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Body mass index in elementary school children, metropolitan area food prices and food outlet density

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Summary *Objective*: The aim of this study was to examine the association between food prices and food outlet density and changes in the body mass index (BMI) among elementary school children in the USA.
Methods: The Early Childhood Longitudinal Study followed a nationally representative sample of kindergarten children over 4 years. We merged individual-level data to (a) metropolitan data on food prices and (b) per capita number of restaurants, grocery stores and convenience stores in the child's home and school zip code. The dependent variables were BMI changes over 1 and 3 years. We analysed mean changes with least-squares regression, and median changes and 85th percentile changes with quantile regression. We controlled for baseline BMI, age, real family income and sociodemographic characteristics.
Results: Lower real prices for vegetables and fruits were found to predict a significantly lower gain in BMI between kindergarten and third grade; half of that effect was found between kindergarten and first grade. Lower meat prices had the opposite effect, although this effect was generally smaller in magnitude and was insignificant for BMI gain over 3 years. Differences across subgroups were not statistically significant due to smaller sample sizes in subgroup analyses, but the estimated effects were meaningfully larger for children in poverty, children already at risk for overweight or overweight in kindergarten, and Asian and Hispanic children. There were no significant effects for dairy or fast-food prices, nor for outlet density, once we had controlled for individual characteristics and random intercepts to adjust standard errors for the sampling design.
Discussion: The geographic variation in fruit and vegetable prices is large enough to explain a meaningful amount of the differential gain in BMI among elementary school children across metropolitan areas. However, as consumption information was not

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available, we cannot confirm that this is the actual pathway. We found no effects of food outlet density at the neighbourhood level, possibly because availability is not an issue in metropolitan areas.

Introduction

Childhood overweight has increased rapidly over the past two decades,[1,2] and concerns about childhood obesity have reached the highest levels of policy making in the USA, as well as in the UK and other industrialized countries. Legislation considered by the US Congress includes the 'Improved Nutrition and Physical Activity Act', or 'IMPACT', which earmarks funds for programmes that create 'opportunities for students to make informed choices regarding healthy eating behaviours' and increase after-school physical activity. Although it is generally believed that local food supply characteristics, such as relative prices of different types of foods and outlet density, affect what children eat, there has been no study of national scope on the relationship between the change in children's body mass index (BMI) and local food supply characteristics in the USA nor, as far as we know, in other countries.

We examined how the variation in real prices (i.e. US$ prices relative to cost of living) of different types of foods across localities and the variation in food outlet density in children's neighbourhoods relates to changes in BMI between kindergarten and third grade. The data analysed were from the Early Childhood Longitudinal Study—Kindergarten Class (ECLS-K), a nationally representative dataset for the USA that followed a cohort of kindergarten children from the 1998–1999 school year, merged with zip-code-level data on food outlets from the Census and metropolitan-level data on food prices from the American Chambers of Commerce Researchers Association (ACCRA).

Differential availability and affordability of foods have been suggested as important contributors to income and racial/ethnic disparities in obesity rates. The poor tend to live in areas with fewer large supermarkets and more convenience and small stores, which can result in higher prices for comparable items.[3] US studies ranging back to the 1960s have consistently found that large suburban supermarkets have the lowest prices, and small grocery stores and convenience stores have the highest prices.[3] For some neighbourhoods, the opening of a supermarket can be a major event. The announcement of plans to build a large supermarket in downtown Los Angeles, an area that has been without a large supermarket for decades, warranted an article in the *Los Angeles Times*[4] several years before this supermarket is likely to open. Higher food prices (as well as limited product selection) at convenience stores and small stores could lead to consumption of foods with higher energy density, which are much cheaper for the same amount of calories than fresh fruit or vegetables.[5,6] At the same time, the energy density of a diet has also been implicated as a cause of obesity.[5-7] Drewnowski and Specter concluded that the lower prices per calorie for energy-dense foods contribute to higher obesity rates among lower-income populations.[5]

Economic models suggest that lower food prices will increase consumption. Economists typically assume that this will automatically increase caloric intake. One study attributed the largest share of weight gain among adult Americans to an increase in the number of restaurants per capita over time, and a secondary role to the relative prices for all foods.[8] However, insights from the nutrition field suggest that increased consumption of low-energy foods might actually lower caloric intake.[5-7] Increased fruit consumption, for example, has been linked to a lower BMI.[9] However, economic studies of obesity have not yet distinguished between types of food, such as price changes for fresh produce compared with meats, which is a central hypothesis in the nutrition field.[5]

