5-2020

Does Proximity to Fast Food Cause Childhood Obesity? Evidence from Public Housing

Jeehee Han
Syracuse University, jhan09@syr.edu

Amy Ellen Schwartz
Syracuse University, amyschwartz@syr.edu

Brian Elbel

CENTER FOR POLICY RESEARCH

THE MAXWELL SCHOOL

WORKING PAPER SERIES

Does Proximity to Fast Food Cause Childhood Obesity? Evidence from Public Housing

Jeehee Han, Amy Ellen Schwartz, and Brian Elbel

Paper No. 228
June 2020 (Revised from May 2020)

ISSN: 1525-3066

Maxwell Syracuse University | Center for Policy Research
426 Eggers Hall
Syracuse University
Syracuse, NY 13244-1020
(315) 443-3114/ email: ctrpol@syr.edu
http://www.maxwell.syr.edu/CPR_Working_Papers.aspx

CENTER FOR POLICY RESEARCH – Summer 2020

Leonard M. Lopoo, Director
Professor of Public Administration and International Affairs (PAIA)

Associate Directors

Margaret Austin
Associate Director, Budget and Administration

John Yinger
Trustee Professor of Economics (ECON) and Public Administration and International Affairs (PAIA)
Associate Director, Center for Policy Research

SENIOR RESEARCH ASSOCIATES

Badi Baltagi, ECON
Robert Bifulco, PAIA
Leonard Burman, PAIA
Carmen Carrión-Flores, ECON
Alfonso Flores-Lagunes, ECON
Sarah Hamersma, PAIA
Madonna Harrington Meyer, SOC
Colleen Heflin, PAIA
William Horrace, ECON
Yilin Hou, PAIA
Hugo Jales, ECON
Jeffrey Kubik, ECON
Yoonseok Lee, ECON
Amy Lutz, SOC
Yingyi Ma, SOC
Katherine Michelmore, PAIA
Jerry Miner, ECON
Shannon Monnat, SOC
Jan Ondrich, ECON
David Popp, PAIA
Stuart Rosenthal, ECON
Michah Rothbart, PAIA
Alexander Rothenberg, ECON
Rebecca Schewe, SOC
Amy Ellen Schwartz, PAIA/ECON
Ying Shi, PAIA
Saba Siddiki, PAIA
Perry Singleton, ECON
Yulong Wang, ECON
Peter Wilcoxen, PAIA
Maria Zhu, ECON

GRADUATE ASSOCIATES

Rhea Acuña, PAIA
Mariah Brennan, SOC. SCI.
Ziqiao Chen, PAIA
Yoon Jung Choi, PAIA
Dahae Choo, ECON
Stephanie Coffey, PAIA
Giuseppe Germinario, ECON
Myriam Gregoire-Zawilski, PAIA
Jeehee Han, PAIA
Mary Helander, SOC. SCI.
Hyoung Kwon, PAIA
Mattie Mackenzie-Liu, PAIA
Maeve Maloney, ECON
Austin McNeill Brown, SOC. SCI.
Qasim Mehdi, PAIA
Claire Pendergrast, SOC
Krushna Ranaware, SOC
Christopher Rick, PAIA
Huong Tran, ECON
Joaquin Urrego, ECON
Yao Wang, ECON
Yi Yang, ECON
Xiaoyan Zhang, Human Dev.
Bo Zheng, PAIA
Dongmei Zuo, SOC. SCI.

STAFF

Joseph Boskovski, Manager, Maxwell X Lab
Katrina Fiacchi, Administrative Specialist
Michelle Kincaid, Senior Associate, Maxwell X Lab
Emily Minnoe, Administrative Assistant
Candi Patterson, Computer Consultant
Samantha Trajkovski, Postdoctoral Scholar
Laura Walsh, Administrative Assistant

Abstract

We examine the causal link between proximity to fast food and the incidence of childhood obesity among low-income households in New York City. Using individual-level longitudinal data on students living in public housing linked to restaurant location data, we exploit the naturally occurring within-development variation in distance to fast food restaurants to estimate the impact of proximity on obesity. Since the assignment of households to specific buildings is based upon availability at the time of assignment to public housing, the distance between student residence and retail outlets—including fast food restaurants, wait-service restaurants, supermarkets, and corner stores—is plausibly random. Our credibly causal estimates suggest that childhood obesity increases with proximity to fast food, with larger effects for younger children who attend neighborhood schools.

JEL No.: R38, I12, J13, L83

Keywords: Urban Neighborhoods, Food Environment, Child Health and Obesity, Public Housing

Authors: Jeehee Han, Center for Policy Research, Maxwell School of Citizenship and Public Affairs, Syracuse University, jhan09@syr.edu; Amy Ellen Schwartz, Center for Policy Research, Maxwell School of Citizenship and Public Affairs, Syracuse University; Brian Elbel, New York University

Acknowledgement

This study was supported by the National Institutes of Health (R01HD070739, R01DK097347, and R01DK108682). The funder had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript. The authors would like to thank the New York City Department of Education, the New York City Department of Health and Mental Hygiene, Zac McDermott, Joanna Rae Bailey, Meryle Weinstein, and Jeremy Sze for providing data and support. We also thank seminar participants at the Maxwell School at Syracuse University, the American Real Estate and Urban Economics Association, and the Urban Economics Association.

*This publication is forthcoming in *Regional Science and Urban Economics*

1. Introduction

Does proximity to fast food outlets and "unhealthy" food increase obesity among low-income children? In the United States, nearly one fifth of low-income children are obese, facing elevated risks of adult obesity, hypertension, and cardiovascular disease, among other serious complications that may lead to premature death (Bridger, 2009; Ogden et al., 2018; Sahoo et al., 2015). One commonly proffered culprit is the high density of fast food and relative scarcity of "healthy" food outlets in low-income neighborhoods, which facilitate consumption of high-calorie, low-nutrient food and spur obesity. Despite persuasive evidence of a correlation between obesity and the food environment in low-income neighborhoods, there is a dearth of credible evidence on the *causal* effects of proximity to fast food for two key reasons. First, both individual weight and residential location are likely to reflect a set of common underlying individual or family characteristics, such as income or educational attainment, making it difficult to isolate the effects of proximity to fast food per se. Second, individual-level data linking weight measures to proximity to fast food are scarce, typically only available for small samples or in limited detail. In this paper, we leverage the plausibly random within-development location of families living in public housing - a novel strategy - and use longitudinal individual-level data on weight, residential location, and neighborhood food outlets for New York City (NYC) public school students to derive credibly causal estimates of the impact of proximity to fast food on weight outcomes.

The key to our identification strategy is the plausibly random within-development variation in food environment driven by the tenant selection and assignment process of NYC public housing. First, NYC public housing applicants cannot indicate their preference for precise residential location in the assignment process. Second, it takes approximately 38 months on average to get to the top of the waiting list for NYC public housing, and the long wait time discourages applicants from rejecting offers. Thus the unit assignment within a development depends upon the vacancies at the time of assignment and generates the plausibly random variation in proximity to food outlets that we leverage to isolate causal effects of proximity to fast food on weight outcomes.

We draw on a rich individual-level longitudinal dataset on 143,859 K-12 NYC public school students who lived in public housing at some point between academic years 2009 and 2016. In addition to socio-demographic characteristics, the data include residential location and annual height and weight measures. Using data on the locations of food outlets citywide, we then calculate the distance from each student's residential location to the nearest fast food restaurant (and to other food outlets). The large sizes of public housing developments in NYC yield substantial within-development variation in proximity to food outlets, and we find no statistically significant evidence of selection.

To preview our results, we find that, indeed, proximity to fast food increases the probability a child is obese. More specifically, the probability of being obese increases 0.6 percentage points for every 0.1 mile closer a student lives to the nearest fast food restaurant, and the probability of being overweight (which includes obesity) increases by 1.1 percentage points. In contrast, we find no evidence that proximity to other types of food outlets - wait-service restaurants, supermarkets, or corner stores - has any impact on weight outcomes. Stratifying by grade level reveals the largest effects are among students in grades 3-8, where the incidence of obesity increases 1.4 percentage points and the incidence of overweight increases up to 1.9 percentage points for every 0.1 mile closer to the nearest fast food. Effects are even larger among older elementary and middle school students attending neighborhood schools (located less than a half-mile from home) who are likely to patronize neighborhood food outlets: the incidence of obesity increases 1.7 percentage points, and the incidence of overweight increases 2.1 percentage points for every 0.1 mile closer to the nearest fast food. An average city block is 0.05 mile in NYC, and these estimates respectively represent a 6 percent and a 4.7 percent increase in the obesity and overweight rates from a two-block difference in distance to fast food. Effects among younger students (grades K-2) and older students (grades 9-12) are close to zero and not statistically significant. Results are robust to alternative measures of the food environment, such as variables capturing the presence or number of fast food restaurants within different radiuses from home. In short, we find credibly causal evidence that proximity to fast food increases obesity and overweight among low-income children, and students in grades 3-8 (typically ages 8-13) are the most vulnerable. Our results suggest that place-based interventions to limit access to or consumption of fast food may be effective in reducing the obesity rates among low-income children in urban areas.

This paper is organized as follows. We first review prior literature and the theoretical motivation that inform our approach to examine the relationship between proximity to fast food and childhood obesity. In Section 3, we describe the institutional setting of public housing in NYC that provides plausibly exogenous variation in student proximity to fast food. Section 4 presents the individual-level weight outcome data, food environment measures, and descriptive statistics of our sample. Most importantly, we show within-development variation in proximity to fast food among students in public housing and test whether the variation in the local food environment is uncorrelated with student demographic characteristics. In Section 5, we provide the estimating equations for our empirical strategy. We present results and a series of robustness checks in Section 6 and conclude with discussion and implications for policy in Section 7.

