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Examining the Link Between Gentrification, Children's Egocentric Food Environment, and Obesity

Christopher Rick
Syracuse University, carick@syr.edu

Jeehee Han
Texas A&M, jeeheehan@tamu.edu

Spencer Shanholtz
Syracuse University, sashanho@syr.edu

Amy Ellen Schwartz
amyschwartz@syr.edu

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Christopher Rick, Jeehee Han*, Spencer Shanholtz, and Amy Ellen Schwartz

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426 Eggers Hall
Syracuse University
Syracuse, NY 13244-1020
T 315.443.3114 **E** ctrpol@syr.edu
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Abstract

While advocates argue that gentrification changes the neighborhood food environment critical to children's diet and health, we have little evidence documenting such changes or the consequences for their health outcomes. Using rich longitudinal, individual-level data on nearly 115,000 New York City children, including egocentric measures of their food environment and BMI, we examine the link between neighborhood demographic change ("gentrification") and children's access to restaurants and supermarkets and their weight outcomes. We find that children in rapidly gentrifying neighborhoods see increased access to fast food and wait-service restaurants and reduced access to corner stores and supermarkets compared to those in non-gentrifying areas. Boys and girls have higher BMI following gentrification, but only boys are more likely to be obese or overweight. We find public housing moderates the deleterious effect of gentrification on children's weight outcomes, possibly due to different changes to the food environment.

Keywords: Gentrification, Food Environment, Childhood Obesity, Public Housing

Authors: Christopher Rick, Center for Policy Research, Department of Economics, Syracuse University, carick@syr.edu; Jeehee Han*, Bush School of Government and Public Service, Texas A&M, jeeheehan@tamu.edu; Spencer Shanholtz, Center for Policy Research, Department of Economics, Syracuse University, sashanho@syr.edu; Amy Ellen Schwartz, Center for Policy Research, Department of Economics, Syracuse University, amyschwartz@syr.edu

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*Corresponding author

1. Introduction

As gentrification spreads through America's cities, neighborhood advocates lament the rise in restaurants and supermarkets catering to higher-income newcomers that displace those serving lower-income customers and with potential consequences for original residents, including children. Whether children's access to food stores - that is, their "egocentric food environment" - actually changes with gentrification is not well documented, and we know little about potential deleterious effects on children's health or weight. Indeed, the effect of an influx of higher-income, college-educated residents into low-income neighborhoods, or "gentrification," on children's food environment and weight is theoretically ambiguous. On one hand, gentrification may bring in supermarkets or restaurants offering healthier foods, such as high-end grocers, like Whole Foods, or salad chains, like Chop't and Sweetgreen, or reduce fast food options, which may improve children's diet and, ultimately, their weight (Couture et al., 2019). Gentrification may reduce neighborhood crime, encouraging exercise or frequent trips to grocery stores, which may improve children's diet and weight outcomes (Day et al., 2007). On the other hand, gentrification may drive out food outlets offering affordable, healthy food targeted to low-income households, as they are replaced by supermarkets catering to higher-income new residents (Pearsall, 2012; Meltzer, 2016). More generally, gentrification may mean rising rents - or other prices - that strain the budgets of low-income families and reduce their ability to purchase a healthy, nutritious diet. Yet, there is limited evidence on the effect of gentrification on children's health and obesity due, in part, to the scarcity of requisite data (Schnake-Mahl et al., 2020).

In this paper, we draw on rich, longitudinal data on New York City (NYC) public school students to examine the changes in children's weight and egocentric food environment in gentrifying and non-gentrifying neighborhoods. To do so, we link individual-level weight data to census-tract-level income and education measures and point-specific data on food outlets, including their type and location. While previous work typically relies upon census tract or neighborhood level measures of the food environment, we use addresses of food outlets and student residential locations[1] to provide precise, egocentric measures of each child's access to food outlets. Our sample includes more than 800,000 observations of nearly 115,000 NYC public school students, who were in grades K-5 and lived in low-income neighborhoods in 2010, continuously enrolled in NYC public schools until 2016. We use census-tract-level data to distinguish between neighborhoods that were rapidly gentrifying, moderately gentrifying, or non-gentrifying (i.e., persistently low-income) during this period.

Using a student fixed effects specification, we examine the extent to which children's food environment and weight outcomes changed more (or less) in rapidly gentrifying neighborhoods compared to moderately gentrifying or persistently low-income neighborhoods. These models will yield credibly causal estimates if, with student fixed effects and covariates, the weight outcomes of students living in the gentrifying neighborhoods would have evolved similarly to students living in persistently poor neighborhoods. We explore whether there are different changes following gentrification for students by gender or racial/ethnic subgroups. Finally, we compare students living in public housing to those in other types of housing to gauge the potential for public housing to protect students from the effects of gentrification on the food environment and weight outcomes.

We find that meaningful changes in students' egocentric food environment and weight outcomes accompany gentrification. Students in gentrifying neighborhoods see more fast food restaurants and fewer "corner stores" (retail food outlets less than 3,000 square feet) near home than students in persistently low-income neighborhoods. As for wait-service restaurants, we see increases in rapidly

[1] Residential latitude and longitude coordinates.

gentrifying neighborhoods but decreases in moderately gentrifying neighborhoods. We also find fewer supermarkets (retail food outlets at least 3,000 square feet) in rapidly gentrifying neighborhoods following gentrification, but a very small change in moderately gentrifying neighborhoods.

For weight, we find consistent evidence that the prevalence of children's obesity increases in rapidly gentrifying neighborhoods. Boys living in rapidly gentrifying neighborhoods are roughly 1.0 percentage points (pp) more likely to be obese - a roughly five percent increase from the average obesity rate of 23.3 percent - after five years than boys in persistently low-income neighborhoods. We find little evidence of a meaningful effect among girls. As for race/ethnicity, we find Asian and Hispanic students are most likely to experience the negative effects of gentrification than Black or White students. Specifically, Asian boys are roughly 3.0 pp more likely to be obese or overweight and Black and White girls in moderately gentrifying neighborhoods are 2.0 and 2.5 pp, respectively, less likely to be obese after five years compared to Hispanic peers in similar neighborhoods. Critically, we find no negative health effects of rapid gentrification for boys living in public housing; the probability of being obese is 1.2 pp lower than others in gentrifying neighborhoods but not in public housing, making the net effect close to zero. While we cannot disentangle the precise mechanisms, our results suggest public housing plays a role in moderating the negative effects of gentrification.

This study is, to our knowledge, the first to estimate the impact of gentrification on access to food for low-income students - that is, children's egocentric food environment - and consequences for weight outcomes. Using rich individual-level data, we explore the changes in the food environment and weight outcomes for children in gentrifying neighborhoods compared to those in persistently poor neighborhoods. We find that gentrification changes the food environment and negatively affects children's weight outcomes, suggesting is, gentrification's negative impact on children's health may work through changes in the food environment and may contribute to existing health disparities across racial groups. Further research exploring whether - and how - the changes in neighborhood resources wrought by gentrification affects neighborhood children - and residents more generally - is clearly warranted, as is strategic policymaking to mitigate those effects.

2. Background and Literature Review

2.1. Gentrification and the Food Environment

Despite the ubiquity of the term "gentrification" in the popular press and scholarly writing, there is no clear consensus about a precise definition among urban scholars. HUD (2016) describes gentrification as the "change that occurs when a traditionally low-income neighborhood experiences an influx of new higher-income residents." While past studies have adopted slightly different definitions of gentrification, most define gentrified neighborhoods as census tracts with initially low incomes that later have increases in household incomes and/or education (Dragan et al., 2019, 2020).[2] Note that the changes in neighborhood demographics may not imply displacement of original residents, as much of the previous research yields little evidence of displacement and finds that most low-income renters remain in their neighborhoods as incomes and rents rise (Dragan et al., 2020; Ding et al., 2016; Ellen & O'Regan, 2011; Freeman & Braconi, 2004; Vigdor et al., 2002).[3]

By changing a neighborhood's demographics, however, gentrification may change the lifestyle of existing residents through differences in amenity preferences (Hyra, 2015; Hyra et al, 2019), which may induce changes in the neighborhood food environment. Couture et al. (2019) suggest young, college-

[2] Most studies define neighborhoods as "low-income" with the potential to gentrify as census tracts with low mean or median household income ((Freeman, 2005; McKinnish et al., 2010; Ellen & O'Regan, 2011; Dragan et al. 2020). Neighborhoods are defined as gentrified if they have increases in median household income or college-educated population (Freeman, 2005; McKinnish et al., 2010; Ellen & O'Regan, 2011; Owens, 2012; Ding et al., 2016; Dragan et al., 2019, 2020).
[3] An exception, Brummet and Reed (2019) find a modest increase in displacement. More recent studies have turned to examine whether residentially stable, low-income residents are harmed – or benefit –from gentrification as their surroundings change (Dragan et al., 2019; Dastrup & Ellen, 2016).

educated newcomers may increase demand for new, healthier food options. Increased commercial activity may further encourage openings of food stores and change the retail food environment (Meltzer, 2016). Indeed, new restaurants openings and the evolution of food culture often serve as the first indicator of gentrification (Hyde, 2014; Anguelovski, 2015; Glaeser et al., 2018). Improved access to healthy food outlets may have positive health outcomes, as residents of neighborhoods with more supermarkets have been shown to have a healthier diet (e.g., higher intake of fruit and vegetables) and lower obesity rates (Elbel, 2020; Cobb et al., 2015; Bodor et al., 2010; Laraia et al., 2004). In other words, gentrification may bring more restaurants and grocery stores that increase residents' access to healthier food.