Thus, it is not clear whether geographic variation in prices or supply can account for any noticeable differences in weight across populations. This paper will focus on weight gain among children. We tested whether prices for different types of food at the metropolitan level, and the type and density of food outlets (grocery stores, convenience stores, fast-food restaurants and full-service restaurants) in a child's neighbourhood (defined by home and school zip codes) are associated with differential rates of BMI change. We also tested whether effects differ by race/ethnicity, gender, poverty status or children at risk for becoming overweight.

Methods

The individual-level data came from the ECLS-K, which surveyed a nationally representative cohort of kindergarten children from over 1000 schools in the USA during the 1998–1999 school year. The sample was selected using a multistage cluster sampling design, where schools were selected first, followed by selection of children within schools. The ECLS-K is a panel dataset that collected baseline data in the autumn of kindergarten (Wave 1) followed by additional waves in the spring of kindergarten (Wave 2), the autumn of first grade (Wave 3), the spring of first grade (Wave 4), and the spring of third grade (Wave 5). In each wave, the ECLS-K collected information on children's anthropometric outcomes, as well as detailed data on parental background characteristics, sociodemographics and lifestyles. The most complete height/weight data were collected in the three spring surveys (Waves 2, 4, and 5), which we use here. Unlike studies that rely on self-reported measures of height and weight (such as the Behavioural Risk Factor Surveillance System), the ECLS-K measured children's height and weight at each data collection point. The ECLS-K collected data on the change in BMI between kindergarten and third grade for 13,282 children.

The major advantage over other national surveys is that we had access to detailed geographic identifiers, including zip (postal) codes for the children's schools and homes. We used this geographic information to merge zip code, metropolitan- and county-level characteristics with individual-level data.

The two main datasets for obtaining contextual information were the US Census Bureau's 1999 Zip Code Business Patterns files and the ACCRA food price data. The statistics issued, by industry, in the Zip Code Business Patterns are classified by the 1997 North American Industry Classification System. Supermarkets are distinguished from convenience stores at the five-digit classification; other specialty food markets and convenience stores or food markets that are part of a gasoline station have separate codes. Similar breakdowns distinguish between full-service restaurants and limited-service ('fast-food') restaurants. We merged these data on food outlets with the individual-level data from the ECLS-K using home zip codes and, in alternate models, school zip codes. For this analysis, the main explanatory variable was the food supply outlet in the child's home or, in the alternative specifications, the child's school zip code. Fewer full grocery stores and more convenience stores with limited availability of fresh produce in the neighbourhood may reduce consumption of fresh produce, since individuals may need to travel longer distances or experience a longer waiting time in order to obtain that food. At the same time, greater availability of fast-food restaurants relative to full-service restaurants would reduce the time opportunity costs of consuming fast-food.

The second source of contextual data was the ACCRA data (formerly 'American Chamber of Commerce Researchers Association') for food prices. The ACCRA data have been published quarterly since 1968 and are the premier source of data on cost-of-living differentials in about 311 metropolitan areas in the USA. They do not distinguish possible price variations across neighbourhoods within a city, and the smallest geographic unit available is either a city or metropolitan area. For the price analysis, the main explanatory variables were relative food prices in a child's home city or metropolitan area. We used price data from the fourth quarter in 1999, which corresponds to the autumn of first grade in the ECLS-K data and therefore best describes prices between baseline (spring of kindergarten) assessment of BMI and spring of first grade follow-up. We also constructed price indices for different food groups for the full calendar year and discussed how this affects the results.