2. Literature review

2.1. The Link between Obesity and Proximity to Fast Food

A large body of descriptive studies, from a range of settings, provide compelling evidence on the association between unhealthy food environment and the prevalence of obesity. National studies linking individual weight outcomes with the food environment data at the county-level (Mehta & Chang, 2008), zip-code level (Gibson, 2011), and census tract-level (Chen et al., 2016; Dubowitz et al., 2012) find that higher density of fast food restaurants and lower density of supermarkets are associated with increased probability of obesity for individuals in the neighborhood. Studies focusing on southern states also find that individuals in census tracts with more supermarkets are less likely to be obese, while those in census tracts with more fast food restaurants and corner stores are more likely to be obese (Morland et al., 2006; Morland & Everson, 2009).

Studies on children further document that *micro-neighborhood* food environments are associated with obesity risks. A school-level analysis by Davis and Carpenter (2009) finds having a fast food restaurant within a half-mile of school is associated with higher probabilities of being obese among middle and high school students. A more recent study by Elbel et al. (2020) examines the weight outcomes of children attending NYC public schools and the individual-level variation in distance to fast food *within census tracts*. They find that living more than 0.025 mile (about half of a city block) from the nearest fast food restaurant is associated with lower obesity and overweight risks.

Why might access to fast food affect obesity? Put simply, closer proximity to a fast food outlet lowers the relative travel cost of purchasing fast food, which may lead to increased fast food consumption and, in turn, a high-calorie diet. Previous research on consumption decisions, including McCarthy (1999) and Bellettini and Kempf (2013), suggests longer distance and travel time increase the opportunity cost and the effective price the consumers pay. The food environment literature (see Anderson & Matsa, 2011; Cutler, Glaeser, & Shapiro, 2003; Dunn, 2010) also builds upon the theory that food purchasing decisions are based on a function of the monetary price of the meal and other disutility, including the value of forgone time used to access or prepare the meal. As the distance to fast food decreases, the time and the cost spent on traveling to purchase fast food decrease, yet the relative time and cost of purchasing groceries and preparing home-cooked meals increase. Thus, among two individuals (if all else equal but their distances to fast food), the person living closer to a fast food restaurant is more likely to purchase fast food on a given day. Athens, Duncan, and Elbel (2016) provide evidence to support the hypothesis that proximity to fast food outlets and supermarkets are predictors of fast food dining frequency.[1]

Residential proximity to fast food, however, may be correlated with weight outcomes through other avenues. Families with a higher propensity for obesity - say a taste for fast food - may choose residential locations closer to fast food. More generally, there may be underlying individual or family characteristics that determine both residential location and propensity for obesity. While we are unaware of direct evidence on the underlying factors, a variety of existing studies have documented differences in the demographic characteristics of neighborhoods with different food environments. For example, Lewis et al. (2005) and Galvez et al. (2008) find that neighborhoods with higher density of fast food restaurants are also likely to have higher concentrations of racial minorities and low-income households (see Berger et al., 2019; Block, Scribner, & DeSalvo, 2004; Powell, Chaloupka, & Bao, 2007 for more). Studies also document that areas with greater access to supermarkets are predominantly white (Powell, Slater, Mirtcheva, & Chaloupka, 2007; Richardson, Boone-Heinonen, Popkin, & Gordon-Larsen, 2012).

[1] Yet a recent empirical study finds that exposing low-income households to the same produces and prices available to high-income households do not change their demand for healthy groceries (Allcott et al., 2019).

Disparities in weight outcomes across residential locations may reflect underlying differences in individual- or household-level characteristics, apart from the effects of the food environment per se. The key empirical challenge is to isolate the impact of the food environment from these underlying differences.

2.2. Quasi-Experimental Evidence

Despite the abundant descriptive evidence linking obesity to fast food availability, relatively few papers focus on estimating the causal effects. Four key papers use access to highways as an instrument for fast food locations to identify the causal relationship between food environment and obesity outcomes. First, Anderson and Matsa (2011) use distance to interstate highways as an instrument to examine the effect of distance to the nearest fast food restaurant, focusing on rural areas in 11 states. They employ a two-sample instrumental variable technique, using ZIP code centroids for restaurant data and telephone area code centroids for obesity data. They find no significant relationship between distances to the nearest restaurant (both fast food and full-service) and weight outcomes.

Two other studies by Dunn (2010) and Dunn, Sharkey, and Horel (2012), however, find detrimental effects of living near fast food restaurants on obesity outcomes for racial minorities and female populations. Dunn (2010) uses the number of interstate highway exits in each county as an instrument for county-level variation in the number of fast food restaurants. He categorizes counties into urban, rural, and medium-density counties across the nation and finds that obesity risks increase with the number of fast food restaurants, specifically among non-whites and females in medium-density counties. Dunn, Sharkey, and Horel (2012) focus on households in central Texas and use distance to a major highway – including not only interstates but also Texas highways – as an instrument to identify the effects of distance to the nearest fast food and the number of fast food restaurants near home on obesity outcomes. They find that both living closer to the nearest fast food and having more fast food restaurants within 1 mile and within 3 miles from home results in a statistically significant increase in the probability of being obese for non-white residents.

Potential explanations for heterogeneity in the effects of living near fast food across racial and gender subgroups include differential preferences and travel costs. First, the distance elasticity of fast food demand may be higher for minority groups due to differences in preferences. For example, ethnic cuisines differ in key ingredients that may require further travel to particular food outlets (Bitler & Haider, 2011). Easier access to fast food restaurants increases the opportunity cost of traveling further distances to purchase products for ethnic cuisines. The above studies, however, do not provide evidence for the effects of the availability of other food retails, such as large supermarkets, which is a common data limitation for past studies. Further, Dunn et al. (2012) explain that the travel cost may be higher for racial minorities because they are less likely to own vehicles than their white counterparts. If white residents are highly mobile, their exposure to the food environment near home will only take up a small portion of their total food environment exposure. Dunn (2010) also provides a potential explanation that females may respond differently to the presence of fast food due to differences in household responsibilities. In other words, their opportunity cost for traveling further distances may be higher.

Alviola, Nayga, Thomsen, and Smartt (2014) use distance to a major highway as an instrument to examine the causal relationship between school-level food environment and obesity rates. They examine the number of fast food restaurants near high schools in Arkansas and find each additional fast food restaurant within a mile from school increases school-level obesity rates by 1.23 percentage points.

Another notable study by Currie, DellaVigna, Moretti, and Pathania (2010) uses two different approaches to investigate the impact of proximity to fast food on weight outcomes. First, they examine school-level obesity rates for fifth, seventh, and ninth graders in California and compare schools that have any fast food restaurants within a tenth of a mile, a quarter-mile, and a half-mile from school. Here, the identification assumption is that small differences in proximity do not correlate to unobservable differences between the groups. They find that having a fast food restaurant within one tenth of a mile rather than a quarter of a mile from school increases school-level obesity rates by 1.7 percentage points for ninth graders. They find small and statistically insignificant effects for fifth and seventh graders. Second, using birth certificate data in Michigan, New Jersey, and Texas, they examine the impact of living near fast food on weight gain between pregnancies among women who have at least two children. They find smaller yet significant effects of having a fast food restaurant within a half-mile of a residence.

Currie et al. (2010) also suggest the difference in the magnitude of the results between students and mothers is driven by relative travel costs. If traveling the same distance incurs lower travel costs for adults, students will be more affected by fast food restaurants in the immediate proximity. Following this logic, travel costs are likely to be lower for older students than younger students, implying that younger students will be more sensitive to proximity, conditional on autonomy in food consumption decisions. Put differently, among students old enough to purchase their own food, younger students might be more responsive to fast food availability nearby due to difficulties driving, walking, or using public transportation to travel further distances for food. However, the two existing studies on children - Alviola et al. (2014) and Currie et al. (2010) - focus on high school grade students with little attention on *younger children*.

Previous studies also do not provide evidence on the causal impact of the *residential* food environment on childhood obesity. While past studies on student obesity focus on the school food environment, many elementary and middle school students are not allowed to leave school for lunch and are less likely to be affected by the food environment surrounding their school (Mirtcheva & Powell, 2009). This could potentially explain the null effects of fast food restaurants around school on obesity outcomes for younger students in Currie et al. (2010). After school hours, students can substitute home-prepared meals with fast food near home or consume fast food in addition to home-prepared meals. Especially for younger students, who are more likely to attend a school close to home, fast food near home may take up a larger part of their total food environment exposure. Thus, residential food environment has important implications for student food consumption decisions, and its estimated effects for younger students are likely to differ from that of older students.

Finally, previous quasi-experimental studies typically lack data on *non-restaurant food outlets* that may also affect food consumption decisions and obesity outcomes. In particular, supermarkets or corner stores may be alternatives to fast food restaurants, and proximity to these food outlets will shape the cost of purchasing fast food. Furthermore, distance to fast food may be correlated with distance to corner stores with low-quality food sources and inversely correlated with distance to high-quality supermarkets, complicating the interpretation of the coefficients on fast food. In this study, we have data on individual-level weight outcomes for school-aged children in all grades and their food environment around home, including distances to different types of food outlets, which we use to estimate the effects of proximity to fast food on childhood obesity.