On the other hand, gentrification may bring in restaurants and food stores less affordable to low-income households and increase access to unhealthy food sources, like fast food restaurants. As neighborhoods gentrify and commercial rents increase, affordable food outlets serving marginalized, low-income residents may decline (Pearsall, 2012; Meltzer, 2016). At the same time, increased commercial activity may mean more may fast food restaurants or small grocery stores ("corner stores"). Unlike supermarkets, corner stores more likely stock prepared, high-calorie food and are less likely to offer fresh produce, which is often more expensive than less healthy options in corner stores (Lucan et al., 2010; Gebauer & Laska, 2011; Cavanaugh et al., 2013; Findholt et al., 2014).[4] Rhodes-Bratton et al. (2018) find that both healthy and unhealthy food options increase in gentrifying neighborhoods compared to other persistently low-income neighborhoods in NYC; however, they find no significant differences in childhood obesity rates.

[4] Corner stores are typically smaller stores than grocery stores or supermarkets. (Han et al., 2020). In this paper, supermarkets are defined as food stores larger than 3,000 square feet and corner stores as food stores with less than 3,000 square feet following previous work.

2.2. How Might the Food Environment Affect Residents' Health?

Changes to the food environment that follow gentrification may affect children's food consumption decisions by changing the food options available near home. Put simply, the changing proximity to healthy or unhealthy food may affect food purchasing and, ultimately, consumption. Previous research suggests that food purchasing decisions reflect both the monetary price and the value of lost time used to access or prepare the meal (Anderson & Matsa, 2011; Cutler et al., 2003). Closer proximity to nearby food outlets lowers the relative travel time and cost of purchasing food compared to those of purchasing food from elsewhere. For example, as the distance to fast food decreases, the time and cost of accessing fast food decreases, while the *relative* time and cost of purchasing healthier food increases. Thus, for two otherwise similar children living different distances to fast food, the child living closer to a fast food restaurant is more likely to purchase unhealthy fast food on a given day. Athens et al. (2016) find that closer proximity to fast food outlets and further proximity to supermarkets are predictors of increased fast food dining frequency. Indeed, quasi-experimental studies find compelling evidence that closer proximity to fast food closer at home or at school lead to increased risks of childhood obesity (Han et al., 2020; Alviola et al., 2014; Currie et al., 2010).[5]

For urban children, in particular, relatively small differences in proximity to food stores may be meaningful. While rural or suburban residents may rely upon cars to travel long distances to food outlets, urban residents are more likely to walk or rely upon public transportation to visit restaurants and food

[5] Note that there is conflicting evidence for whether the food environment is strongly associated with food-related behaviors for adults. While there is evidence of a weak relationship between proximity and grocery shopping decisions (Cobb et al. 2015), others find that household finances, more than proximity to markets, drive food decisions (French et al., 2010) or that consumers often consciously bypass stores in their neighborhood to shop at stores that sell more affordable or nutritious foods (Cannuscio et al., 2013).

stores, such that changing access by even a fraction of a mile may have a meaningful effect on travel time.[6] Previous work in NYC, for example, shows student weight outcomes are responsive to small differences in proximity to fast food. Han et al. (2020) find that, among children living in public housing, living two blocks (or 0.1 mile) closer to the nearest fast food restaurant significantly increases the probability of being obese by 5.4%. Elbel et al. (2020), drawing on data on more than 3.5 million observations of NYC public school students, find that living more than half of a city block (0.025 mile) from the nearest fast food restaurant is associated with obesity rates reduced by 2.5% to 4.4%.

The implications of a changing food environment, however, may differ across racial and ethnic subgroups due to differences in preferences, resources, or travel costs, among other potential differences. For example, ethnic cuisines differ in ingredients and may require further travel to specific grocery stores (Bitler & Haider, 2011). The loss of ethnic grocers in gentrifying neighborhoods may have particularly pernicious effects for low-income, minority populations. Nearby fast food may be a more cost-effective option for families if the alternative requires travel to distant stores. Therefore, changes in the food environment due to gentrification may have heterogeneous effects on children from different racial and ethnic subgroups.[7]

2.3. How Might Gentrification Affect Residents' Health?

In addition to the food environment, gentrification may change other aspects of a neighborhood related to residents' health. There may be infrastructure improvements in the neighborhoods, like additional - or better - parks or bike lanes, that promote healthy living or healthier environmental

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[6] Urban households may experience greater challenges reaching stores if they do not own cars and live far from transit. While 95% of highest income households use a personal car to shop for food, only 65%–68% of lowest income households do (Ver Ploeg et al. 2015).

[7] Previous descriptive works find that there are substantial race/ethnic disparities in BMI in the United States. Hispanic and Black children are disproportionately obese and have greater annual increases when compared to their White or Asian counterparts of the same socioeconomic status (Ogden et al. 2014; Krueger et al., 2014).

conditions. Gyms or other fitness establishments may open to cater to new residents but might also attract existing residents. Improved walkability, reduction in crime rates, and perceived safety may further encourage exercise and healthier food consumption. A survey-based study finds that street and apartment renovations, which often accompany gentrification, are associated with a significant increase in the perceived safety of children, as well as more frequent trips to the grocery store (Day et al., 2007).

Despite the considerable attention paid to the link between gentrification and neighborhood amenities, including the food environment, and the link between food environment and children's health, less attention has been paid to the direct link between gentrification and children's health. Rhodes-Bratton et al. (2018) use weight data for 5-year-olds in NYC and find no differences between children in gentrifying and non-gentrifying sub-borough areas.[8] Drawing on New York State Medicaid claims data, Dragan et al. (2019) examine health outcomes of nearly 72,000 children in NYC, ages 9-11. They compare the health outcomes of children who grew up in low-income neighborhoods that gentrified to those in persistently poor neighborhoods and find that living in a gentrifying neighborhood does not significantly change a child's probability of being clinically diagnosed as overweight or obese but contributes to marginal increases in being diagnosed with anxiety. These clinical data, however, may not capture effects on student weight away from the clinical thresholds or in children whose weight is not observed in Medicaid data. Further, relying on cross-sectional data and using individual-level covariates may be insufficient to control for unobservable differences between students. While this study provides benchmark measures of identifying gentrifying neighborhoods and the first insights into the effects of gentrification on children's health, we use annual weight data for students and individual fixed effects to account for unobservable differences to examine to investigate the link between gentrification and

[8]Sub-borough areas are geographical units similar to community districts.

children's health.

2.4. Gentrification, Housing, and Health

The net impacts of gentrification may depend not only on the changes in neighborhood amenities, including healthy (or unhealthy) food outlets, but also on the changing rent and what is left for households to spend on food. Low-income renters in gentrifying neighborhoods are likely to bear the cost of rising rents, which may result in a reduced amount of household income available for healthy food (Freeman & Braconi, 2004; Whittle et al., 2015).[9] Fletcher et al. (2009) find that increased rent of $500 per year is associated with an approximately three percentage point increase in food insecurity rate. Meyers et al. (2005) also find that children from renter households who receive housing subsidies are less likely to be undernourished than those from otherwise comparable households.

Families in public housing may, therefore, experience gentrification differently than market-rate renters (owners or other residents), as they are not subject to rising rents (Ellen & Captanian, 2020). In NYC, many public housing developments – built decades ago in predominantly low-income areas – are in neighborhoods that gentrified and now surrounded by relatively high-income households (Dastrup & Ellen, 2016).[10] Despite the prevalence of public housing in gentrifying neighborhoods, little is known about whether public housing residents have different health trajectories following gentrification than neighbors in private housing. Since the rent in public housing will not rise with gentrification, public housing may provide opportunities for recipient families to afford rent in gentrifying neighborhoods and

[9] Renters in subsidized housing spent less on health care than unassisted low-income renters did, suggesting that housing assistance leads to health benefits (Pfeiffer, 2018).

[10] Approximately 12 percent of housing units in gentrifying areas of the city are public housing units and an additional one-quarter are privately-owned subsidized housing (Ellen, 2018). Neighborhoods in NYC with public housing that experienced gentrification between 1990 and 2000 remain racially and economically integrated in 2016. This contrasts sharply with those neighborhoods without public housing that gentrified in the 1990s and are now predominantly white and high-income (Ellen & Torrats-Espinosa, 2019). Simply put, neighborhoods without public housing that gentrified early are less diverse than gentrified neighborhoods with public housing.

insulate them from the potentially negative effects of gentrification. However, public housing residents may suffer from the loss of amenities catering to low-income residents. Therefore, whether living in public housing or receiving housing subsidy moderates the impact of gentrification is an underexamined empirical question we aim to explore in this paper.

3. Data, Measures, and Sample

3.1. Student-Level Weight and Food Environment Data

We draw on a rich set of longitudinal, student-level data for NYC public school students, K-12, in AY 2010-2016, from the NYC Department of Education. Data include student residential location and height and weight measures from an annual FitnessGram®. We calculate Body Mass Index (*BMI*), standardized by the age and sex group as *z*-scores at the national level (*z-BMI*). In addition, we construct binary indicators for *obese* (BMI at or above the 95th percentile for their age and sex group) and *overweight* (BMI at or above the 85th percentile) based on Centers for Disease Control and Prevention guidelines. Data also include student-level sociodemographic data, including gender, race/ethnicity, grade, primary language spoken at home, educational program participation (e.g., English language learners and students with disabilities), and eligibility for free or reduced-price lunch, from which we construct an indicator, *Ever Poor*, identifying students eligible at least once between AY 2010-2016. In addition, we link student residential locations to data on the locations of New York City Housing Authority (NYCHA) buildings to create an identifier for students residing in public housing units (*PH* equals one for students in public housing).