The ACCRA food price information consists of a grocery price list containing 63 items, 16 for specific foods at home, which we grouped into three categories: (1) meats (T-bone steak, ground beef, sausage, tuna, frying chicken); (2) fruits and vegetables (potatoes, bananas, lettuce, sweet peas, tomatoes, peaches, frozen corn); and (3) dairy products (1/2 gallon milk, 12 eggs, margarine, parmesan). We created a fourth index for food away from home, based on three items collected in the ACCRA data: the average price of a McDonald's quarter-pounder with cheese (collected for at least five different restaurants if there were more than five in the area or at all McDonald's in the area if there were less than five); the average price of an 11′–12′ thin crust regular cheese pizza (no extra cheese) at Pizza Hut and/or Pizza Inn; and the average price of a fried chicken drumstick and thigh at Kentucky Fried Chicken and/or Church's Fried Chicken (lowest price is reported, whether with or without 'extras'). The prices of each of the component foods were available at the MSA level. Price indices for each of the above food groups were constructed for each area as follows. We first computed the weighted average of prices of items in the food group. The weights were based on the item's share in the consumer basket for meats, dairy, and fruits and vegetables. For the fast-food group, we simply averaged the three items in that group. Next, we created an index that captured the price of the weighted basket in each area relative to the average for all areas (set at 100). Finally, we divided the above quantity by the overall cost-of-living index for the area to get a measure of relative food prices in real terms. For example, food prices in Boston are relatively low because the overall cost of living (and especially housing prices) is high, as is per capita income. We merged these price indices with individual-level data from the ECLS-K by Metropolitan Statistical Area (MSA). The overall cost-of-living index ranged from 86 to 137. There was one noticeable anomaly, namely Manhattan/New York city, with a cost-of-living index of 240. When excluding New York city, the estimated effect of food prices becomes slightly larger in magnitude; we show these results in a sensitivity analysis.

The ACCRA data have a number of limitations, but there appears to be no better data source that has a similarly comprehensive regional coverage. The first limitation in the ACCRA data that cannot be circumvented without new primary data collection is that prices are averaged over large geographic areas, so no data are available for neighbourhood definitions within a city. Establishments from which data are collected are not necessarily representative and are likely to be biased towards higher-income households. Other limitations are sampling errors and non-coverage of some areas, especially less-urbanized areas, and different areas are covered in different time periods. ACCRA indices are not comparable over time and reporting also varies; therefore, we could not exploit price variation over time. As a consequence of incomplete price information in the ACCRA data (many children live outside areas for which ACCRA provides data), our sample size was reduced from 13,282 to 7651 children with data on BMI in kindergarten and third grade, and price data. Due to missing data for other variables, the main analysis was based on 6918 children (8008 children if BMI changes between kindergarten and first grade alone were analysed). These children attended schools in 724 different school zip codes, which were located in 59 metropolitan areas in 37 states.

Dependent and explanatory variables

Our main dependent variable was the change in BMI (weight in kilograms divided by height in metres squared) between spring of kindergarten and spring of third grade. We also analysed how BMI changed within the first year, i.e. between spring of kindergarten and spring of first grade. Although height and weight were measured by the study team, coding and data entry errors still occurred (such as reversing, omitting or doubling digits), resulting in some extreme BMIs (e.g. under 10 or over 40) and corresponding changes. Although random errors in dependent variables do not create biases in very large samples, results in any finite sample are sensitive to gross data errors. We therefore omitted the largest and smallest changes (1%) from the analysis.

Our two sets of primary explanatory variables were: (a) price indices for meat, fruits and vegetables, dairy, and fast-food, standardized to have a standard deviation of 1, in the MSA of residence; and (b) per capita number of grocery stores, convenience stores, full-service restaurants, fast-food restaurants, and the ratio of grocery stores to convenience stores and of full-service restaurants to fast-food restaurants in the residence zip code. We initially estimate dseparate models, and later considered sensitivity analyses including both simultaneously. We also analysed characteristics of the school zip code (rather than residence zip code), but results are essentially identical because most elementary school children live in the same zip code as their school. This may be different for adolescents in high schools, which are larger and more centralized than elementary schools.

We controlled for individual characteristics in all cases, including baseline BMI (spring of kindergarten), birth weight, real family income (income adjusted by the cost of living in the area), sex, mother's educational achievement (four categories) and race/ethnicity. To take into account the likely non-linear effects of income, we used linear splines with knots at the 25th, 50th and 75th percentile of real income. The measure of real income was total family income, not per capita income. In addition, all our models included parent-reported typical hours per day of television watching, parent-reported days per week of physical activity, hours per week of physical education in school, and number of activities that parent participates in with the child, such as reading, storytelling etc. These variables were measured at the baseline, i.e. spring of kindergarten. Omitting the top and bottom 1% of BMI changes and missing data on other covariates resulted in a final sample size of 6918 when analysing BMI change between kindergarten and third grade, and 8008 when analysing BMI change between kindergarten and first grade.