3. Public Housing and Residential Location

We focus on students living in public housing, because the institutional setting of public housing - and that of NYC public housing, in particular - provides plausibly random variation in individual proximity to fast food within a development. Public housing is a federally funded housing assistance program, administered and managed by local housing authorities like the NYC Housing Authority (NYCHA). A public housing development typically consists of one or more concentrated blocks of standardized high-rise (and sometimes low-rise) apartment buildings. NYCHA is the nation's largest public housing system, containing 2,418 buildings in 149 developments dispersed across the city's five boroughs - Manhattan, Bronx, Brooklyn, Queens, and Staten Island (NYCHA, 2019). With roughly 174,000 households living in NYC public housing, an average NYCHA development has more than 16 buildings and approximately 150 residents per building.

To be clear, public housing is a place-based housing assistance program, in which program recipients are assigned to specific units that they can either "take or leave." It differs from other tenant-based programs like the housing choice vouchers, which allow households to choose their neighborhoods and housing units in the private market. The assignment process into NYC public housing units makes it difficult for public housing applicants to choose the precise residential location of their preference. Furthermore, most inner-city public housing developments are oversubscribed, requiring local housing authorities to have long waiting lists and systemized processes of assigning tenants to public housing units. There is also a long waiting list to get into NYCHA public housing units. In this section, we describe NYCHA's tenant assignment process that provides tenants little control over their choice of specific buildings, although they can specify some preference over locations.

More specifically, households can list up to two preferred boroughs on the application but are not permitted to list any preference for individual developments or buildings. After receiving applications, NYCHA assigns priority codes to eligible households, based on family size, income, needs (e.g., emergencies), and date of application (NYCHA, 2020). NYCHA then conducts interviews to place households on its waiting list. While the details of the process differ by priority code, all households have limited choice of housing units.

Applicants can select one preferred development during the process, conditional on the development containing an anticipated vacancy.[2] A computer matches applicants to vacant units in the selected development. Applicants can receive up to two offers (i.e., applicants are permitted to reject the initial offer), but applications will be closed if applicants fail to choose a development within 30 days or if applicants reject the second offer (NYCHA, 2020). "Emergency applicants," while prioritized in the tenant selection process, may only select a preferred borough rather than a particular development.[3] They are matched to vacant units in the selected borough "without regard to any preference by the applicant for a particular development in that borough" (NYCHA, 2020). Emergency applicants can also reject their initial offer, but their application will be closed if they reject the second offer. To summarize, the choice of development is constrained by anticipated vacancies around the time of the initial offer, and the choice of particular units or buildings within a development is more explicitly restricted.

A city-wide oversubscription for NYCHA public housing is likely to further discourage applicants from rejecting offers. From time to time, NYCHA closes its waiting list to control the volume of the applications it receives. Therefore, rejecting the second offer would increase households' uncertainty around whether they can create new applications to get back on the waiting list. Previous research suggests only a few households turn down the initial set of offers for housing assistance programs with long waiting lists, since starting over the application may entail a substantial wait for and uncertainty regarding the availability of another unit (Coley, Sullivan, & Kuo, 1997; Rosenbaum, 1995; DeLuca & Rosenbaum, 2003).[4] In the past five years, the average time between "date entered waiting list" and the

[2] Development selection should be from one of the two boroughs listed in their initial application form.

[3] Emergency applicants are households with children that are either homeless, victims of domestic violence, or intimidated witnesses, and borough selection should also be from one of the two boroughs listed on their initial application form.

[4] Drawing on student-level data in England, Weinhardt (2014) finds that precise timing of moving to neighborhoods with oversubscribed social housing is uncorrelated with any observable individual characteristics, suggesting households that apply for housing assistance programs with long waiting lists are likely to accept available offers regardless of their individual taste.

"admission date" for NYCHA public housing has been more than 38 months (HUD, 2019). This process creates random variation in the precise location of a student's residence (and the subsequent food environment) within a public housing development, which we leverage to isolate the causal impact of proximity to fast food on children.

A small number of previous studies exploit the assignment process in public housing to identify causal estimates of neighborhood effects on individual outcomes. Two are particularly relevant. Oreopoulos (2003) focuses on the Toronto public housing program, in which applicants cannot specify development preferences, to examine the effects of neighborhoods on long-run labor market outcomes. Gou and Maurin (2007) focus on public housing in France, where public housing managers have a very limited set of units to offer each year to eligible families, to estimate neighborhood effects on academic success. Thus, both studies leverage the resulting quasi-random assignment to a particular public housing development and, therefore, neighborhood to isolate causal estimates of neighborhood effects. We employ a similar methodology but also exploit the within-development variation in proximity to neighborhood (dis)amenities. To summarize, we exploit the institutional setting of public housing that assigns children in different micro-neighborhood food environments to derive credibly causal estimates of living near fast food restaurants.

4. Data and Sample

4.1. Student-Level Data

Our analyses draw on a rich set of longitudinal, student-level data for NYC public school students, K-12, in AY 2009-2016. Administrative data from the NYC Department of Education (NYCDOE) include student residential location, school attended, socio-demographic variables, such as gender, race/ethnicity, grade, primary language spoken at home, and poverty status,[5] educational program participation (e.g., students with disabilities and English language learners), and critically, student height and weight measures from an annual FitnessGram®. The FitnessGram® measures provide weight and height of students every year, which we use to calculate student body mass index (BMI). We follow the Centers for Disease Control and Prevention guidelines and define students as *obese* if their BMI is at or above the 95th percentile of their age and sex group and *overweight* if their BMI is at or above the 85th percentile. In addition to the two binary weight outcome variables, we calculate the z-score of the BMI (*zBMI*), standardized by age and sex group, to examine the estimated effects on the weight distribution for later robustness checks. We link student residential location to data on the locations of NYCHA developments to create an identifier for each public housing development, which we use to derive a set of development fixed effects.

We also link the student-level data to the locations of restaurants and supermarkets. We follow Elbel et al. (2020) to create four food retail outlet variables derived from two data sources. Specifically, we use data on NYC restaurants from the NYC Department of Health and Mental Hygiene, including information on locations and the type of service provided (fast food or wait-service). We calculate the straight-line distance (in miles) between student residential location and the nearest fast food restaurant (*DistFF*) and the nearest wait-service restaurant (*DistWaitService*).[6] We then link to data on the locations and characteristics of food stores from the New York State Department of Agriculture and Markets to calculate distances to the nearest large supermarket (store greater than 6,000 square feet) and the nearest corner store (less than 2,000 square feet), respectively *DistSupermarke*t and

[5] Poverty status is defined by whether students were ever eligible for free or reduced-price lunch (household incomes below 185 percent of the federal poverty level) in AY 2001-2016.

[6] Street network distances were correlated with straight-line distances at more than 90 percent.

DistCornerStore. While our analyses focus on these continuous measures of student distance to food outlets, we create a set of binary variables indicating the presence of each food outlet type within 0.1 mile from home (e.g., *AnyFF*) as an alternate specification. We also create density measures by counting the total number of food outlets within 0.1 mile and within 0.25 mile from home (e.g., *NumFF10* and *NumFF25*).

Finally, we calculate the straight-line distance between home and school attended in miles (*DistSch*). Using this, we create an indicator variable, *SchNear*, that identifies those who attend schools within a half-mile from home. Students in kindergarten, first, and second grade who travel less than a half-mile for school do not qualify for district-provided school buses in NYC and are, therefore, more likely to walk to school in the neighborhood. We also create *SchFar* to identify those who live far away (half-mile or more) from school and are thus eligible for school buses in the early grades. A second set of variables, *SchNear36* and *SchFar36*, is similarly defined using a one-mile threshold, which determines school bus eligibility for students in grades 3-6.[7]

4.2. Sample and Descriptive Statistics

Our analysis focuses on the students living in NYCHA public housing developments. The sample consists of 486,178 observations of K-12 NYC public school students in public housing for AY 2009-2016. Students missing weight and height data or residential location are not included in the sample. We

[7] Half-mile and one-mile thresholds are used by the NYCDOE to determine school bus eligibility (NYCDOE, 2020). K-2 students are eligible for school buses when they live further than half a mile from school, and students in grades 3-6 are eligible when they live more than a mile from school. Students in grades 7-12 are not eligible for school bus regardless of their distance between home and school; however, students in grades 7-8 living in Staten Island would be eligible for school buses at 1 mile. For other types of pupil transportation, students are eligible for half-fare and full-fare MetroCards. Students in grades K-2 are eligible for half-fare if they travel less than 0.5 mile for school and for full-fare if more than 0.5 mile; students in grades 3-6 are eligible for half-fare if they travel between 0.5 to 1 mile for school and for full-fare if they travel more than 1 mile; students in grades 7-12 are eligible for half-fare if they travel between 0.5 to 1.5 mile for school and for full-fare if they travel more than 1.5 mile.

further exclude outliers of non-poor students, who comprise less than 2 percent of the students living in public housing. Table 1 provides summary statistics of our analytic sample in all grades and by grade level. In addition to stratifying by elementary (K-5), middle (6-8), and high school grades (9-12), we separate students in grades K-2 from those in grades 3-5 to explore plausible heterogeneity within elementary school grade kids.

Table 1 shows that 23.2 percent of students in our analytic sample are obese and 40.9 percent are overweight. Obesity rates differ across grade levels, where students in grades 3-5 are more likely to be obese (27 percent) and high school students are less likely to be obese (19.5 percent) than students in other grade levels. A majority of our analytic sample are either Hispanic (47.4 percent) or black (46.2 percent), and less than 10 percent, across all grade levels, are Asian or white. Approximately half of the students are female (51.5 percent). Moreover, students in higher grade levels are likely to travel further distances for school. While less than a quarter of elementary school students attend schools more than a half-mile from home, almost 90 percent of high school students attend schools outside a half-mile radius from home. However, there is less, if any, variation in distances to the nearest food outlets across grade levels. On average, students live approximately 0.1 mile (around two city blocks in NYC) from the nearest fast food restaurant regardless of grade level.