Critically, we link student residential location to restaurant and food store locations to construct *egocentric* measures of each student's food environment. 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), and data on food stores (corner stores and supermarkets) from the New York State Department of Agriculture and Markets. Following Elbel et al. (2020) and Han et al. (2020), we focus on four types of food outlets: fast food restaurant, wait-service restaurant, corner store (less than 3,000 square feet), and large grocery/supermarket (larger than 3,000 square feet). We use two egocentric measures of access to each type of food outlet: the *number* of outlets within 0.25 mile (roughly five city blocks) from the student's home and the *distance* to the nearest food outlet from home (in feet).[11] All distances are calculated using network walking distances.

Note that these egocentric food environment measures are specific to student residential locations so there is variation within census tract in food environment and even on the same city block. While previous empirical work typically exploits variation across census tracts, our detailed data allow us to provide more nuanced implications for the changing food environment that may vary beyond typical definitions of neighborhood. Broadly, census-tract-level food environment data may less accurately represent the food environment salient for individual students. Census tracts can be quite large, such that in some less-dense tracts in the city, a food outlet more than three miles away from home could be captured in a child's food environment. Conversely, food outlets across the street from a student's house (but outside the census tract boundary) would not be included in a child's food environment using census tract measures. Using tract-level measures may mask large heterogeneity in child-level egocentric food environment, which we are able to capture using rich, detailed data in this study.

3.2. Measures of Gentrification and Mobility

To identify gentrifying neighborhoods, we use census-tract-level data from the 2010 and 2016

[11] We consider other buffers also widely used in the food environment literature, including 0.1 miles and 0.5 miles (160 and 800 meters), relevant for children and adolescents for robustness checks (Colabianchi et al., 2007; Timperio et al., 2004; Duncan et al., 2014; Currie et al., 2010; Han et al., 2020).

American Community Surveys from the U.S. Census. We define gentrification closely following Dragan et al. (2020) using mean income in 2010 to define census tracts as low-income and using the change in percentage of college educated between 2010 and 2016 to identify the influx of higher-income residents. We define gentrified neighborhoods as census tracts in the bottom half of the NYC mean income distribution in 2010 - instead of the bottom 40th percentile used in Dragan et al. (2020) - and with growth in the percentage of college educated in the top 25th percentile between 2010 and 2016. We create binary indicators *RapidGent* (rapidly gentrifying) and *ModGent* (moderately gentrifying), where *Rapidgent* equals one if the tract is in the top 10th percentile of the growth in college-educated share and *ModGent* equals one if the tract is between the top 10th and 25th percentiles. Initially low-income census tracts with growth in college-educated residents in the bottom 75th percentile are considered persistently low-income and are the comparison group.

We identify students living in rapidly or moderately gentrifying or persistently low-income based upon their location in 2010 - even if they have subsequently moved - and use their 2010 location to calculate their egocentric measures of proximity to food outlets. In this way, we include students in the rapidly gentrifying or moderately gentrifying group based on 2010 location even though they may have moved, because displacement may also be an effect of gentrification. This means that some students in the rapidly gentrifying group live through gentrification while others lived only a subset of the years in the gentrifying neighborhood. As detailed below, this may mean our empirical work measures "intent-to-treat" estimates of the difference between students living in gentrifying neighborhoods and in non-gentrifying neighborhoods and may yield conservative estimates of the "effect" of gentrification.

Similarly, the indicator for public housing (*PH*) is fixed to their 2010 residential location. Put simply, if they lived in public housing in 2010, we treat them as if they always lived in public housing. However, unlike the fixed measures of a student's neighborhood (e.g., *RapidGent*, *ModGent, or PH*), food environment measures for a student's fixed 2010 location change over time, because restaurants open, close, or move location. In this case, all changes to a student's food environment are attributed to changes in the locations of food outlets and not changes to residential location. In an alternate "treatment on the treated" specification, we exclude students from our analytic sample who move residential location - so that students in gentrifying neighborhoods are all exposed to gentrification in their neighborhood - to examine whether displacement changes our baseline estimates for gentrification's link with student food environment and weight outcomes.

3.3. Sample

Our analyses focus on the set of students enrolled in NYC public schools in grades K-5 that live in low-income neighborhoods in 2010 - our baseline year - and are continuously enrolled through 2016. Since we follow students for 6 years, student observations range in grade K-12. Our sample includes 800,555 observations of 114,365 students, examining the trajectory of their weight outcomes over the seven years between 2010 and 2016. To test whether the results are sensitive to the sample selection criteria, we explore two alternative samples. First is the sample of students in K-5 2010 cohorts and continuously enrolled through 2014 (145,390 students). Second is the sample of students in K-5 2010 cohorts and following them through 2016, whether or not they are continuously enrolled (243,630 students).

[Table 1]

Table 1 provides baseline summary statistics for our K-5 cohorts in 2010. Overall, 23.1 percent of our sample is obese, and 41.3 percent is overweight. Average z-BMI is 0.6. An average student has 14.5 fast food and 3.8 wait-service restaurants within one-quarter mile of their home, while they have 9.7 corner stores and about one supermarket within that distance. Unsurprisingly, given the higher number of fast food and corner stores, the average distance to the closest fast food restaurant is 634.6 feet (corner store is 604.1 feet) from home, compared to the closest wait-service restaurant that is 1,107 feet (supermarket is 1,303 feet) from home. Most students are either Hispanic (50.7%) or Black (23.8%). About 11.4 percent - 12,996 students - live in public housing. Nearly half move at least once between 2010 and 2016.

We see baseline differences in student's weight outcomes, food environment, and student characteristics by neighborhood type. Roughly 7.4 percent lived in census tracts that rapidly gentrify by 2016, 15.5 percent in tracts that moderately gentrify, and 77.1 percent in persistently low-income tracts. Students in rapidly gentrifying neighborhoods are less likely to be obese (20.2 percent) than those in persistently poor and moderately gentrifying tracts (23.3 and 23.5 percent). Students in rapidly gentrifying neighborhoods start off having higher average density of and closer proximity to fast food and wait-service restaurants than other students. Notably, there are nearly ten wait-service restaurants within a quarter mile of students in rapidly gentrifying neighborhoods, compared to about 3 for those in persistently poor areas. The density of and proximity to corner stores and supermarkets is similar on average across neighborhoods that gentrify. While most of our analytic sample are either Hispanic or Black, they are less likely to live in rapidly gentrifying neighborhoods (36.7 percent for Hispanic and 22.3 percent for Black). We see little difference in poverty or mobility by neighborhood, but smaller shares of public housing children in gentrifying neighborhoods - 12.4 percent of students in persistently poor tracts are in public housing, compared to 10 percent in moderately gentrifying and 3.9 percent in rapidly gentrifying tracts.

4. Empirical strategy

The centerpiece of our empirical work is a regression model linking measures of the food environment and weight outcomes to our gentrification indicators and student characteristics:

$$Y_{ict} = \beta_0 + \beta_1 \, RapidGent_c{*}Year_t + \beta_2 \, ModGent_c{*}Year_t + \beta_3 \, Year_t + \beta_4 \, X_{ict} + \delta_i + \tau_t + \varepsilon_{ict} \quad (1)$$

where Y_{ict} is the food environment or weight outcome measure for student *i* from census tract *c* in year *t*, such as fast food restaurants, wait-service restaurants, corner stores, or supermarkets within a quarter mile of home and student obesity, overweight, and z-BMI measures. All models include year fixed effects (τ_t) to account for any idiosyncratic shock in a given year; a time trend variable, *Year,* which captures commons trends from 2010 to 2016, measured from 0 to 6[12]; and student fixed effects (δ_i) to capture unobserved, time-invariant student characteristics, as well as a vector of time-varying student characteristics, X_{it}. *RapidGent and ModGent* are interacted with *Year* to capture trends in gentrifying neighborhoods. Note that the student fixed effects preclude the inclusion of *RapidGent* and *ModGent* directly, since they do not vary within student (by construction). Our main coefficient of interest, β_1, captures the average annual change in the food environment or weight outcomes for students in rapidly gentrifying neighborhoods over and above changes in persistently low-income neighborhoods (the omitted group). Put differently, β_1 captures the excess weight gain (or loss) among students in gentrifying neighborhoods compared to those in stable neighborhoods. Similarly, β_2 captures the average annual change in outcomes for students in moderately gentrifying neighborhoods. Notice that β_1 and β_2 can be viewed as an estimate of the impact of living in a gentrifying neighborhood if our student fixed effects and time-varying variables sufficiently control for selection into neighborhoods. In the presence of the

[12] Note that to estimate this model with both a time trend and year fixed effects we omit two of the year fixed effects. 2010 and 2011 are the omitted years.

covariates and student fixed effects, this yields credibly causal estimates of the impact of gentrification if - in the absence of gentrification - the weight outcomes of students living in the gentrifying neighborhoods would have evolved similarly to students in other neighborhoods.