All models were estimated using STATA 8.0.[10] The survey design sampled children clustered in schools within geographic regions, and we used hierarchical (multilevel) models with school random effects to adjust for correlations across observations within the same area for mean (i.e. least-squares) regression. We also conducted sensitivity analyses using non-parametric clustering adjustment and different cluster specifications (home zip code, MSA). We studied how effects differ at different parts of the BMI distribution, and used quantile regression for the median and 85th percentile. No software is available to adjust standard errors for the survey design in quantile regression, and we therefore report these results as a sensitivity test. We have also reported results from subgroup analyses. Point estimates are unbiased and provide the best estimate of an effect size; however, because the sample sizes were small, even substantively large effects could not be detected reliably.

Results

Table 1 shows BMI changes for boys and girls. The average gain between spring of kindergarten and third grade for all children in the analysis sample was 2.15 BMI units and the median gain was 1.5 units. Even in kindergarten, the median (50th percentile) BMI in the ECLS-K sample was about 0.5 units heavier than the 50th percentile of the growth chart. The growth charts are based on historical representative data for the USA collected prior to the obesity epidemic and are widely used by physicians to assess children's physical progress.[11] This gap between the 50th percentile in the ECLS-K sample and the 50th percentile in the growth chart widened by the end of first grade, and more than doubled by the end of third grade to 1.3 BMI units for boys and 1 BMI unit for girls.

Table 2 shows the descriptive statistics for the analysis sample. The standard deviation in our price indices was normalized to 1, which will make the estimates easier to interpret. However, the range across cities in the USA is substantial; the maximum in our data was about twice as large as the minimum (or 4.3 standard deviations higher). Unstandardized, the minimum and maximum values were 0.67 and 1.23 for meats, 0.56 and 1.22 for dairy, 0.704 and 1.26 for fruits and vegetables, and 0.46 and 1.21 for fast-food.

For the multivariate analysis, we focused initially on price indices and tested whether there were interactions between the price indices and race/ethnicity and poverty; however, the coefficients were not significant as a set, nor was any single coefficient significant (the point estimates, however, differed by a meaningful amount and we therefore show stratified results in Table 4). We tested food price groups simultaneously and found that dairy or fast-food prices were never significant at $P<0.10$ in any initial specification. Table 3 shows the results for our final specification that excluded dairy and fast-food prices, and did not include interactions between prices and sociodemographics. The price index for fruits and vegetables was highly significant, indicating that increasing fruit and vegetable prices by one standard deviation would raise the BMI by 0.11 BMI units [95% confidence interval (CI): 0.05, 0.18] by third grade; about half of that effect occurred in the first year between kindergarten and first grade (0.054 units; 95% CI 0.01, 0.10). The coefficients on meat prices had the opposite sign, but were not statistically significant in a 3-year analysis.

Individual characteristics had the expected sign. In particular, heavier children at baseline were more likely to experience a greater increase in BMI ($P<0.001$); older children gained more ($P=0.004$); girls gained more than boys ($P<0.001$); black children gained significantly more than white children or other minorities ($P<0.001$); children whose mother had completed college gained less ($P=0.007$); and children who watched more television gained more ($P=0.001$). One-year changes (kindergarten to first grade) were generally consistent with the 3-year results, but because the effect sizes were smaller, they were statistically significant less often. Maternal education and race, for example, became insignificant in the short-run analysis.

Table 4 shows a number of alternative specifications to test the sensitivity of results. The estimated magnitude of fruit and vegetable prices was robust to changes in: merging prices to home or school zip code; including or excluding dairy and fast-food prices; the type of adjusting for

Table 1 Increase in body mass index (BMI) over time.

	Boys ($n=3489$)			Girls ($n=3427$)		
	Mean	Median	50th percentile growth chart	Mean	Median	50th percentile growth chart
BMI in kindergarten	16.4	16.0	15.4	16.3	15.8	15.2
BMI in first grade	16.8	16.2	15.5	16.7	16.1	15.5
BMI in third grade	18.5	17.5	16.2	18.5	17.4	16.4

Note: unweighted for estimation sample.

Table 2 Descriptive statistics for sample ($n=6918$).