Critical to our study is the within-development variation in distances to fast food. To explore this, we plot the distribution of *DistFF* in each of the 139 public housing developments in Figure 1. In this figure, each line shows the range of student distance to the nearest fast food at 5% and 95% of the distribution in a given development. The first range plot presented in Figure 1, for example, shows that one student would have to travel 0.2 mile (around four city blocks) further to reach the nearest fast food restaurant from home compared to another student *in the same development*. The plotted range of *DistFF* within developments suggests the within-development distance between buildings can span multiple blocks and place children in substantially different micro-neighborhood food environments. A decomposition of the variation in *DistFF*, in a one-way analysis of variance (ANOVA), indicates that almost half of the variation (47.8 percent) is within developments and only slightly more (52.2 percent) is between developments.

4.3. Exploring the Within-Development Variation in Local Food Environments

Before turning to models, we explore the empirical support for the claim that the within-development variation in distance between residence and fast food is plausibly random. To do so, we estimate a series of regression models that examine the correlation between distance to the nearest food outlet and student characteristics, using a set of development and year fixed effects. We use *DistFF*, *DistWaitService*, *DistSupermarket*, and *DistCornerStore* as the outcome and link them to a vector of student demographic variables, including gender, race/ethnicity (Asian, black, or white, using Hispanic as the reference group) and grade level (grades 3-5, grades 6-8, or grades 9-12, using grades K-2 as the reference group).

The results in Table 2 provide little evidence of a meaningful relationship between distance to food outlets and student characteristics. The magnitudes of *all* coefficients are substantively unimportant, ranging from -0.002 to 0.001, although some are statistically significant.[8] The coefficient for *black*, for example, indicates that black students are 0.001 mile, or five feet, further away from the nearest fast food restaurant than Hispanic students living in the same development. This represents one fiftieth of a typical city block in NYC. Similarly, estimates suggest older students (in middle school and high school grades) live 0.001 mile further from the nearest fast food restaurant than younger kids

[8] Results are robust to standardizing coefficients (see online appendix). Differences in distances to food outlets are small and not economically meaningful across student demographic characteristics.

(grades K-2) in the same development. These distances are not economically meaningful and bolster our confidence that the causal interpretation of our estimates is warranted.

5. Empirical Strategy

5.1. Regression Models

As described previously, we exploit the exogenous within-development variation in distance to fast food and identify the effects of proximity to fast food by comparing weight outcomes among students living in the same development but in different buildings (thus with different micro-neighborhood food environments). Our baseline model contains the following elements:

$$Y_{idt} = \beta_0 + \beta_1 \mathit{DistFF}_{idt} + \gamma X_{idt} + \delta_d + \tau_t + \varepsilon_{idt} \quad (1)$$

where Y_{idt} represents the weight outcome (*obese* and *overweight*) of student i in development d in year t. DistFF_{idt} captures student distance to the nearest fast food restaurant in miles. A vector of student characteristics (shown in Table 1) are included in the equation as X_{idt}, and year fixed effects, τ_t, control for secular trends. Finally, δ_d are development fixed effects, such that our coefficient of interest, β_1, is identified by the variation in *DistFF* within developments. An alternate specification includes and controls for student distance to other food outlets (*DistWaitService*, *DistSupermarket*, and *DistCornerStore*), which may also affect the relative travel cost for *DistFF* and child weight outcomes.

We first estimate this baseline model on our full analytic sample of students in all grades (K-12) and then stratify by grade levels to shed light on heterogeneity across grades, as discussed in earlier sections. We then explore differences in the estimated effects of *DistFF* between students who live near enough to school to be in the early grades "walk zone" of a half-mile and those who live farther away with the following model:

$$Y_{idt} = \beta_0 + \beta_1\,DistFFxSchNear_{idt} + \beta_2\,DistFFxSchFar_{idt}$$

$$+ \beta_3\,SchNear_{idt} + \gamma X_{idt} + \delta_d + \tau_t + \varepsilon_{idt} \quad (2)$$

where we fully interact *DistFF* with binary indicators of student distance to school, *SchNear* and *SchFar*, to allow the estimated impact of *DistFF* to vary by student distance to school. Again, we first estimate this model on the full analytic sample and then stratify by grade level, with and without controlling for distances to other food outlets. Following previous studies that find stronger effects of proximity to fast food on obesity outcomes among minorities and women, we also examine heterogeneity by student race/ethnicity and gender.

5.2 Robustness Checks

We also explore the robustness of our results to alternative specifications and measures. First, we re-estimate our models using *zBMI*, instead of the binary indicators *obese* and *overweight*. Second, we explore alternative ways of capturing the food environment, substituting continuous distance measures with binary indicators, such as *AnyFF*. We also control for the density of food outlets by within different radiuses from home, including *NumFF10* and *NumFF25*. Finally, we use alternative measures for distance to school, replacing *SchNear* and *SchFar* with *SchNear36* and *SchFar36*, constructed using a one-mile threshold, and using the continuous measure of student distance between home and school in miles, *DistSch*, instead of the indicator variables.

6. Results

6.1. Impact of Proximity to Fast Food by Grade Level

Baseline results in Table 3 show the estimated impact of proximity to fast food on student weight outcomes for K-12 students. Consistently negative and statistically significant coefficients for *DistFF* suggest that proximity to fast food increases student probability of being obese and overweight. Indeed, every additional 0.1 mile (or two city blocks) separating the nearest fast food restaurant from a student's residence decreases the probability of being obese by approximately 0.6 percentage points. The effects on overweight range between 0.93 to 1.11 percentage point increases, depending on the inclusion of distances to other food outlets in the model. We see little evidence that proximity to other food outlets matters. Coefficients on the distances to other food outlets (see full results in Table A.1) are small and statistically insignificant.

As described earlier, we estimate the impact of *DistFF* by student grade level and report separate coefficients for students in grades K-2, grades 3-5, grades 6-8, and grades 9-12. Estimates in Table 4 suggest that the baseline effects are largely driven by older elementary school students (in grades 3-5) and middle school students (in grades 6-8). For every 0.1 mile a student lives further away from the nearest fast food, the probability of being obese decreases by 1.39 to 1.42 percentage points and overweight decreases by 1.66 to 1.86 percentage points for students in grades 3-8 (see Table 4 Columns 2 and 4). To understand the magnitude of the effects, consider the group mean obesity rate of 27 percent for older elementary school students and 25.6 percent for middle school students (see Table 1). A 1.39 to 1.42 percentage point increase translates to approximately a 5.4 percent increase in obesity rate for living two blocks closer to the nearest fast food.

In contrast, the estimated effects on K-2 students and high school students are smaller in magnitude and, more importantly, statistically insignificant across all models using different weight outcomes and controls for distance to other food outlets. Students in grades K-2 may not be old enough to exercise independent food consumption decisions regardless of fast food locations near home. High school students, who tend to travel the furthest for school (see Table 1), may have exposure to food environment outside their residential neighborhood and, therefore, appear to be less sensitive to the micro-neighborhood food environments near home.

6.2. Does School Proximity Matter?

Estimates in Table 5 show that the impact of proximity to fast food near home differs by distance to school among students in all grade levels, except for K-2 students. Negative coefficients of *DistFF* for students attending neighborhood schools (coefficient on *DistFFxSchNear*) are always larger in magnitude than the corresponding coefficient for students attending schools farther away (*DistFFxSchFar*).[9] For example, among students in grade 3-5 (see Table 5 Panel B Columns 1 and 2), the estimated effects of *DistFFxSchNear* on obesity is larger by approximately 0.6 percentage points for every 0.1-mile increase compared to those of *DistFFxSchFar* (-0.144 vs. -0.081 and -0.158 vs. -0.095). The impact of living near fast food on obesity outcomes is almost 1.78 times larger for students attending schools nearby. We also find similar patterns for obesity outcomes among middle school students (see Table 5 Panel C). The impact of living 0.1 mile closer to fast food increases probability of obese by 1.43 to 1.68 percentage points for students attending neighborhood schools, approximately 0.5 percentage points larger than those attending schools farther away. These estimates imply that every 0.1 mile closer

[9] For each model in Table 5, we test whether the coefficients for the interaction terms are statistically different from each other and report the p-value of the joint F-test.

a student lives to fast food translates into approximately a 6 and 7 percent increase in obesity rates (and a 4.2 and 4.7 percent increase in overweight rates) respectively for older elementary students and middle school students that attend neighborhood schools.

As for high school students, in Panel D, the coefficient on *DistFFxSchNear* indicates statistically significant, negative effects on overweight. The estimates suggest living 0.1 mile closer to the nearest fast food increases high school students' probability of being overweight by approximately 1.3 percentage points, and the effect is statistically different from that of *DistFFxSchFar*. Thus, even for high school students, those attending neighborhood schools are affected by fast food near home. To understand the magnitude of the effects, consider the base overweight rate of 37 percent for high school students (see Table 1). An increase in the probability of being overweight by 1.3 percentage points represents a 3.5 percent increase in overweight rates.

Overall, the detrimental effects of living near fast food are largest among those students who are most likely to have meaningful autonomy in food decisions and, at the same time, are likely to spend a significant amount of their free time in their residential neighborhood. Results are robust to clustering standard errors at the development level (see Table A.2 and more on online appendix). Although standard errors are slightly larger, our key coefficients are still statistically significant at conventional levels.