Following the health literature, we stratify our sample by sex for all weight outcome models to separately examine the effects for girls and boys. We then explore heterogeneity in our coefficients of interest, β_1 and β_2, in two dimensions - first by the race of the students and second by residency in public housing. As discussed in earlier sections, the impact of gentrification and food environment may vary by student race and by housing. To be concrete, we interact gentrification indicators with three categorical race variables: Asian, Black, and White (Hispanic as the reference group). For public housing residency, we interact gentrification indicators with public housing residency, *PH*.

For robustness checks, we first re-estimate models using census tract fixed effects, η_c, and cohort fixed effects, γ_g, instead of student fixed effects to leverage variation in student egocentric food environment within census tracts, as well as their weight outcomes. Second, as described earlier, we examine the robustness of our results to an alternative set of samples that include students who are not continuously enrolled over our sample period. Finally, to explore whether the changes in the access to food resources mediate the relationship between gentrification and student health outcomes. We re-estimate weight models for residentially stable students with controls for a full set of food environment measures. We exclude students that move during the sample period from this robustness check because they are not exposed to the changing food environment.

5. Results

5.1. How Does the Food Environment Change After Gentrification?

[Table 2]

We find increased availability of restaurants - both fast food and wait-service - but decreased access to food stores - corner stores and supermarkets - in rapidly gentrifying neighborhoods. As shown in Table 2, columns 1-2, the number of fast food and wait-service restaurants within a quarter mile from home increases over time for students in rapidly gentrifying neighborhoods (an annual increase of 0.073 and 0.547, respectively), compared to students in persistently low-income neighborhoods. For example, over a five-year period, a neighborhood that rapidly gentrifies would have, on average, roughly one-third more fast food restaurants and three more wait-service restaurants near home than students in persistently low-income neighborhoods. Proximity measures show similar results (see columns 5-6), where students in rapidly gentrifying neighborhoods live closer to fast food and wait-service restaurants over time; for every year, distance to the nearest fast food and wait-service restaurants decreased by a modest 23 and 15 feet, respectively. On the contrary, the number of corner stores and supermarkets near students in rapidly gentrifying neighborhoods decreases (columns 3-4). These students also live further away from their nearest corner store, with no significant differences in their proximity to supermarkets (columns 7-8).

Findings are quite similar for moderately gentrifying neighborhoods in children's access to fast food restaurants and corner stores, but we find decreased availability of wait-service restaurants and improved access to large supermarkets. There are more fast food restaurants (0.062) and fewer corner stores (-0.055) for students in moderately gentrifying neighborhoods, relative to peers living in persistently low-income neighborhoods. The sign of the changes in access to these "unhealthy" food outlets are consistent with those for rapidly gentrifying census tracts. However, the number of wait-service restaurants decreases by 0.026 per year for students in moderately gentrifying tracts. More importantly, students live closer to the nearest supermarket by roughly 54 feet over a five-year period (annual change of more than 10 feet). The number of supermarkets also increases by 0.002 per year.

Taken together, these results suggest that students in both rapidly and moderately gentrifying neighborhoods have increased availability of fast food outlets near home. This trend, however, is less prominent in moderately gentrifying neighborhoods. There is also evidence of increased access to large supermarkets in moderately gentrifying neighborhoods, which are considered healthier food outlets than fast food restaurants. Thus, rapid gentrification appears to worsen the food environment for children, with mixed results for moderate gentrification, leading to our next empirical question of whether these changes in the food environment accompany changes in student weight outcomes.

5.2. Do Student Weight Outcomes Change with Gentrification?

[Table 3]

As shown in Table 3, we find a statistically significant relationship between gentrification and weight outcomes. Boys in rapidly gentrifying neighborhoods, in particular, have higher probabilities of being obese (0.002 pp higher every year) and overweight (0.003 pp), as well as higher z-BMI (0.009 standard deviation), compared to boys in persistently low-income tracts. These estimates are all statistically significant at conventional levels and translate to an increase in the probability of being obese and overweight by 1.0 pp (the coefficient 0.002 times 5) and 1.5 pp, respectively, and an increase in z-BMI by 0.045 standard deviation over a five-year period. To understand the magnitude of the estimates, a 1.2 pp increase translates to more than a five percent increase from the baseline obesity rate of 23.3 percent found in Table 1. Following rapid gentrification, girls have higher z-BMI (0.003 in column 6) than those in persistently low-income neighborhoods.

The negative health effects of gentrification seem to be concentrated only among students in rapidly gentrifying neighborhoods, as we find no meaningful, negative relationship between moderate gentrification and student health. While most coefficients are statistically insignificant, we find statistically significant, negative coefficients for female obesity (-0.001 in column 1) and male z-BMI outcomes (-0.003 in column 6). Results suggest a reduced incidence of obesity for girls and decreased z-BMI for boys in moderately gentrifying neighborhoods.

5.3. Do Weight Changes differ by Race?

[Table 4]

Results in Table 4 suggest the link between gentrification and weight outcomes differs across racial groups, with Hispanic and Asian children faring worse than White or Black children. For example, we find that, compared to Hispanic children, Black children in both rapidly and moderately gentrifying neighborhoods have lower risks of obesity and overweight. Black boys in rapidly gentrifying neighborhoods are less likely to be overweight (-0.004) and have lower z-BMI (-0.011). Black girls in moderately gentrifying neighborhoods have lower risks of being obese (-0.004) and overweight (-0.003), with a lower z-BMI (-0.010). The estimates are consistent in magnitude and direction among all Black students. For Asian students in rapidly gentrifying neighborhoods, we find boys are at higher risk of being obese (0.060 pp each year) compared to Hispanic boys in similar neighborhoods; we find consistently positive and statistically significant coefficients for obese, overweight, and z-BMI. For White children, we see the effects of gentrification concentrated on those in moderately gentrifying neighborhoods, specifically with a decrease in female obesity risk and in overweight and z-BMI for boys compared to their Hispanic counterparts.

We discuss in the literature review that ethnic minorities might be particularly vulnerable to changes in food stores near home, because ethnic cuisines may require travel to specific grocery stores (Bitler & Haider, 2011). Nearby fast food may become a more cost-effective option for families if the relative cost of grocery shopping increases for ethnic cuisines due to loss of ethnic grocers and increased availability of fast food restaurants in gentrifying neighborhoods. The heterogeneity in weight outcomes across racial subgroups may reflect the differential cost of changes to food access following gentrification.

5.4. How Do Students in Public Housing Fare?

[Table 5]

The changes in the food environment for public housing neighborhoods appear to offset the increased availability of restaurants or decreased availability of food stores that follow gentrification. In Table 5, we find that rapid gentrification decreases the number of fast food (-0.240) and wait-service (-0.248) restaurants available for public housing children over time, while rapid gentrification itself increases the availability of both restaurant types (0.098 and 0.540, respectively). These point estimates can be translated to roughly one fewer fast food restaurant and one fewer wait service restaurant within a quarter-mile from home for public housing children relative to other children in rapidly gentrifying neighborhoods over a five-year period. The nearest fast food and wait-service restaurants also become relatively farther away from public housing residents in rapidly gentrifying neighborhoods (columns 5-6). Despite decreased access to restaurants, public housing children have, on average, 2.5 more corner stores and corner stores 35 feet closer to home over a five-year period (columns 3 and 7) than children in other housing. While the number of supermarkets decreases for public housing children in rapidly gentrifying neighborhoods, they become closer by roughly 6 feet every year.

For moderately gentrifying neighborhoods, public housing children have increased access to food stores than peers in other housing. The number of corner stores and supermarkets within a quarter mile from home increases for public housing children (0.073 and 0.076, respectively), while moderate gentrification itself decreases the number (-0.063 and -0.006, respectively). Public housing children in moderately gentrifying neighborhoods also live closer to the nearest food stores, reducing the distance to the nearest supermarket by nearly 500 feet (or 1.5 city blocks) over the six years. The results are not sensitive to using different distance thresholds.

[Table 6]

Results in Table 6 show that the adverse health effects of gentrification (shown in Table 3) are moderated for students living in public housing. Boys in public housing and in rapidly gentrifying neighborhoods are less likely to be obese (-0.012) or overweight (-0.010) and have lower z-BMI (-0.024) over time, compared to peers in other housing. These estimates are all statistically significant at conventional levels. Girls in public housing in rapidly gentrifying neighborhoods also experience a statistically significant decrease in their z-BMI (-0.016) but little to no significant change in the incidence of obesity or overweight. Thus, public housing may insulate boys from the effects of gentrification more than girls, though girls are insulated from passing clinical thresholds for obese or overweight. Note that the estimated direct effects of rapid gentrification in Table 6 remain positive and statistically significant for boys' obesity and overweight outcomes and for both boys' and girls' z-BMI measures - similar to the baseline estimates seen in Table 3. The negative and statistically significant coefficients for public housing children, however, offset the adverse effects of rapid gentrification and suggest further reduction in the likelihood of childhood obesity.

Again, results for children in moderately gentrifying neighborhoods suggest the potentially positive role of public housing on weight outcomes. Girls in public housing are less likely to be overweight (-0.007) and both girls and boys have lower z-BMI (-0.019 and -0.011, respectively) than peers in other housing on the private market in moderately gentrifying neighborhoods. Differential changes to the food environment for children in public housing, as seen in Table 5, may play a part in moderating the negative weight effects of gentrification. However, when additionally controlling for students' food environment (see Appendix Table 6), the coefficients for gentrification among public housing children remain negative and statistically significant, suggesting that other features of public housing besides differential food access may contribute to the differential impact.