Variable and definition	Mean	SD
Continuous individual variables		
Age in months at kindergarten assessment	74.6	4.33
Days/week that child gets exercise that causes rapid breathing, perspiration, and a rapid heartbeat for 20 continuous minutes or more (spring of kindergarten)	3.85	2.21
Hours/day that child watches television (spring of kindergarten)	2.01	1.15
No. of activities (up to nine) that parent participates in with the child (autumn of kindergarten)	7.51	2.62
Hours/week of physical education instruction in school (spring of kindergarten)	1.01	0.84
Birth weight (pounds)	7.38	1.25
Categorical variables	*%*	
Girls	49.6	
Below poverty line	16.4	
White	59.3	
Black	12.8	
Hispanic	18.4	
Asian	5.8	
Other	3.7	
Annual family income <$15 000	11.9	
≥15 000 to <25 000	11.4	
≥25 000 to <35 000	11.4	
≥35 000 to <50 000	15.1	
≥50 000 to <75 000	22.6	
≥75 000 Maternal education	27.6	
Less than high school diploma	11.3	
High school diploma or equivalent	33.3	
Some college	26.9	
Bachelor's degree or higher	28.5	
Food price indices	*Mean*	
Meats	10.6	1
Dairy	7.52	1
Fruits and vegetables	7.90	1
Fast-food	7.05	1
Food outlets		
No. of grocery stores per 1000 persons in the zip code	0.302	0.260
No. of convenience stores per 1000 persons in the zip code	0.149	0.138
No. of fast-food restaurants per 1000 persons in the zip code	0.805	0.613
No. of full-service restaurants per 1000 persons in the zip code	0.861	0.814

Note: unweighted statistics for estimation sample.

survey design; including or excluding New York city; and using average annual prices or prices for the quarter in the middle between kindergarten and first grade assessments. While some specifications showed significant effects of meat prices, there was no consistent pattern, especially when comparing 1- and 3-year changes.

Table 4 also shows results for subgroups. Although girls gain more weight than boys in this age group, there is no evidence of any differential effect of fruit and vegetable prices. For children in families with income below the poverty line and Hispanics, the estimated effects are noticeably larger than those for the full population. While this is likely to capture a real effect, we do not have the statistical power to conclude that the difference compared with the general population is statistically significant. Both the subgroup analysis of children whose BMI is above the age/sex-specific 85th percentile in kindergarten or the 85th quantile regression (which estimates the effect of food prices at the 85th percentile of BMI change) show a slightly stronger effect of fruit and vegetable prices on BMI gain than the full population mean effect.

We estimated similar models with per capita measures of food outlets and a different set of models with relative shares of fast-food restaurants compared with full-service restaurants, or convenience stores compared with grocery stores. However, we found no robust effects for any of these supply variables, either individually or as a set. The per capita number of restaurants sometimes became significant, but this result disappeared when we included prices or switched to a different method for adjusting for the clustering. The per capita number of fast-food restaurants remained significant at $P<0.10$, with more restaurants associated with faster BMI gain but not at standard levels of significance. In contrast, including the supply variables had little effect on the estimated magnitude of the price indices. This conclusion was unaffected by whether we used supply variables describing the child's home or the school area. Given the absence of any meaningful associations, we have not shown any results for outlet density.

Fig. 1 graphically displays the effect of local fruit and vegetable prices on BMI gain between kindergarten and third grade. It orders a small subset of metropolitan areas in the data by their relative real prices for fruits and vegetables, from the lowest (Visalia, CA) to the highest (Mobile, AL). We then simulate the BMI gain of a national sample of kindergarten children under these prices and show the effect relative to the observed national BMI change (2.18 units). Fig. 1 isolates the effect of differences in sociodemographic characteristics across areas to answer the question: if families with identical real income and identical sociodemographic characteristics lived in two cities, how much would the BMI of kindergarten children change as a consequence of the variations in real

Table 3 Main regression results.