6.3. Heterogeneity by Race and Gender and Robustness Checks

In Table 6, our analyses reveal considerable heterogeneity in impact across demographic groups, consistent with findings from previous research. First, we see negative and statistically significant effects of *DistFF* for black students, with similar evidence for Hispanic students. For black students, living 0.1 mile closer to fast food increases the probability of being obese by 0.9 to 1.05 percentage points and overweight by 1.08 to 1.17 percentage points. For Hispanic students the effects on overweight ranges between 0.8 to 1.28 percentage points. We see little evidence of the effects on weight outcomes among Asian and white students.[10] In Table 7, we report separate results by gender and find that boys are more sensitive to proximity to fast food near home than girls. While this may reflect greater autonomy granted to boys than girls, other underlying mechanisms are possible and warrant further research.

The findings from our series of robustness checks suggest the results are not sensitive to alternative measures and specifications. First, results are robust to measuring weight outcomes using *zBMI*, rather than indicators for obese or overweight (see Table A.3 and more on online appendix). Living 0.1 mile closer to the nearest fast food increases student BMI by approximately 0.03 standard deviations, or 4.3 percent of the sample's mean *zBMI*. Second, results are substantively unchanged by alternative measures of the food environment (see Table A.4). The probability of being obese is 0.6 percentage points higher (and overweight is 0.7 percentage points higher) for students who travel less than 0.1 mile to the nearest fast food restaurant. Third, results are substantively unchanged by including controls for density of the fast food restaurants (see Table A.5). Finally, we examine whether alternative specifications for distance to school yield similar results. Models with interaction terms using *SchNear36* and *SchFar36* (see Table A.7) and *DistSch* (see Table A.8) in place of *SchNear* and *SchFar* consistently show that students who travel further distances to school are less likely to be affected by *DistFF*. We also see in Table A.6 that including *DistSch* as a control, instead of interacting *DistSch* with *DistFF*, does not change the coefficients for *DistFF*. In other words, the moderating effects of attending schools nearby on

[10] Note that the differences in effects by race/ethnicity may reflect income differences across racial and ethnic subgroups within our low-income populations. Unfortunately, our data do not include information on household income, but future research exploring the heterogeneity across income groups within public housing and the relationship across racial subgroups is clearly warranted.

the relationship between proximity to fast food near home and weight outcomes are robust to different specifications for distance to school.

7. Discussion and Policy Implications

A wide range of policymakers, advocates, and "urbanists" blame the ease of access to unhealthy food outlets and particularly fast food as the culprit for high obesity rates among low income, minority children. There are, however, few credibly causal empirical findings on the effects of proximity to fast food on childhood obesity, mainly due to the endogenous nature of fast food locations and scarcity of the requisite micro-data linking children weight to the food environment. In this paper, we overcome the two key empirical obstacles using a detailed set of individual-level data on students living in public housing and exploiting their quasi-random assignment into micro-neighborhood food environments. Specifically, we use administrative data on NYC public school students living in public housing and link their weight outcomes and residential locations with all restaurant locations in NYC. We then leverage the plausibly random within-development variation in distance between residence and fast food generated by NYCHA's tenant assignment process to derive credibly causal estimates of the effects of living near fast food. To our knowledge, this is the first paper to use this particular identification strategy.

Our results suggest significant deleterious effects of proximity to fast food for student weight outcomes, with the largest effects among students in grades 3-8 attending neighborhood schools. Economic theory predicts that individuals with relatively higher travel costs are more sensitive to fast food availability in close proximity. Currie et al. (2010), for instance, find that proximity to fast food has larger effects on high school students than pregnant mothers, providing lower travel costs for adults as a potential explanation. In this paper, we exploit a detailed set of data on public housing students in all grades, and our results support the theory that living near fast food has larger impacts on younger students who are likely to have higher travel costs but old enough to make independent food purchasing decisions. In addition to heterogeneity across grade levels, students attending neighborhood schools are also likely to face higher costs traveling outside their residential neighborhood to purchase food, compared to students who attend schools far from home. We also find that students who travel shorter distances to school are more sensitive to fast food proximity in their micro-neighborhood environment. For students in grades 3-8 attending neighborhood schools, the probability of being obese (overweight) increases up to 1.7 (2.1) percentage points for every one tenth mile decrement in distance between home and fast food. These are sizable magnitudes, roughly representing a 12 percent increase in obesity rates (9.4 percent for overweight) for a four-block reduction in distance to the nearest fast food.

We note two key limitations of our study results. First, the location of fast food restaurants may be related to the availability of other neighborhood amenities that may affect student weight outcomes such that our estimates would reflect the combined effects of proximity to fast food and proximity to other unobserved amenities. However, it is reassuring - although not dispositive - that our results are robust to including controls for proximity to other food outlets. Second, our work focuses on public school children living in NYC public housing, a population disproportionately black, Hispanic, and urban. Investigating whether and how proximity to fast food affects higher-income students or those living in lower-density suburban and rural areas with greater reliance on cars remains for future research.

Our study results are particularly relevant to place-based interventions that attempt to limit unhealthy food outlets in an urban context to reduce the prevalence of obesity in low-income, minority neighborhoods. We suggest such interventions might include zoning regulations that restrict openings of fast food outlets in designated areas of a city. In a different vein, school policies regarding the quality or price of school lunch or "open-campus" policies governing student's ability to exit during school lunch periods might also be relevant. In summary, our findings suggest fast food locations near residence have sizable impacts on childhood obesity and warrant the attention of policymakers hoping to identify policy levers to reduce access to or consumption of fast food among poor, urban children.

References

Allcott, H., Diamond, R., Dubé, J. P., Handbury, J., Rahkovsky, I., & Schnell, M. (2019). Food deserts and the causes of nutritional inequality. *The Quarterly Journal of Economics, 134*(4), 1793-1844.

Alviola IV, P. A., Nayga Jr, R. M., Thomsen, M. R., Danforth, D., & Smartt, J. (2014). The effect of fast-food restaurants on childhood obesity: a school level analysis. *Economics & Human Biology*, *12*, 110-119.

Anderson, M. L., & Matsa, D. A. (2011). Are restaurants really supersizing America? *American Economic Journal: Applied Economics*, *3*(1), 152-88.

Athens, J. K., Duncan, D. T., & Elbel, B. (2016). Proximity to fast-food outlets and supermarkets as predictors of fast-food dining frequency. *Journal of the Academy of Nutrition and Dietetics*, *116*(8), 1266-1275.

Bellettini, G., & Kempf, H. (2013). Why not in your backyard? On the location and size of a public facility. *Regional Science and Urban Economics*, *43*(1), 22-30.

Berger, N., Kaufman, T. K., Bader, M. D., Rundle, A. G., Mooney, S. J., Neckerman, K. M., & Lovasi, G. S. (2019). Disparities in trajectories of changes in the unhealthy food environment in New York City: A latent class growth analysis, 1990–2010. *Social Science & Medicine*, *234*, 112362.

Bitler, M., & Haider, S. J. (2011). An economic view of food deserts in the United States. *Journal of Policy Analysis and Management*, *30*(1), 153-176.

Block, J. P., Scribner, R. A., & DeSalvo, K. B. (2004). Fast food, race/ethnicity, and income: a geographic analysis. *American Journal of Preventive Medicine*, *27*(3), 211-217.

Bridger, T. (2009). Childhood obesity and cardiovascular disease. *Pediatrics & Child Health, 14*(3), 177-182.

Chen, D., Jaenicke, E. C., & Volpe, R. J. (2016). Food environments and obesity: household diet expenditure versus food deserts. *American Journal of Public Pealth*, *106*(5), 881-888.

Coley, R. L., Sullivan, W. C., & Kuo, F. E. (1997). Where does community grow? The social context created by nature in urban public housing. *Environment and Behavior*, *29*(4), 468-494.

Currie, J., DellaVigna, S., Moretti, E., & Pathania, V. (2010). The effect of fast food restaurants on obesity and weight gain. *American Economic Journal: Economic Policy*, *2*(3), 32-63.

Cutler, D. M., Glaeser, E. L., & Shapiro, J. M. (2003). Why have Americans become more obese? *Journal of Economic Perspectives*, *17*(3), 93-118.

Davis, B., & Carpenter, C. (2009). Proximity of fast-food restaurants to schools and adolescent obesity. *American Journal of Public Health*, *99*(3), 505-510.

DeLuca, S., & Rosenbaum, J. E. (2003). If low-income blacks are given a chance to live in white neighborhoods, will they stay? Examining mobility patterns in a quasi-experimental program with administrative data. *Housing Policy Debate*, *14*(3), 305-345.

Dubowitz, T., Ghosh-Dastidar, M., Eibner, C., Slaughter, M. E., Fernandes, M., Whitsel, E. A., Bird, C. E., Jewell, A., Margolis, K. L., Li, W., Michael, Y. L., Shih, R. A., Manson, J. E., & Escarce, J. J. (2012). The Women's Health Initiative: The food environment, neighborhood socioeconomic status, BMI, and blood pressure. *Obesity*, *20*(4), 862-871.

Dunn, R. A. (2010). The effect of fast-food availability on obesity: an analysis by gender, race, and residential location. *American Journal of Agricultural Economics*, *92*(4), 1149-1164.

Dunn, R. A., Sharkey, J. R., & Horel, S. (2012). The effect of fast-food availability on fast-food consumption and obesity among rural residents: an analysis by race/ethnicity. *Economics & Human Biology*, *10*(1), 1-13.