5.5. Robustness Checks

We conduct a series of robustness checks and find that our main results are not sensitive to alternative measures and specifications. First, we add census tract and cohort fixed effects - in place of student fixed effects - for food environment outcomes (Appendix Table 1) and weight outcomes (Appendix Table 2) to leverage variation within census tracts and cohorts. The results for the food environment outcomes are similar to our baseline results in Table 2, suggesting that unobserved individual characteristics are not significant confounders of any changes in the individual-level food environment. For weight outcomes, we also find similar results as our baseline results in Table 3, though some coefficients become statistically insignificant. These results in Appendix Table 2 may explain the null effects of gentrification on student weight found in previous studies - including Rhodes-Bratton et al. (2018) and Dragan et al. (2019) - that do not leverage individual fixed effects to control for unobserved, time-invariant differences between children.

Second, we re-estimate with a sample excluding students who move residential location (or "movers") to examine the extent to which displacement may change our baseline estimates for gentrification's impact on student food environment (Appendix Table 3) and weight (Appendix Table 4). As described earlier, in our main specification, we use each student's 2010 residential location to estimate an intent-to-treat effect of living in neighborhoods that eventually gentrify. As shown in Appendix Tables 3 and 4, results do not substantially differ from the baseline results in Tables 2 and 3, which have both movers and stayers in the model. In other words, the estimates from our main specification do not seem to be driven by the students who move to different neighborhoods in our study period, including – but not limited to – those who may be displaced by gentrification.

Third, we explore whether our results are robust to only including students enrolled for seven consecutive years in two different ways. First, we re-estimate the baseline models with a sample of students in grades K-5 in 2010 and are enrolled for five consecutive years (instead of seven) through 2014. This alternate sample has an addition of more than 30,000 unique students (from 114,365 students in our main analytic sample to 145,365). The shorter-term analyses using a larger set of students (in Appendix Tables 5 through 7) show similar point estimates but with modestly less precision. Second, we re-estimate our baseline models using all students enrolled in K-5 in 2010 (not requiring continuous enrollment) and including any of their observations throughout 2016; this alternate sample includes 243,360 unique students and over 1.3 million observations. In the analyses using a larger, unbalanced panel (in Appendix Tables 8 through 10), we find similar yet less precise estimates. Overall, our findings suggest that our main results are not sensitive to excluding students who do not continuously stay in the NYC public school system.

Finally, we explore the role of the food environment in mediating the effects of gentrification on children's weight outcomes, by controlling for the number of fast food restaurants, wait-service restaurants, corner stores, and supermarkets within a quarter mile from students' home. The estimates in Appendix Table 11 are similar, though the adverse health effects of gentrification are slightly larger in magnitude, to our baseline results in Table 3, which suggest that other changes in gentrifying neighborhoods affect children's weight outcomes in the same direction as the changes in the food environment. As seen in Appendix Table 12, we find nearly no difference in the effect of gentrification for children in public housing with or without food controls. Because the estimated effects of gentrification persist after controlling for the food environment, gentrification appears to affect children's weight outcomes in ways above and beyond changes to student egocentric food environment.

6. Conclusion and Policy Recommendations

As gentrification shapes cities across the US, advocates worry about negative changes the neighborhood food environment, with deleterious consequences for children's health. New restaurants and supermarkets may open, or existing food outlets may close to meet the demand of new residents (Hyde, 2014; Anguelovski, 2015; Glaesar et al., 2018; Couture et al., 2019). Gentrification may also increase commercial activity and subsequently change the neighborhood food scene (Meltzer, 2016). A separate body of literature suggest that the surrounding food environment has causal effects on children's obesity risks (Han et al., 2020). There is, however, little evidence linking the effects of gentrification on the food environment and the health outcomes for children in low-income neighborhoods.

In this paper, we document the changes in the food environment that follow gentrification in NYC neighborhoods and find meaningful differences between gentrifying and non-gentrifying neighborhoods. We find that the availability of fast food restaurants - considered obesogenic in previous food environment literature - increases for students living in rapidly gentrifying and moderately gentrifying neighborhoods relative to students in persistently low-income neighborhoods. However, the availability of supermarkets - considered healthy food outlets - also increases for children in moderately gentrifying neighborhoods (but not in rapidly gentrifying neighborhoods), potentially providing residents with healthier food options.

We use longitudinal student-level weight data, including obesity, overweight, and standardized BMI measures, and student egocentric food environment measures. We link these student-level data to indicators of whether their initial neighborhoods gentrify over time. Critically, we leverage student fixed effects models to control for underlying, unobserved differences between students in gentrifying and non-gentrifying neighborhoods. We find that children in rapidly gentrifying neighborhoods are more likely to be obese and overweight than their peers in persistently low-income neighborhoods. The negative health effects of rapid gentrification are largely driven by boys. However, we find some evidence of reduced obesity risks among girls in moderately gentrifying neighborhoods.

To shed light on the role of housing, we examine heterogeneity in gentrification's impact on children's weight by public housing residency. Our results suggest that children in public housing have relatively limited access to fast food and wait-service restaurants but improved access to corner stores and supermarkets over time than peers living elsewhere in similarly gentrifying neighborhoods. Further, public housing children are less likely to become obese or overweight than their peers in similarly gentrifying areas.

Despite the use of rich student-level food environment data, this paper does not capture nor assess the universe of neighborhood amenities that may explain the relationship between gentrification and student weight outcomes. Qualitative work suggests gentrification may change the lifestyle of existing residents through differences in amenity preferences, disruptions in existing social networks, and loss of political voice due to the influx of newcomers (Hyra, 2015; Hyra et al., 2019). For example, a basketball court valued by original neighborhood residents may not be valued by higher-income newcomers. Such shifts in cultural preferences for certain public amenities may occur during neighborhood gentrification and lead to changes in exercise facilities or opportunities, which relate to exercise and may affect children's weight outcomes (Drewnowski et al., 2020). While differences in the availability of exercise opportunities across neighborhoods would be captured through census tract fixed effects included in our robustness checks (Appendix Tables 1 and 2), gentrification may be correlated with unobservable changes in neighborhood amenities, which is an area for future work.

The unique role of subsidized housing in moderating the impact of gentrification is also an area for future study. Heterogeneity in the estimated effects of gentrification by housing (public housing vs. other) may be explained through various channels, including rent, neighborhood amenities (including the surrounding food environment), quality of housing units, and systematic differences between households in public housing and other low-income households in private housing. Families in public housing are not subject to rent increases associated with gentrification and may have relatively little change in disposable income to spend on food compared to families in private housing. Public housing residents may also have easier access to food assistance programs that reduce the cost of obtaining healthier food sources. Recent state government efforts to streamline and integrate existing policies and practices include enrolling eligible families in multiple public assistance programs at once, such as public or subsidized rental housing, Supplemental Nutrition Assistance Program (SNAP), Medicaid, and free or reduced-price lunch or breakfast in schools (Mills et al., 2011). Therefore, public housing residents may receive additional food assistance beneficial for their health, as SNAP benefits, for example, are shown to have positive health effects on participants (East, 2020). While we suggest potential underlying mechanisms through which public housing may moderate the impact of gentrification, further investigation and attention on the role of subsidized housing is warranted.

Our results are particularly relevant to urban planning, transportation, and housing authorities in fast-growing, lower-income areas that have gentrified or are undergoing gentrification. Understanding the consequences of changing neighborhood resources, including retail food outlets, has important implications for low-income residents and their children. Our study suggests gentrification may accelerate the existing health disparities at the disadvantage of children from low-income households. City planners should heed unregulated growth of commercial activities that may inadvertently increase the number of unhealthy food stores, such as fast food restaurants and corner stores, in gentrifying neighborhoods. Zoning and building incentives that encourage affordable grocery stores and supermarkets with fresh produce and dis-incentives for operating unhealthy food stores in low-income or gentrifying neighborhoods are policy options to consider. Other policy solutions include improving affordability and access to healthy food at corner stores that already operate in gentrifying neighborhoods and are likely to serve low-income, minority residents that remain in the area.

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Table 1. Student mean baseline 2010 characteristics by neighborhood type, K-5 cohort in 2010

	All	Neighborhood type: Persistently low-income	Moderately gentrifying ("*ModGent*")	Rapidly gentrifying ("RapidGent")
	(1)	(2)	(3)	(4)
Obese	23.1	23.3	23.5	20.2
Overweight	41.3	41.6	41.7	37.2
z-BMI	0.6	0.6	0.6	0.5
Number of food outlets within 1/4 mile				
Fast food	14.5	14.1	13.3	21.7
Wait-service	3.8	3.4	3.2	9.8
Corner stores	9.7	9.7	9.5	10.7
Supermarket	0.9	0.8	0.8	1.3
Distance to nearest food outlet (in feet)				
Fast food	634.6	637.1	644.6	587.2
Wait-service	1,107.3	1,121.5	1,108.0	958.5
Corner stores	604.1	608.0	584.5	603.6
Supermarket	1,302.6	1,292.3	1,355.0	1,299.8
Public housing	11.4	12.4	10.0	3.9
Ever moves	49.2	49.6	47.0	50.0
Female	51.3	51.4	51.2	51.3
Asian	18.2	17.8	16.1	26.0
Black	23.8	23.3	26.9	22.3
Hispanic	50.7	52.7	47.6	36.7
White	7.3	6.1	9.5	15.0
Ever poor	95.1	95.2	95.0	94.7
English language learner	19.8	20.6	17.1	17.1
Student with disabilities	9.3	9.3	9.5	9.0
Age	8.0	8.0	8.0	8.0
Grade	2.4	2.5	2.4	2.4
Manhattan	10.0	8.5	14.4	15.5
Bronx	27.5	32.3	14.2	5.9
Brooklyn	36.2	31.5	46.8	63.2
Queens	24.8	25.9	23.9	15.4
Staten Island	1.4	1.7	0.6	0.0
N Students	114,365	88,171	17,758	8,436
%	100.0	77.1	15.5	7.4
N Census tracts	1,046	766	182	98
%	100.0	73.2	17.4	9.4

Note: Sample consists of NYC public school students who were in grades K-5 in 2010, continuously enrolled between AY 2010 and 2016, who resided in census tracts in the bottom half of the income distribution in 2010.

