Table 11: Multiple linear regression of sales on school count within 800m, restaurant count within 800m, and restaurant square footage with an interaction term between school count and adjusted gross income quartile

	(1)
VARIABLES	1
rstct800	-1,170
	(983.4)
squarefootmidpoint	34.05***
	(0.353)
schct800	9,738
	(6,124)
2.agiquartile	12,207
	(13,308)
3.agiquartile	18,615
	(13,439)
4.agiquartile	110,763***
	(13,936)
2.agiquartile * schct800	9,175
	(8,261)
3.agiquartile * schct800	16,085*
	(8,369)
4.agiquartile * schct800	-2,350
	(6,783)
Constant	439,907***
	(12,240)
Observations	24,246
R-squared	0.299

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