Elbel, B., Tamura, K., McDermott, Z. T., Wu, E., & Schwartz, A. E. (2020). Childhood Obesity and the Food Environment: A Population-Based Sample of Public School Children in New York City. *Obesity*, *28*(1), 65-72.

Galvez, M. P., Morland, K., Raines, C., Kobil, J., Siskind, J., Godbold, J., & Brenner, B. (2008). Race and food store availability in an inner-city neighbourhood. *Public Health Nutrition, 11*(6), 624-631.

Gibson, D. M. (2011). The neighborhood food environment and adult weight status: estimates from longitudinal data. *American journal of public health*, *101*(1), 71-78.

Goux, D., & Maurin, E. (2007). Close neighbours matter: Neighbourhood effects on early performance at school. *The Economic Journal*, *117*(523), 1193-1215.

Lewis, L. B., Sloane, D. C., Nascimento, L. M., Diamant, A. L., Guinyard, J. J., Yancey, A. K., & Flynn, G. (2005). African Americans' access to healthy food options in South Los Angeles restaurants. *American Journal of Public Health*, *95*(4), 668-673.

McCarthy, P. S. (1999). Public policy and highway safety: a city-wide perspective. *Regional Science and Urban Economics*, *29*(2), 231-244.

Mehta, N. K., & Chang, V. W. (2008). Weight status and restaurant availability: a multilevel analysis. *American Journal of Preventive Medicine*, *34*(2), 127-133.

Mirtcheva, D. M., & Powell, L. M. (2009). Participation in the national school lunch program: Importance of school-level and neighborhood contextual factors. *Journal of School Health*, *79*(10), 485-494.

Morland, K. B., & Evenson, K. R. (2009). Obesity prevalence and the local food environment. *Health & Place*, *15*(2), 491-495.

Morland, K., Roux, A. V. D., & Wing, S. (2006). Supermarkets, other food stores, and obesity: the atherosclerosis risk in communities study. *American Journal of Preventive Medicine*, *30*(4), 333-339.

New York City Department of Education (2020). Transportation Eligibility. Retrieved from https://www.schools.nyc.gov/school-life/transportation/bus-eligibility.

New York City Housing Authority (2019). NYCHA 2019 Fact Sheet. Retrieved from https://www1.nyc.gov/assets/nycha/downloads/pdf/NYCHA-Fact-Sheet_2019_08-01.pdf

New York City Housing Authority (2020). Tenant Selection and Assignment Plan. Retrieved from https://www1.nyc.gov/assets/nycha/downloads/pdf/TSAPlan.pdf

Ogden, C. L., Carroll, M.D., Fakhouri, T. H., Hales, C. M., Fryar, C. D., Li, X., & Freedman, D. S. (2018). Prevalence of obesity among youths by household income and education level of head of household-United States 2011-2014. Morbidity and Mortality Weekly Report, 67(6), 186.

Oreopoulos, P. (2003). The long-run consequences of living in a poor neighborhood. *The Quarterly Journal of Economics*, *118*(4), 1533-1575.

Powell, L. M., Chaloupka, F. J., & Bao, Y. (2007). The availability of fast-food and full-service restaurants in the United States: associations with neighborhood characteristics. *American Journal of Preventive Medicine*, *33*(4), S240-S245.

Powell, L. M., Slater, S., Mirtcheva, D., Bao, Y., & Chaloupka, F. J. (2007). Food store availability and neighborhood characteristics in the United States. *Preventive Medicine*, *44*(3), 189-195.

Richardson, Andrea S., Janne Boone-Heinonen, Barry M. Popkin, and Penny Gordon-Larsen. "Are neighbourhood food resources distributed inequitably by income and race in the USA? Epidemiological findings across the urban spectrum." *BMJ open* 2, no. 2 (2012): e000698.

Rosenbaum, J. E. (1995). Changing the geography of opportunity by expanding residential choice: Lessons from the Gautreaux program. *Housing Policy Debate*, *6*(1), 231-269.

Sahoo, K., Sahoo, B., Choudhury, A. K., Sofi, N. Y., Kumar, R., & Bhadoria, A. S. (2015). Childhood obesity: causes and consequences. *Journal of Family Medicine and Primary Care*, *4*(2), 187.

U.S. Department of Housing and Urban Development. (2019). A picture of subsidized households, 2015-2019 [Data file]. Retrieved from https://www.huduser.gov/portal/datasets/assthsg.html.

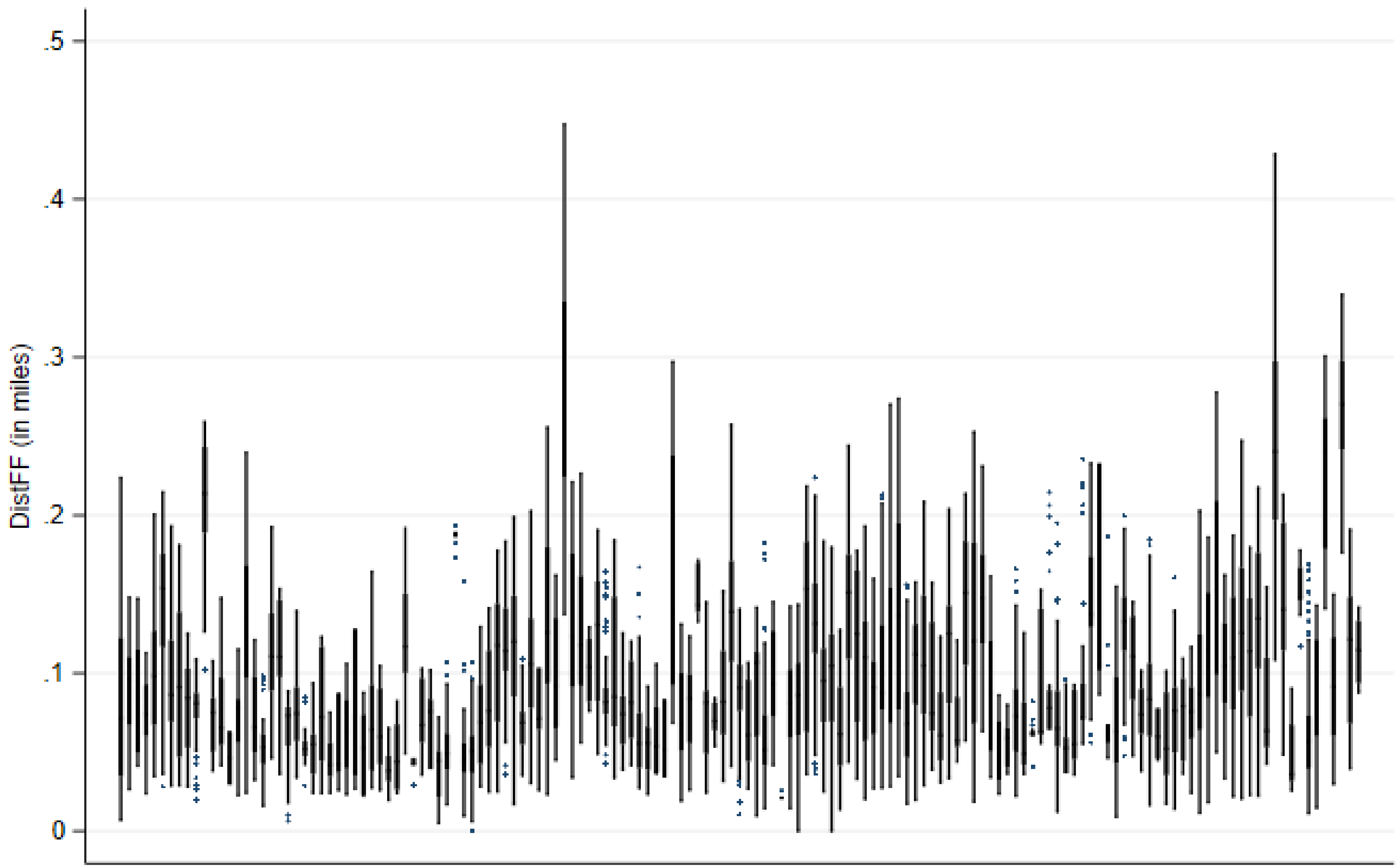
Weinhardt, F. (2014). Social housing, neighborhood quality and student performance. *Journal of Urban Economics*, *82*, 12-31.