Table 2. Results for student food environment, K-5 cohort in 2010, AY 2010-2016

DV:	Number of food outlets within 1/4 mile				Distance to nearest food outlet (in feet)			
	Fast food	Wait-service	Corner store	Supermarket	Fast food	Wait-service	Corner store	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RapidGent*Year	0.073***	0.547***	-0.121***	-0.028***	-3.937***	-2.511***	2.121***	-0.054
	(0.005)	(0.004)	(0.004)	(0.001)	(0.208)	(0.444)	(0.210)	(0.437)
ModGent*Year	0.062***	-0.026***	-0.055***	0.002***	-2.086***	7.383***	0.394***	-10.781***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.150)	(0.321)	(0.152)	(0.315)
Year	-0.162***	0.702***	0.313***	0.004***	0.556	-43.807***	-9.867***	2.705***
	(0.009)	(0.007)	(0.008)	(0.001)	(0.404)	(0.865)	(0.409)	(0.850)
DV Mean	14.2	3.5	9.9	0.9	632.5	1,137.3	596.2	1,295.9
N Observations	800,555	800,555	800,555	800,555	800,555	800,555	800,555	800,555
N Students	114,365	114,365	114,365	114,365	114,365	114,365	114,365	114,365
R2	0.976	0.978	0.961	0.917	0.952	0.911	0.955	0.907

Note: Standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample consists of NYC public school students who were in grades K-5 in 2010, continuously enrolled between AY 2010 and 2016, who resided in census tracts in the bottom half of the income distribution in 2010. All models include student fixed effects and year fixed effects. The main effects of *RapidGent* and *ModGent* are omitted, because they are time-invariant characteristics. Models include time-variant student characteristics on indicators for English language learners and students with disabilities.

Table 3. Results for student weight outcomes, K-5 cohort in 2010, AY 2010-2016

DV:	Obese		Overweight		z-BMI	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
RapidGent*Year	0.000	0.002***	0.001	0.003***	0.003**	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
ModGent*Year	-0.001*	0.001	-0.000	-0.000	-0.002	-0.003**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year	0.005***	0.005***	0.011***	0.011***	0.027***	0.013***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
DV Mean	0.21	0.26	0.40	0.45	0.64	0.73
N Observations	411,005	389,550	411,005	389,550	411,005	389,550
N Students	58,715	55,650	58,715	55,650	58,715	55,650
R2	0.723	0.713	0.724	0.707	0.814	0.798

Note: Standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample consists of NYC public school students who were in grades K-5 in 2010, continuously enrolled between AY 2010 and 2016, who resided in census tracts in the bottom half of the income distribution in 2010. All models include student fixed effects and year fixed effects. The main effects of *RapidGent* and *ModGent* are omitted, because they are time-invariant characteristics. Models include time-variant student characteristics on indicators for English language learners and students with disabilities.

Table 4. Results for student weight outcomes *by race/ethnicity*, K-5 cohort in 2010, AY 2010-2016

DV:	Obese		Overweight		z-BMI	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Asian						
RapidGent*Year	0.001	0.006***	0.006**	0.007***	0.014***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)
ModGent*Year	0.000	0.001	0.003	0.001	0.008**	-0.003
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Year	0.002***	-0.003***	-0.003***	-0.003***	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Black						
RapidGent*Year	-0.002	-0.001	-0.005**	-0.004*	-0.004	-0.011**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)
ModGent*Year	-0.004***	-0.000	-0.003**	-0.003**	-0.010***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
Year	0.006***	0.002***	0.007***	0.001	0.018***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
White						
RapidGent*Year	-0.000	0.004	-0.002	-0.002	0.004	0.001
	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.006)
ModGent*Year	-0.005***	-0.001	-0.003	-0.005**	-0.004	-0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)
Year	0.004***	0.003***	0.004***	0.005***	0.012***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
RapidGent*Year	0.000	0.000	0.001	0.003*	-0.000	0.006*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
ModGent*Year	0.000	0.001	0.000	0.000	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Year	0.003**	0.004***	0.010***	0.011***	0.022***	0.010***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
DV Mean	0.21	0.26	0.40	0.45	0.64	0.73
N Observations	411,005	389,550	411,005	389,550	411,005	389,550
N Students	58,715	55,650	58,715	55,650	58,715	55,650
R2	0.723	0.713	0.724	0.707	0.814	0.798

Note: Standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample consists of NYC public school students who were in grades K-5 in 2010, continuously enrolled between AY 2010 and 2016, who resided in census tracts in the bottom half of the income distribution in 2010. All models include student fixed effects and year fixed effects. The main effects of *RapidGent* and *ModGent* are omitted, because they are time-invariant characteristics. Hispanic students are the reference group omitted in the model. Models include time-variant student characteristics on indicators for English language learners and students with disabilities.

Table 5. Results for student food environment *by housing*, K-5 cohort in 2010, AY 2010-2016

DV:	Number of food outlets within 1/4 mile				Distance to nearest food outlet (in feet)			
	Fast food (1)	Wait-service (2)	Corner store (3)	Supermarket (4)	Fast food (5)	Wait-service (6)	Corner store (7)	Supermarket (8)
Public Housing								
RapidGent*Year	-0.240***	-0.248***	0.493***	-0.047***	6.803***	30.004***	7.185***	-6.180***
	(0.024)	(0.018)	(0.020)	(0.004)	(1.045)	(2.360)	(1.058)	(2.257)
ModGent*Year	-0.045***	0.049***	0.073***	0.076***	-13.460***	53.515***	-2.591***	-82.770***
	(0.011)	(0.008)	(0.009)	(0.002)	(0.491)	(1.109)	(0.497)	(1.061)
Year	0.191***	-0.218***	-0.084***	-0.006***	-0.718***	-12.552***	-8.429***	5.705***
	(0.004)	(0.003)	(0.003)	(0.001)	(0.187)	(0.421)	(0.189)	(0.403)
RapidGent*Year	0.098***	0.540***	-0.144***	-0.027***	-4.258***	-2.456***	1.184***	2.309***
	(0.005)	(0.004)	(0.004)	(0.001)	(0.212)	(0.480)	(0.215)	(0.459)
ModGent*Year	0.071***	-0.034***	-0.063***	-0.006***	-0.750***	2.280***	0.471***	-1.936***
	(0.004)	(0.003)	(0.003)	(0.001)	(0.158)	(0.357)	(0.160)	(0.342)
Year	-0.186***	0.729***	0.322***	0.005***	0.636	-45.136***	-8.899***	-0.061
	(0.009)	(0.007)	(0.008)	(0.001)	(0.405)	(0.914)	(0.409)	(0.874)
DV Mean	14.2	3.5	9.9	0.9	632.5	1,137.3	596.2	1,295.9
N Observations	800,555	800,555	800,555	800,555	800,555	800,555	800,555	800,555
N Students	114,365	114,365	114,365	114,365	114,365	114,365	114,365	114,365
R2	0.976	0.978	0.961	0.917	0.952	0.901	0.955	0.902

Note: Standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample consists of NYC public school students who were in grades K-5 in 2010, continuously enrolled between AY 2010 and 2016, who resided in census tracts in the bottom half of the income distribution in 2010. All models include student fixed effects and year fixed effects. The main effects of *RapidGent* and *ModGent* are omitted, because they are time-invariant characteristics. Students not living in public housing are the reference group omitted in the model. Models include time-variant student characteristics on indicators for English language learners and students with disabilities.

Table 6. Results for student weight outcomes *by housing*, K-5 cohort in 2010, AY 2010-2016

DV:	Obese		Overweight		z-BMI	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
*Public Housing**						
RapidGent*Year	0.002	-0.012***	0.003	-0.010**	-0.016**	-0.024***
	(0.003)	(0.004)	(0.004)	(0.005)	(0.008)	(0.009)
ModGent*Year	-0.000	-0.002	-0.007***	-0.002	-0.019***	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)
Year	0.002***	0.003***	0.004***	-0.001	0.007***	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Main Effects						
RapidGent*Year	0.000	0.003***	0.001	0.004***	0.005***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
ModGent*Year	-0.001	0.001**	0.001	-0.000	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year	0.004***	0.004***	0.011***	0.011***	0.026***	0.013***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
DV Mean	0.21	0.26	0.40	0.45	0.64	0.73
N Observations	411,005	389,550	411,005	389,550	411,005	389,550
N Students	58,715	55,650	58,715	55,650	58,715	55,650
R2	0.728	0.719	0.727	0.711	0.815	0.799

Note: Standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample consists of NYC public school students who were in grades K-5 in 2010, continuously enrolled between AY 2010 and 2016, who resided in census tracts in the bottom half of the income distribution in 2010. All models include student fixed effects and year fixed effects. The main effects of *RapidGent* and *ModGent* are omitted, because they are time-invariant characteristics. Students not living in public housing are the reference group omitted in the model. Models include time-variant student characteristics on indicators for English language learners and students with disabilities.