	BMI change between kindergarten and third grade			BMI change between kindergarten and first grade		
Regressor variable	Coefficient	SE	*P* value	Coefficient	SE	*P* value
Food price indices						
Fruits and vegetables	**0.114**	**0.033**	**<0.001**	**0.054**	**0.022**	**0.016**
Meats	−0.025	0.031	0.414	−0.037	0.022	0.095
Individual characteristics						
Body mass index (spring of kindergarten)	**0.357**	**0.010**	**<0.001**	**0.077**	**0.006**	**<0.001**
Age in months at assessment (spring of kindergarten)	**0.016**	**0.005**	**0.004**	**0.013**	**0.003**	**<0.001**
Girl	**0.179**	**0.046**	**<0.001**	**0.075**	**0.024**	**0.002**
Real family income in $1000 (slope)						
Below 25th percentile	−0.010	0.007	0.133	0.000	0.003	0.999
25th to 50th percentile	0.008	0.005	0.132	0.000	0.003	0.864
50th to 75th percentile	−0.004	0.003	0.200	−0.001	0.002	0.46
Above 75th percentile	−0.001	0.001	0.241	0.000	0.001	0.649
Black	**0.274**	**0.084**	**0.001**	0.068	0.046	0.131
Hispanic	0.082	0.073	0.261	0.030	0.040	0.459
Asian	0.043	0.106	0.685	0.009	0.057	0.869
Other	0.022	0.124	0.861	0.125	0.064	0.052
Maternal education						
High school diploma or equivalent	−0.092	0.085	0.277	−0.022	0.042	0.610
Some college	−0.061	0.091	0.501	−0.008	0.048	0.860
Bachelor's degree or higher	**−0.262**	**0.098**	**0.007**	−0.035	0.051	0.496
Days/week that child gets exercise that causes rapid breathing, perspiration, and a rapid heartbeat for 20 continuous minutes or more (spring of kindergarten)	0.009	0.011	0.392	0.005	0.006	0.332
Hours/day that child watches television (spring of kindergarten)	**0.067**	**0.021**	**0.001**	**0.025**	**0.011**	**0.019**
Hours/week of physical education instruction in school (spring of kindergarten)	−0.002	0.034	0.950	0.001	0.021	0.962
No. of activities (up to nine) that parent participates in with the child (autumn of kindergarten)	−0.008	0.010	0.429	−0.003	0.006	0.616
Birth weight (pounds)	−0.029	0.019	0.122	−0.008	0.010	0.388
Variance decomposition						
Sigma U	0.448			0.413		
Sigma E	1.87			1.03		
Rho (fraction of variance due to u)	0.054			0.138		
Number of observations	6918			8008		

BMI, body mass index. Note: individually significant coefficients at $P<0.05$ in bold. Two-level hierarchical model with individual- and school-level random effects. White mother without high school diploma are reference groups.

prices for fruit and vegetables? Children in our study gained 0.55 units (median) more than they should have according to the growth charts.[11] At the lower end of the price distribution, children in a city with fruit and vegetable prices like Visalia, CA would gain 0.28 BMI units less than the average, i.e. about half the excess gain (it does not exactly correspond to half because that number refers to the mean, not the median). At the other extreme, children in a city with prices like Mobile, AL would gain 0.21 units more than the already excessive weight that children currently gain on average.

Discussion

This paper describes the relationship between BMI change among elementary school children and metropolitan area food prices for different types of foods and the density of food outlets in the neighbourhood. We found that relative food prices are associated with changes in the BMI and obesity rates, and the relationship is significant and robust for fruit and vegetable prices: higher fruit and vegetable prices predict greater BMI increase. At the extreme, price differences across

Table 4 Sensitivity and subgroup analyses.