Table 1. Mean student characteristics for all students and by grade level

	All grades (1)	Grades K-2 (2)	Grades 3-5 (3)	Grades 6-8 (4)	Grades 9-12 (5)
Weight outcomes					
Obese	0.232	0.214	0.270	0.256	0.195
	(0.422)	(0.410)	(0.444)	(0.436)	(0.396)
Overweight	0.409	0.380	0.448	0.445	0.370
	(0.492)	(0.485)	(0.497)	(0.497)	(0.483)
Distance to the nearest food outlet					
DistFF	0.099	0.099	0.099	0.100	0.099
	(0.056)	(0.056)	(0.056)	(0.057)	(0.056)
DistWaitService	0.212	0.213	0.212	0.215	0.211
	(0.168)	(0.169)	(0.167)	(0.172)	(0.164)
DistSupermarket	0.187	0.189	0.187	0.188	0.186
	(0.145)	(0.147)	(0.144)	(0.146)	(0.143)
DistCornerStore	0.096	0.096	0.096	0.097	0.096
	(0.067)	(0.067)	(0.067)	(0.068)	(0.066)
Distance to school attended					
DistSch	1.480	0.613	0.720	1.139	3.053
	(2.211)	(1.458)	(1.542)	(1.706)	(2.663)
SchNear	0.512	0.817	0.770	0.461	0.111
	(0.500)	(0.387)	(0.421)	(0.499)	(0.314)
SchNear36	0.641	0.893	0.854	0.685	0.235
	(0.480)	(0.309)	(0.353)	(0.465)	(0.424)
Student characteristics					
Female	0.515	0.508	0.520	0.520	0.513
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
Hispanic	0.474	0.474	0.475	0.477	0.469
	(0.499)	(0.499)	(0.499)	(0.500)	(0.499)
Asian	0.047	0.039	0.041	0.047	0.059
	(0.213)	(0.194)	(0.199)	(0.211)	(0.236)
Black	0.462	0.467	0.466	0.461	0.456
	(0.499)	(0.499)	(0.499)	(0.499)	(0.498)
White	0.017	0.020	0.018	0.015	0.015
	(0.128)	(0.138)	(0.131)	(0.123)	(0.121)
Grade	5.895	1.029	3.993	7.035	10.269
	(3.605)	(0.808)	(0.818)	(0.817)	(1.093)
Student with disability	0.188	0.157	0.201	0.203	0.190
	(0.391)	(0.364)	(0.401)	(0.402)	(0.392)
English language learner	0.075	0.089	0.084	0.069	0.063
	(0.264)	(0.284)	(0.278)	(0.253)	(0.244)
N	486,178	111,477	113,070	119,687	141,944

Notes: Standard deviations are shown in parentheses. Sample consists of NYC public school students, ever eligible for free and reduced-price lunch and living in NYCHA public housing, for AY 2009-2016. All distances are in miles.

Figure 1. Range of student-level distance to the nearest fast food restaurant, by public housing development



Notes: Each range plot shows student distance to the nearest fast food at the 5% and 95% of the distribution in a given development and the outliers through dots. Sample consists of NYC public school students, ever eligible for free and reduced-price lunch and living in NYCHA public housing, for AY 2009-2016.

Table 2. Relationship between student demographic characteristics and proximity to food outlets

Dependent variable:	DistFF (1)	DistWaitService (2)	DistSupermarket (3)	DistCornerStore (4)
Female	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Hispanic	-	-	-	-
Asian	0.000 (0.000)	-0.001* (0.001)	-0.002*** (0.001)	0.000 (0.000)
Black	0.001*** (0.000)	0.001** (0.000)	0.000 (0.000)	0.001*** (0.000)
White	-0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.000 (0.001)
Grades K-2	-	-	-	-
Grades 3-5	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Grades 6-8	0.001*** (0.000)	-0.000 (0.000)	0.001*** (0.000)	0.000* (0.000)
Grades 9-12	0.001*** (0.000)	-0.001 (0.000)	0.001*** (0.000)	0.000 (0.000)
N	486,178	486,178	486,178	486,178
Year FX	Y	Y	Y	Y
Development FX	Y	Y	Y	Y

Notes: Robust standard errors are shown in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).
Each column is a different regression. Sample consists of NYC public school students, ever eligible for free and reduced-price lunch and living in NYCHA public housing, for AY 2009-2016.

Table 3. Baseline impact of proximity to fast food on weight outcomes, K-12

Dependent variable:	Obese (1)	Obese (2)	Overweight (3)	Overweight (4)
DistFF	-0.058***	-0.062***	-0.093***	-0.111***
	(0.016)	(0.019)	(0.018)	(0.022)
N	486,178	486,178	486,178	486,178
Dist. to other food	-	Y	-	Y
Student characteristics	Y	Y	Y	Y
Year FX	Y	Y	Y	Y
Development FX	Y	Y	Y	Y

Notes: Robust standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1).
Each column is a different regression. Distance to other food include mile-distances to the nearest wait-service restaurant, supermarket, and corner stores. Student characteristics include gender, race/ethnicity, grade, primary language spoken at home, special education, and limited English proficiency status. Sample consists of NYC public school students, ever eligible for free and reduced-price lunch and living in NYCHA public housing, AY 2009-2016.

Table 4. Baseline impact of proximity to fast food on weight outcomes *by grade level*

Dependent variable:	Obese (1)	Obese (2)	Overweight (3)	Overweight (4)
Panel A: Grades K-2 only				
DistFF	0.000	0.023	-0.050	-0.065
	(0.032)	(0.039)	(0.037)	(0.046)
N	111,477	111,477	111,477	111,477
Panel B: Grades 3-5 only				
DistFF	-0.129***	-0.142***	-0.149***	-0.166***
	(0.034)	(0.042)	(0.038)	(0.047)
N	113,070	113,070	113,070	113,070
Panel C: Grades 6-8 only				
DistFF	-0.115***	-0.139***	-0.153***	-0.186***
	(0.032)	(0.040)	(0.037)	(0.045)
N	119,687	119,687	119,687	119,687
Panel D: Grades 9-12 only				
DistFF	-0.003	-0.001	-0.039	-0.044
	(0.027)	(0.033)	(0.033)	(0.040)
N	141,944	141,944	141,944	141,944
For all Panels:				
Dist. to other food	-	Y	-	Y
Student characteristics	Y	Y	Y	Y
Year FX	Y	Y	Y	Y
Development FX	Y	Y	Y	Y

Notes: Robust standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1).
Each column in each panel is a different regression. See notes in Table 3 for variable and sample descriptions.

Table 5. Impact of proximity to fast food on weight outcomes *by grade level and whether a student attends a school within 0.5 mile from home*

Dependent variable:	Obese (1)	Obese (2)	Overweight (3)	Overweight (4)
Panel A: Grades K-2 only				
DistFFxSchNear	-0.004	0.019	-0.059	-0.074
	(0.032)	(0.039)	(0.038)	(0.046)
DistFFxSchFar	0.017	0.041	-0.014	-0.029
	(0.039)	(0.045)	(0.046)	(0.053)
P-value for joint F-test	0.451	0.446	0.179	0.180
N	111,477	111,477	111,477	111,477
Panel B: Grades 3-5 only				
DistFFxSchNear	-0.144***	-0.158***	-0.174***	-0.191***
	(0.035)	(0.043)	(0.039)	(0.047)
DistFFxSchFar	-0.081**	-0.095**	-0.073	-0.090*
	(0.040)	(0.047)	(0.045)	(0.053)
P-value for joint F-test	0.026	0.026	0.046	0.045
N	113,070	113,070	113,070	113,070
Panel C: Grades 6-8 only				
DistFFxSchNear	-0.143***	-0.168***	-0.175***	-0.208***
	(0.036)	(0.043)	(0.041)	(0.048)
DistFFxSchFar	-0.096***	-0.120***	-0.139***	-0.171***
	(0.034)	(0.041)	(0.039)	(0.047)
P-value for joint F-test	0.061	0.059	0.203	0.195
N	119,687	119,687	119,687	119,687
Panel D: Grades 9-12 only				
DistFFxSchNear	-0.031	-0.029	-0.126**	-0.129**
	(0.043)	(0.047)	(0.052)	(0.057)
DistFFxSchFar	-0.001	0.001	-0.032	-0.036
	(0.027)	(0.034)	(0.033)	(0.041)
P-value for joint F-test	0.389	0.390	0.031	0.031
N	141,944	141,944	141,944	141,944
For all Panels:				
Dist. to other food	-	Y	-	Y
Student characteristics	Y	Y	Y	Y
Year FX	Y	Y	Y	Y
Development FX	Y	Y	Y	Y

Notes: Robust standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1).
Each column in each panel is a different regression. See notes in Table 3 for variable and sample descriptions. We test whether the coefficients for DistFFxSchNear and DistFFxSchFar are statistically different from each other and present the p-value of the joint F-test.

Table 6. Baseline impact of proximity to fast food on weight outcomes *by race/ethnicity*

Dependent variable:	Obese (1)	Obese (2)	Overweight (3)	Overweight (4)
Panel A: Asian only				
DistFF	-0.082 (0.060)	-0.058 (0.076)	-0.014 (0.080)	-0.016 (0.102)
N	22,912	22,912	22,912	22,912
Panel B: Hispanic only				
DistFF	-0.016 (0.024)	-0.045 (0.030)	-0.080*** (0.028)	-0.128*** (0.034)
N	230,252	230,252	230,252	230,252
Panel C: Black only				
DistFF	-0.105*** (0.022)	-0.090*** (0.027)	-0.117*** (0.026)	-0.108*** (0.031)
N	224,794	224,794	224,794	224,794
Panel D: White only				
DistFF	0.232* (0.121)	0.225 (0.146)	0.064 (0.141)	0.018 (0.170)
N	8,090	8,090	8,090	8,090
For all Panels:				
Dist. to other food	-	Y	-	Y
Student characteristics	Y	Y	Y	Y
Year FX	Y	Y	Y	Y
Development FX	Y	Y	Y	Y

Notes: Robust standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1).
Each column in each panel is a different regression. See notes in Table 3 for variable and sample descriptions.

Table 7. Baseline impact of proximity to fast food on weight outcomes *by gender*

Dependent variable:	Obese (1)	Obese (2)	Overweight (3)	Overweight (4)
Panel A: Male only				
DistFF	-0.113***	-0.112***	-0.108***	-0.116***
	(0.023)	(0.028)	(0.026)	(0.032)
N	235,740	235,740	235,740	235,740
Panel B: Female only				
DistFF	-0.004	-0.015	-0.074***	-0.104***
	(0.022)	(0.026)	(0.025)	(0.031)
N	250,438	250,438	250,438	250,438
For all Panels:				
Dist. to other food	-	Y	-	Y
Student characteristics	Y	Y	Y	Y
Year FX	Y	Y	Y	Y
Development FX	Y	Y	Y	Y

Notes: Robust standard errors are shown in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Each column in each panel is a different regression. See notes in Table 3 for variable and sample descriptions.