Appendix Table 1. Results for student food environment, *with census tract and cohort fixed effects*, K-5 cohort in 2010, AY 2010-2016

DV:	Number of food outlets within 1/4 mile				Distance to nearest food outlet (in feet)			
	Fast food (1)	Wait-service (2)	Corner store (3)	Supermarket (4)	Fast food (5)	Wait-service (6)	Corner store (7)	Supermarket (8)
RapidGent*Year	0.079***	0.550***	-0.115***	-0.027***	-4.636***	-2.246***	1.579***	-0.421
	(0.014)	(0.008)	(0.009)	(0.001)	(0.635)	(0.784)	(0.612)	(0.850)
ModGent*Year	0.062***	-0.025***	-0.054***	0.002**	-2.232***	7.496***	0.282	-10.862***
	(0.010)	(0.006)	(0.007)	(0.001)	(0.458)	(0.566)	(0.441)	(0.613)
Year	-0.090***	0.716***	0.379***	0.009***	-3.061**	-47.289***	-14.052***	0.314
	(0.028)	(0.017)	(0.018)	(0.003)	(1.256)	(1.550)	(1.209)	(1.680)
DV Mean	14.2	3.5	9.9	0.9	632.5	1,137.3	596.2	1,295.9
Student FE	No	No	No	No	No	No	No	No
Census tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N Observations	800,555	800,555	800,555	800,555	800,555	800,555	800,555	800,555
N Students	114,365	114,365	114,365	114,365	114,365	114,365	114,365	114,365
R2	0.741	0.848	0.752	0.559	0.477	0.678	0.552	0.589

Note: Standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample consists of NYC public school students who were in grades K-5 in 2010, continuously enrolled between AY 2010 and 2016, who resided in census tracts in the bottom half of the income distribution in 2010. All models include *census tract fixed effects, cohort fixed effects, and year fixed effects*. The main effects of *RapidGent* and *ModGent* are omitted, because they are time-invariant characteristics. Models include student characteristics, including race/ethnicity, indicators for English language learners and students with disabilities, and whether they were ever poor (eligible for free or reduced-price lunch).

Appendix Table 2. Results for student weight outcomes, *with census tract and cohort fixed effects*, K-5 cohort in 2010, AY 2010-2016

DV:	Obese		Overweight		z-BMI	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
RapidGent*Year	0.000	0.002*	0.001	0.003**	0.004	0.009**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)
ModGent*Year	-0.001	0.001	0.000	-0.000	-0.001	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
Year	0.007***	0.006**	0.015***	0.013***	0.037***	0.019***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)
DV Mean	0.21	0.26	0.40	0.45	0.64	0.73
Student FE	No	No	No	No	No	No
Census tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
N Observations	411,005	389,550	411,005	389,550	411,005	389,550
N Students	58,715	55,650	58,715	55,650	58,715	55,650
R2	0.035	0.034	0.042	0.035	0.056	0.044

Note: Standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample consists of NYC public school students who were in grades K-5 in 2010, continuously enrolled between AY 2010 and 2016, who resided in census tracts in the bottom half of the income distribution in 2010. All models include student fixed effects and year fixed effects. The main effects of *RapidGent* and *ModGent* are omitted, because they are time-invariant characteristics. Models include time-variant student characteristics on indicators for English language learners and students with disabilities.

Appendix Table 3. Results for student food environment, *excluding movers*, K-5 cohort in 2010, AY 2010-2016

DV:	Number of food outlets within 1/4 mile				Distance to nearest food outlet (in feet)			
	Fast food (1)	Wait-service (2)	Corner store (3)	Supermarket (4)	Fast food (5)	Wait-service (6)	Corner store (7)	Supermarket (8)
RapidGent*Year	0.109***	0.395***	-0.147***	-0.020***	-4.732***	-3.586***	1.890***	-1.314**
	(0.007)	(0.005)	(0.005)	(0.001)	(0.289)	(0.621)	(0.298)	(0.616)
ModGent*Year	0.068***	-0.016***	-0.048***	0.005***	-2.612***	7.281***	0.548***	-12.291***
	(0.005)	(0.003)	(0.004)	(0.001)	(0.203)	(0.437)	(0.210)	(0.434)
Year	-0.150***	0.674***	0.281***	0.005***	1.185**	-43.349***	-10.279***	2.671**
	(0.013)	(0.009)	(0.010)	(0.002)	(0.558)	(1.200)	(0.576)	(1.191)
DV Mean	13.3	5.0	10.8	0.9	657.6	1,030.0	598.4	1,274.3
N Observations	406,511	406,511	406,511	406,511	406,511	406,511	406,511	406,511
N Students	29,575	28,498	29,575	28,498	29,575	28,498	29,575	28,498
R2	0.975	0.975	0.961	0.916	0.955	0.913	0.956	0.907

Note: Standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample consists of NYC public school students who were in grades K-5 in 2010, continuously enrolled between AY 2010 and 2016, who resided in census tracts in the bottom half of the income distribution in 2010 *and did not move residential location between AY 2010 and 2016*. All models include student fixed effects and year fixed effects. The main effects of *RapidGent* and *ModGent* are omitted, because they are time-invariant characteristics. Models include time-variant student characteristics on indicators for English language learners and students with disabilities.

Appendix Table 4. Results for student weight outcomes, *excluding movers*, K-5 cohort in 2010, AY 2010-2016

DV:	Obese		Overweight		z-BMI	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
RapidGent*Year	-0.001	0.002	-0.000	0.004***	0.001	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
ModGent*Year	-0.001	-0.001	-0.000	-0.000	-0.003**	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Year	0.005***	0.008***	0.013***	0.012***	0.028***	0.012**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)
DV Mean	0.21	0.26	0.41	0.46	0.64	0.74
N Observations	207,025	199,486	207,025	199,486	207,025	199,486
N Students	29,575	28,498	29,575	28,498	29,575	28,498
R2	0.728	0.717	0.730	0.709	0.819	0.802

Note: Standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample consists of NYC public school students who were in grades K-5 in 2010, continuously enrolled between AY 2010 and 2016, who resided in census tracts in the bottom half of the income distribution in 2010 *and did not move residential location between AY 2010 and 2016*. All models include student fixed effects and year fixed effects. The main effects of *RapidGent* and *ModGent* are omitted, because they are time-invariant characteristics. Models include time-variant student characteristics on indicators for English language learners and students with disabilities.

Appendix Table 5. Results for student food environment, K-5 cohort in 2010, *AY 2010-2014*

DV:	Number of food outlets within 1/4 mile				Distance to nearest food outlet (in feet)			
	Fast food	Wait-service	Corner store	Supermarket	Fast food	Wait-service	Corner store	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RapidGent*Year	-0.153***	0.588***	-0.129***	-0.043***	-4.609***	-0.098	2.134***	-2.482***
	(0.007)	(0.005)	(0.006)	(0.001)	(0.304)	(0.652)	(0.315)	(0.648)
ModGent*Year	0.066***	-0.039***	-0.042***	0.001	-4.623***	10.377***	-1.086***	-10.654***
	(0.005)	(0.003)	(0.004)	(0.001)	(0.218)	(0.468)	(0.226)	(0.465)
Year	-0.125***	0.662***	0.318***	0.008***	1.017***	-45.210***	-9.771***	2.753***
	(0.008)	(0.005)	(0.007)	(0.001)	(0.355)	(0.760)	(0.367)	(0.756)
DV Mean	13.4	4.6	10.7	0.8	643.3	1,050.6	586.4	1,279.8
N Observations	726,950	726,950	726,950	726,950	726,950	726,950	726,950	726,950
N Students	145,390	145,390	145,390	145,390	145,390	145,390	145,390	145,390
R2	0.977	0.980	0.958	0.919	0.956	0.921	0.958	0.915

Note: Standard errors are shown in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). Sample consists of NYC public school students who were in grades K-5 in 2010, continuously enrolled *between AY 2010 and 2014*, who resided in census tracts in the bottom half of the income distribution in 2010. All models include student fixed effects and year fixed effects. The main effects of *RapidGent* and *ModGent* are omitted, because they are time-invariant characteristics. Models include time-variant student characteristics on indicators for English language learners and students with disabilities.

Appendix Table 6. Results for student weight outcomes, K-5 cohort in 2010, *AY 2010-2014*

DV:	Obese		Overweight		z-BMI	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
RapidGent*Year	-0.000	0.001	0.002*	0.002	0.001	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
ModGent*Year	-0.000	0.001	0.001	-0.002*	-0.003	-0.004*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Year	0.001	-0.002	0.006*	0.000	0.025***	-0.001
	(0.002)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)
DV Mean	0.21	0.26	0.40	0.46	0.63	0.76
N Observations	311,013	298,822	311,013	298,822	311,013	298,822
N Students	74,393	70,997	74,393	70,997	74,393	70,997
R2	0.766	0.760	0.763	0.750	0.835	0.818

Note: Standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample consists of NYC public school students who were in grades K-5 in 2010, continuously enrolled *between AY 2010 and 2014*, who resided in census tracts in the bottom half of the income distribution in 2010. All models include student fixed effects and year fixed effects. The main effects of *RapidGent* and *ModGent* are omitted, because they are time-invariant characteristics. Models include time-variant student characteristics on indicators for English language learners and students with disabilities.