Dependent variable	BMI change between kindergarten and third grade		BMI change between kindergarten and first grade	
	Fruit and vegetables	Meats	Fruit and vegetables	Meats
Reference model from Table 3 1999 Q4 prices, home zip	**0.114*** (0.033)**	−0.025 (0.031)	**0.054** (0.022)**	−0.037* (0.022)
Sensitivity to data specifications				
1999 Q4 prices, school zip	**0.115*** (0.033)**	−0.026 (0.032)	**0.066*** (0.022)**	−0.036* (0.22)
1999 Q4 prices, home zip, without New York city	**0.094*** (0.032)**	−0.059* (0.034)	0.043* (0.023)	**−0.058** (0.025)**
1999 full year prices, home zip	**0.088** (0.038)**	−0.039 (0.042)	0.041* (0.024)	**−0.071*** (0.024)**
1999 full year prices, school zip	**0.077** (0.036)**	−0.045 (0.035)	**0.052** (0.024)**	**−0.090*** (0.023)**
Sensitivity to modelling specifications				
Include dairy, fast-food prices	**0.098*** (0.037)**	−0.049 (0.039)	0.044* (0.025)	**−0.054** (0.027)**
No hierarchical model, non-parametric school clustering adjustment of standard errors	**0.108*** (0.032)**	−0.022 (0.028)	**0.054*** (0.020)**	−0.033* (0.020)
Median regression (standard errors uncorrected)	**0.092*** (0.025)**	0.001 (0.023)	**0.049*** (0.013)**	−0.012 (0.012)
85th Percentile regression (standard errors uncorrected)	**0.135** (0.057)**	−0.001 (0.052)	**0.053** (0.025)**	**−0.069*** (0.024)**
Subgroup analyses				
Children in poverty	**0.176** (0.063)**	0.006 (0.063)	0.054 (0.036)	−0.020 (0.034)
Children at risk for overweight/overweight in kindergarten	**0.158*** (0.070)**	−0.056 (0.063)	0.067* (0.040)	**−0.095** (0.038)**
Boys only	**0.115*** (0.043)**	−0.065 (0.040)	0.039 (0.028)	−0.043 (0.027)
Girls only	**0.112*** (0.041)**	0.023 (0.039)	**0.072*** (0.027)**	−0.035 (0.026)
African American only	0.005 (0.094)	0.108 (0.079)	**0.105** (0.052)**	−0.005 (0.045)
Hispanic only	**0.211*** (0.063)**	−0.042 (0.065)	0.033 (0.031)	0.013 (0.033)
Asian only	0.161 (0.101)	−0.010 (0.101)	**0.156** (0.058)**	−0.106 (0.057)

BMI, body mass index. Note: individually significant coefficients at $P<0.05$ in bold. Unless specified differently, results are based on two-level hierarchical model with individual- and school-level random effects and the same specification as in Table 3. Standard errors in parentheses ***: statistically significant at $P<0.01$; **: statistically significant at $P<0.05$; *: statistically significant at $P<0.10$.

metropolitan areas in the study accounted for a gain of almost 0.5 BMI units between kindergarten and third grade. This is similar in magnitude to the excess body mass that children gain under the assumption that the 50th percentile on the growth chart reflects healthy BMI gain. Even smaller differences in relative real prices across food types, e.g. between Atlanta, GA and Baton Rouge,

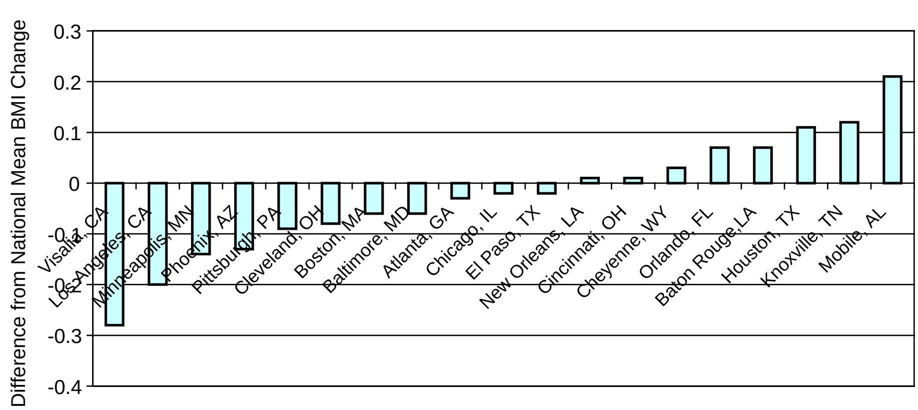

Figure 1 Effect of local food prices on the change in body mass index (BMI) between kindergarten and third grade. Note: predicted differences to national mean BMI change as a function of local real food prices, after adjusting for sociodemographic differences and having standard of living (real income) across areas.

LA, are substantively important because they correspond to one-fifth of excess body mass gain.

Our sample size was not sufficient for detailed stratified analyses by population subgroups. We did not find any significant differences between racial and ethnic groups in how they react to differential fruit and vegetable prices. However, this does not mean that such effects are absent; only that our study was not large enough to detect anything but very large differences between groups (e.g. only differences that are of the same magnitude as the estimated average effects). For example, point estimates suggest that the protective effect (i.e. lower weight gain) of lower vegetable and fruit prices is 1.5 times larger for children in poverty than for other children. However, this difference is not statistically significant given our sample sizes.