Appendix

Table A.1. Full results for the impact of proximity to food outlets on weight outcomes

Dependent variable:	Obese (1)	Overweight (2)
DistFF	-0.062*** (0.019)	-0.111*** (0.022)
DistWaitSerivce	0.004 (0.008)	-0.004 (0.009)
DistSupermarket	-0.000 (0.009)	-0.002 (0.011)
DistCornerStore	0.003 (0.017)	0.036* (0.020)
N	486,178	486,178
Student characteristics	Y	Y
Year FX	Y	Y
Development FX	Y	Y

Notes: Robust standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Each column is a different regression. See notes in Table 3.

Table A.2. Impact of proximity to fast food on weight outcomes, K-12, clustered standard errors

Dependent variable:	Obese (1)	Obese (2)	Overweight (3)	Overweight (4)
DistFF	-0.058** (0.029)	-0.062* (0.033)	-0.093*** (0.034)	-0.111*** (0.042)
N	486,178	486,178	486,178	486,178
Dist. to other food	-	Y	-	Y
Student characteristics	Y	Y	Y	Y
Year FX	Y	Y	Y	Y
Development FX	Y	Y	Y	Y

Notes: Standard errors are clustered at the development level and are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Each column is a different regression. See notes in Table 3 for variable and sample descriptions.

Table A.3. Impact of proximity to fast food on zBMI

Dependent variable:	zBMI (1)	zBMI (2)
DistFF	-0.266*** (0.043)	-0.245*** (0.053)
N	486,178	486,178
Dist. to other food	-	Y
Student characteristics	Y	Y
Year FX	Y	Y
Development FX	Y	Y

Notes: Robust standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Each column is a different regression. See notes in Table 3 for variable and sample descriptions.

Table A.4. Impact of proximity to fast food on weight outcomes, *using binary distance measures*

Dependent variable:	Obese (1)	Obese (2)	Overweight (3)	Overweight (4)
AnyFF	-0.006*** (0.002)	-0.006*** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)
N	486,178	486,178	486,178	486,178
Dist. to other food	-	Y	-	Y
Student characteristics	Y	Y	Y	Y
Year FX	Y	Y	Y	Y
Development FX	Y	Y	Y	Y

Notes: Robust standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1).
Each column is a different regression. See notes in Table 3 for variable and sample descriptions.

Table A.5. Impact of proximity to fast food on weight outcomes, *controlling for density measures*

Dependent variable:	Obese (1)	Obese (2)	Overweight (3)	Overweight (4)
Panel A: Baseline proximity measure controlling for density				
DistFF	-0.069*** (0.017)	-0.069*** (0.021)	-0.112*** (0.020)	-0.127*** (0.024)
NumFF10	-0.001** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
NumFF25	0.000* (0.000)	0.000 (0.000)	0.000* (0.000)	-0.000 (0.000)
N	486,178	486,178	486,178	486,178
Panel B: Alternative proximity measure controlling for density				
AnyFF	-0.008*** (0.002)	-0.008*** (0.002)	-0.009*** (0.002)	-0.009*** (0.002)
NumFF10	-0.001*** (0.000)	-0.001*** (0.000)	-0.001** (0.000)	-0.001*** (0.000)
NumFF25	0.000** (0.000)	0.000 (0.000)	0.000* (0.000)	0.000 (0.000)
N	486,178	486,178	486,178	486,178
For all Panels:				
Dist. to other food	-	Y	-	Y
Num. of other food	-	Y	-	Y
Student characteristics	Y	Y	Y	Y
Year FX	Y	Y	Y	Y
Development FX	Y	Y	Y	Y

Notes: Robust standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1).
Each column in each panel is a different regression. See notes in Table 3 for variable and sample descriptions.

Table A.6. Impact of proximity to fast food on weight outcomes *by grade level*, *controlling for distance to school*

Dependent variable:	Obese (1)	Obese (2)	Overweight (3)	Overweight (4)
Panel A: Grades K-2 only				
DistFF	0.001 (0.032)	0.024 (0.039)	-0.049 (0.037)	-0.065 (0.046)
DistSch	-0.001 (0.001)	-0.001 (0.001)	-0.002** (0.001)	-0.002** (0.001)
N	111,477	111,477	111,477	111,477
Panel B: Grades 3-5 only				
DistFF	-0.128*** (0.034)	-0.142*** (0.042)	-0.149*** (0.038)	-0.166*** (0.047)
DistSch	-0.002** (0.001)	-0.002** (0.001)	-0.001 (0.001)	-0.001 (0.001)
N	113,070	113,070	113,070	113,070
Panel C: Grades 6-8 only				
DistFF	-0.113*** (0.032)	-0.138*** (0.040)	-0.152*** (0.037)	-0.185*** (0.045)
DistSch	-0.002*** (0.001)	-0.002*** (0.001)	-0.001* (0.001)	-0.001* (0.001)
N	119,687	119,687	119,687	119,687
Panel D: Grades 9-12 only				
DistFF	-0.003 (0.027)	-0.001 (0.033)	-0.039 (0.033)	-0.044 (0.040)
DistSch	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
N	141,944	141,944	141,944	141,944
For all Panels:				
Dist. to other food	-	Y	-	Y
Student characteristics	Y	Y	Y	Y
Year FX	Y	Y	Y	Y
Development FX	Y	Y	Y	Y

Notes: Robust standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1).
Each column in each panel is a different regression. See notes in Table 3 for variable and sample descriptions.

Table A.7. Impact of proximity to fast food on weight outcomes *by grade level and whether a student attends a school within 1 mile from home*

Dependent variable:	Obese (1)	Obese (2)	Overweight (3)	Overweight (4)
Panel A: Grades K-2 only				
DistFFxSchNear36	0.003 (0.032)	0.026 (0.039)	-0.047 (0.038)	-0.063 (0.046)
DistFFxSchFar36	-0.021 (0.044)	0.002 (0.049)	-0.068 (0.052)	-0.083 (0.058)
N	111,477	111,477	111,477	111,477
Panel B: Grades 3-5 only				
DistFFxSchNear36	-0.134*** (0.035)	-0.148*** (0.043)	-0.161*** (0.039)	-0.179*** (0.047)
DistFFxSchFar36	-0.103** (0.044)	-0.116** (0.050)	-0.088* (0.049)	-0.105* (0.056)
N	113,070	113,070	113,070	113,070
Panel C: Grades 6-8 only				
DistFFxSchNear36	-0.115*** (0.034)	-0.139*** (0.041)	-0.153*** (0.038)	-0.186*** (0.046)
DistFFxSchFar36	-0.115*** (0.036)	-0.139*** (0.043)	-0.153*** (0.041)	-0.185*** (0.049)
N	119,687	119,687	119,687	119,687
Panel D: Grades 9-12 only				
DistFFxSchNear36	-0.039 (0.033)	-0.038 (0.038)	-0.086** (0.040)	-0.091* (0.047)
DistFFxSchFar36	0.007 (0.028)	0.008 (0.034)	-0.027 (0.033)	-0.031 (0.041)
N	141,944	141,944	141,944	141,944
For all Panels:				
Dist. to other food	-	Y	-	Y
Student characteristics	Y	Y	Y	Y
Year FX	Y	Y	Y	Y
Development FX	Y	Y	Y	Y

Notes: Robust standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1).
Each column in each panel is a different regression. See notes in Table 3 for variable and sample descriptions.

Table A.8. Impact of proximity to fast food on weight outcomes *by grade level and distance to school*

Dependent variable:	Obese (1)	Obese (2)	Overweight (3)	Overweight (4)
Panel A: Grades K-2 only				
DistFF	-0.002	0.021	-0.059	-0.075
	(0.033)	(0.040)	(0.039)	(0.047)
DistFFxDistSch	0.004	0.004	0.016	0.016
	(0.012)	(0.012)	(0.015)	(0.015)
DistSch	-0.001	-0.001	-0.004*	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
N	111,477	111,477	111,477	111,477
Panel B: Grades 3-5 only				
DistFF	-0.142***	-0.156***	-0.159***	-0.176***
	(0.036)	(0.043)	(0.040)	(0.048)
DistFFxDistSch	0.018	0.018	0.013	0.013
	(0.013)	(0.013)	(0.015)	(0.015)
DistSch	-0.004**	-0.004**	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
N	113,070	113,070	113,070	113,070
Panel C: Grades 6-8 only				
DistFF	-0.147***	-0.171***	-0.161***	-0.194***
	(0.035)	(0.042)	(0.040)	(0.048)
DistFFxDistSch	0.027**	0.027**	0.007	0.007
	(0.011)	(0.011)	(0.012)	(0.012)
DistSch	-0.006***	-0.006***	-0.002	-0.002
	(0.001)	(0.001)	(0.002)	(0.002)
N	119,687	119,687	119,687	119,687
Panel D: Grades 9-12 only				
DistFF	-0.039	-0.038	-0.080*	-0.085*
	(0.034)	(0.039)	(0.041)	(0.048)
DistFFxDistSch	0.011*	0.011*	0.012	0.013
	(0.007)	(0.007)	(0.008)	(0.008)
DistSch	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
N	141,944	141,944	141,944	141,944
For all Panels:				
Dist. to other food	-	Y	-	Y
Student characteristics	Y	Y	Y	Y
Year FX	Y	Y	Y	Y
Development FX	Y	Y	Y	Y

Notes: Robust standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1).
Each column in each panel is a different regression. See notes in Table 3 for variable and sample descriptions.