Appendix Table 7. Results for student weight outcomes *by housing*, K-5 cohort in 2010, *AY 2010-2014*

DV:	Obese		Overweight		z-BMI	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Public Housing						
RapidGent*Year	0.002	-0.008	-0.005	-0.010	-0.018	-0.053***
	(0.005)	(0.006)	(0.007)	(0.007)	(0.013)	(0.014)
ModGent*Year	0.000	0.001	-0.012***	-0.000	-0.027***	-0.024***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.006)	(0.007)
Year	0.002**	0.002	0.004***	-0.004***	0.008***	-0.005*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
RapidGent*Year	-0.000	0.002	0.003**	0.002	0.003	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
ModGent*Year	-0.000	0.001	0.002*	-0.002*	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Year	0.001	-0.003	0.005*	0.001	0.024***	-0.000
	(0.002)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)
DV Mean	0.21	0.26	0.40	0.46	0.63	0.76
N Observations	311,013	298,822	311,013	298,822	311,013	298,822
N Students	74,393	70,997	74,393	70,997	74,393	70,997
R2	0.766	0.760	0.763	0.750	0.835	0.818

Note: Standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample consists of NYC public school students who were in grades K-5 in 2010, continuously enrolled *between AY 2010 and 2014*, who resided in census tracts in the bottom half of the income distribution in 2010. All models include student fixed effects and year fixed effects. The main effects of *RapidGent* and *ModGent* are omitted, because they are time-invariant characteristics. Students not living in public housing are the reference group omitted in the model. Models include time-variant student characteristics on indicators for English language learners and students with disabilities.

Appendix Table 8. Results for student food environment, *unbalanced panel*, K-5 cohort in 2010, AY 2010-2016

DV:	Number of food outlets within 1/4 mile				Distance to nearest food outlet (in feet)			
	Fast food	Wait-service	Corner store	Supermarket	Fast food	Wait-service	Corner store	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RapidGent*Year	0.075***	0.495***	-0.141***	-0.027***	-4.099***	-1.785***	2.246***	-0.339
	(0.004)	(0.003)	(0.003)	(0.001)	(0.176)	(0.389)	(0.177)	(0.370)
ModGent*Year	0.054***	-0.021***	-0.045***	0.001**	-2.403***	8.837***	-0.064	-9.684***
	(0.003)	(0.002)	(0.002)	(0.000)	(0.125)	(0.275)	(0.125)	(0.262)
Year	-0.100***	0.600***	0.323***	0.008***	1.087***	-46.091***	-10.416***	2.890***
	(0.007)	(0.005)	(0.006)	(0.001)	(0.301)	(0.665)	(0.302)	(0.633)
DV Mean	13.1	4.5	10.8	0.9	648.2	1,063.5	582.3	1,274.5
N Observations	1,313,281	1,313,281	1,313,281	1,313,281	1,313,281	1,313,281	1,313,281	1,313,281
N Students	243,630	243,630	243,630	243,630	243,630	243,630	243,630	243,630
R2	0.976	0.977	0.962	0.918	0.955	0.914	0.958	0.912

Note: Standard errors are shown in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). Sample consists of NYC public school students who were in grades K-5 in 2010, *present anytime between AY 2010 and 2016*, who resided in census tracts in the bottom half of the income distribution in 2010. All models include student fixed effects and year fixed effects. The main effects of *RapidGent* and *ModGent* are omitted, because they are time-invariant characteristics. Models include time-variant student characteristics on indicators for English language learners and students with disabilities.

Appendix Table 9. Results for student weight outcomes, *unbalanced panel*, K-5 cohort in 2010, AY 2010-2016

DV:	Obese		Overweight		z-BMI	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
RapidGent*Year	-0.001	0.001	-0.000	0.002**	-0.000	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
ModGent*Year	-0.000	0.001*	0.001	-0.001	-0.000	-0.003**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Year	0.002	-0.002	0.007***	0.001	0.027***	-0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.005)	(0.005)
DV Mean	0.21	0.25	0.40	0.44	0.64	0.73
N Observations	579,624	565,066	579,624	565,066	579,624	565,066
N Students	122,263	121,367	122,263	121,367	122,263	121,367
R2	0.766	0.760	0.763	0.750	0.835	0.818

Note: Standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample consists of NYC public school students who were in grades K-5 in 2010, *present anytime between AY 2010 and 2016*, who resided in census tracts in the bottom half of the income distribution in 2010. All models include student fixed effects and year fixed effects. The main effects of *RapidGent* and *ModGent* are omitted, because they are time-invariant characteristics. Models include time-variant student characteristics on indicators for English language learners and students with disabilities.

Appendix Table 10. Results for student weight outcomes *by housing*, *unbalanced panel*, K-5 cohort in 2010, AY 2010-2016

DV:	Obese		Overweight		z-BMI	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Public Housing						
RapidGent*Year	0.000	-0.005	0.001	-0.005	-0.013*	-0.021***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.007)	(0.008)
ModGent*Year	0.002	-0.002	-0.008***	-0.003	-0.013***	-0.017***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Year	0.002***	0.002***	0.003***	-0.001	0.008***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RapidGent*Year	-0.001	0.001**	0.000	0.002**	0.001	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
ModGent*Year	-0.000	0.001**	0.001**	-0.001	0.001	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year	0.002	-0.002	0.006**	0.001	0.025***	-0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.005)	(0.005)
DV Mean	0.21	0.25	0.40	0.44	0.64	0.73
N Observations	579,624	565,066	579,624	565,066	579,624	565,066
N Students	122,263	121,367	122,263	121,367	122,263	121,367
R2	0.745	0.739	0.744	0.731	0.827	0.813

Note: Standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample consists of NYC public school students who were in grades K-5 in 2010, *present anytime between AY 2010 and 2016*, who resided in census tracts in the bottom half of the income distribution in 2010. All models include student fixed effects and year fixed effects. The main effects of *RapidGent* and *ModGent* are omitted, because they are time-invariant characteristics. Students not living in public housing are the reference group omitted in the model. Models include time-variant student characteristics on indicators for English language learners and students with disabilities.

Appendix Table 11. Results for student weight outcomes, *controlling for food environment*, K-5 cohort in 2010, AY 2010-2016, excluding movers

DV:	Obese		Overweight		z-BMI	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
RapidGent*Year	-0.001	0.002**	0.000	0.004***	0.003	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
ModGent*Year	-0.001	-0.001	-0.000	-0.000	-0.003**	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Year	0.005**	0.008***	0.012***	0.012***	0.028***	0.012**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)
DV Mean	0.21	0.26	0.40	0.45	0.64	0.73
Controls for food environment	Yes	Yes	Yes	Yes	Yes	Yes
N Observations	207,025	199,486	207,025	199,486	207,025	199,486
N Students	29,575	28,498	29,575	28,498	29,575	28,498
R2	0.728	0.718	0.730	0.709	0.819	0.802

Note: Standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample consists of NYC public school students who were in grades K-5 in 2010, continuously enrolled between AY 2010 and 2016, who resided in census tracts in the bottom half of the income distribution in 2010 *and did not move residential location between AY 2010 and 2016*. All models include student fixed effects and year fixed effects. The main effects of *RapidGent* and *ModGent* are omitted, because they are time-invariant characteristics. Models include time-variant student characteristics on indicators for English language learners and students with disabilities, as well as the number of fast food restaurants, wait-service restaurants, corner stores, and supermarkets within a quartile mile from students' home.

Appendix Table 12. Results for student weight outcomes *by housing, controlling for food environment*, K-5 cohort in 2010, AY 2010-2016, excluding movers

DV:	Obese		Overweight		z-BMI	
	Female (1)	Male (2)	Female (3)	Male (4)	Female (5)	Male (6)
Public Housing						
RapidGent*Year	0.005	-0.009	0.007	-0.005	-0.005	-0.027**
	(0.005)	(0.006)	(0.006)	(0.006)	(0.011)	(0.013)
ModGent*Year	-0.002	0.002	-0.011***	0.001	-0.020***	-0.006
	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)	(0.006)
Year	0.002**	0.002**	0.003***	-0.002*	0.005***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
RapidGent*Year	-0.001	0.003***	0.000	0.004***	0.003	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
ModGent*Year	-0.001	-0.001	0.001	-0.000	-0.001	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Year	0.005**	0.008***	0.012***	0.012***	0.027***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)
DV Mean	0.21	0.26	0.40	0.45	0.64	0.73
Controls for food environment	Yes	Yes	Yes	Yes	Yes	Yes
N Observations	207,025	199,486	207,025	199,486	207,025	199,486
N Students	29,575	28,498	29,575	28,498	29,575	28,498
R2	0.728	0.718	0.730	0.709	0.819	0.802

Note: Standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample consists of NYC public school students who were in grades K-5 in 2010, continuously enrolled between AY 2010 and 2016, who resided in census tracts in the bottom half of the income distribution in 2010 *and did not move residential location between AY 2010 and 2016*. All models include student fixed effects and year fixed effects. The main effects of *RapidGent* and *ModGent* are omitted, because they are time-invariant characteristics. Models include time-variant student characteristics on indicators for English language learners and students with disabilities, as well as the number of fast food restaurants, wait-service restaurants, corner stores, and supermarkets within a quartile mile from students' home.