We initially expected food outlets to play an important role, but no association was found. It may be that using residence or school zip codes to define a neighbourhood is not an accurate measure to capture neighbourhood food supply or that there are other measurement issues. In particular, the size and quality of food outlets may be more important than density, and the Business Patterns data do not distinguish between big supermarkets and small local stores. Children in poverty in our sample lived in neighbourhoods with slightly more (rather than fewer) establishments classified as grocery stores. This finding parallels earlier case studies that found a higher density of food stores in poorer or minority neighbourhoods.[12,13] One of the reasons is a difference in the size of stores, and stores in lower-income neighbourhoods tend to be smaller.[12–14] Smaller stores can be more densely located than large stores. We do not have detailed information about store size at the national level and it is a limitation in our study. However, the absence of an effect on weight change in our data could also be an indication that density, or at least the variation in density, of food outlets has a smaller impact on diet than commonly assumed. In a New York city case study, although a smaller share of stores in the poorer neighbourhood carried all recommended 'diabetes-healthy' foods than in the richer neighbourhood, there were more stores per resident in the low-income neighbourhood that carried fresh fruit and vegetables, a larger share of residents in the low-income area lived in a Census block that had at least one food store compared, and food prices were uniformly lower in the low-income neighbourhood.[12] In Glasgow, researchers also found more food stores in lower-income neighbourhoods than in wealthier neighbourhoods.[13] The notion of 'food deserts' (poor urban areas where residents cannot buy affordable, healthy food) has been influential in policy circles, but evidence for widespread 'food deserts' is unclear.[15] It is more likely that areas with limited access to food are rural or semi-rural.[13]

Our measures for food prices are at the metropolitan level and we have no measures for neighbourhood differences, which may be a limitation. However, it is also possible that within-city variations are minor compared with regional price differences. Stores that are located geographically close are competing for shoppers from the same area, which limits variations in prices within a city. In contrast, variations in real food prices across metropolitan areas are substantial and can be twice as high in one metropolitan area compared with another.

This study cannot establish the causal pathway because we can only associate food prices and changes in BMI. We did not observe actual consumption of fruit and vegetables, and food prices might also reflect cultural differences in consumption (e.g. demand) rather than supply costs alone. Is it plausible that fruit and vegetable prices can affect consumption sufficiently to affect weight gain? On one hand, research from the US Department of Agriculture concluded that prices nationwide are sufficiently low that even low-income families can afford the recommended amounts of fruit and vegetables (that study does not address regional variation).[16] On the other hand, low-income families in the USA spend much less on fruit and vegetables and, in a given week, are twice as likely as higher-income families not to buy any fruits or vegetables (19 vs 10%).[17] Small changes in income do not appear to affect purchases, but there is a strong response to prices. It has been estimated that a 10% reduction in price for fruits and vegetables increases consumption by 7.2%, which is about twice the effect of price reductions for beef or bread.[18] Only dairy products and fruit juice were estimated to have a similarly strong response to changes in their own price; other food items had a lower response, with no noticeable differences across income groups.[18] Increases in fruit and vegetable consumption may be most beneficial for children who consume the least. According to our point estimates, the protective effect of lower fruit and vegetable prices is 1.5 larger among children in poverty.

What are the policy implications? Changing regional prices is not a feasible or realistic policy. However, price interventions are possible when targeted at a selected group. The US Department of Agriculture recently started a pilot programme that provided fresh and dried fruits and vegetables free to children in about 100 schools.[19] An evaluation of the pilot programme found high student interest, and the pilot has been popular with parents, teachers and school administrators. It is not clear whether the programme affects obesity rates or weight gain differently in participating schools compared with non-participating schools; this is an important area that should be studied to determine the potential effectiveness of such a programme to combat childhood obesity. Schools received $94 per student and if the project was implemented nationwide for 48.2 million children in public schools, estimated costs would be around $4.5 billion.[19] In comparison, the 2005 USDA budget for food assistance, which includes food stamps, school meals and a special programme for pregnant women and preschool children, is around $52 billion. Informational interventions, which change the value that consumers place on fruits and vegetables, may also be helpful, especially in areas where children gain the most weight. However, the cost-effectiveness of such programmes is not known.

In summary, this study has provided some initial evidence for an association between weight gain among elementary school children and relative food prices in their environment. In particular, lower real prices for vegetables and fruits relative to other goods and services (including other foods, housing) may slow excess weight gain.

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