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Economics of Food Energy Density and Adolescent Body Weight

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We present a simple microeconomic behavioral model showing that decreases in the price of energy-dense foods increase body weight if the price of obtaining a calorie from dense food is lower than that of less dense food. Estimates of the determinants of adolescent BMI suggest that the price of high-density food is negatively related to BMI whereas the price of low density food is positively related. Restaurant availability is not associated with weight, but increases in supermarket density predict lower weight. Quantile regressions show that most of the changes in body weight occur in the top quintile of the conditional distribution of BMI.

Introduction

Would taxing fast food or reducing access to fast food outlets, subsidizing fruit and vegetable consumption, or increasing access to supermarkets be effective policy instruments to reduce obesity? We present estimates of the determinants of US adolescents' body weight outcomes from 1997 to 2003, focusing on the effects of the prices of energy-dense foods (foods high in calories per unit mass, such as cheeseburgers or fried chicken) versus the price of less dense foods such as fruit and vegetables, and on access to supermarkets and restaurants. We are motivated by the tripling of obesity among adolescents over the last thirty years (Ogden *et al*. 2006), the paucity of evidence relating food prices and accessibility to weight outcomes, and a simple theoretical argument showing that changes in caloric consumption depend on the relative price per calorie of various foods. In part because dietary and exercise habits formed in adolescence predict adult outcomes (Whitaker *et al*. 1997), the determinants of adolescent outcomes are of particular interest.

Food taxes or subsidies of various forms have frequently been suggested in both the academic and popular literatures as potential policy tools for addressing the obesity crisis, yet little direct evidence on the efficacy of such taxes exists. Even if it can be shown that price mechanisms such as taxes or subsidies can effectively reduce body weight, it does not necessarily follow that such mechanisms are sound policy; these policies may face objections on equity or other philosophical grounds, and may have unintended consequences. For example, Lakdawalla *et al*. (2005) show that higher prices of minced (ground) beef are associated with higher rates of anaemia. They also point out that taxing food may be a poor instrument for addressing obesity because obesity is a result of *over*-consumption as opposed to food consumption *per se*. For all of these reasons, a finding that food taxation could be used to reduce obesity rates does not imply that food taxation should be used to reduce obesity rates. Nonetheless, it is necessary to assess whether price mechanisms have a measurable effect on body weight in order to evaluate policy responses based on food prices or availability.

Our empirical work uses two food price measures: an index measuring the price of a fast food meal and an index measuring the price of fruit and vegetables. The price of a fast food meal proxies local prices of energy-dense foods, whereas the price of fruit and vegetables proxies the prices of less energy-dense foods. Economic explanations of the obesity epidemic have tended to focus on the price of a calorie, whereas the public health literature frequently emphasizes the price of energy-dense foods (such as cheeseburgers or fried chicken) relative to less dense foods (such as fruit and vegetables) and the effects of each at a biological level. Physiological explanations for the relationship between obesity and energy density can be briefly sketched: increases in the proportion of dense food in the diet (Putnam *et al.* 2002) have led to greater obesity because dense foods provide neurobiological reward for evolutionary reasons (Mela 1999; Smith 2002), are easier to metabolize (Golay and Bobbioni 1997) and are less satiating (Rolls 1995), so that increases in density are not fully offset by decreases in volume. It has been well established that the price of a calorie tends to be lower if it is obtained from a dense food, e.g. a calorie is more than 100 times more expensive if obtained from lettuce than from butter (Drewnowski *et al.* 2004; Drewnowski and Specter 2004). Taxes on dense foods and subsidies to less dense foods may, then, reduce obesity, and these policies are commonly suggested instruments to address the obesity epidemic (e.g. Brownell and Horgen 2004).

The literature on food energy density has not formalized the notion that decreases in the price of dense foods will tend to increase total caloric consumption: if dense foods become relatively cheaper, we could observe offsetting decreases in the consumption of less dense foods, such that total calories change or even decrease. We show in a simple theoretical model that the effect on weight of changes in the prices of dense and less dense foods depends on the relative price of a calorie of dense as opposed to less dense foods. In contrast to explanations rooted in physiology, we show that, if a calorie is cheaper to acquire by purchasing a dense food than a less dense food, then an increase in the price of dense foods will tend to decrease weight whereas an increase in the price of less dense foods will increase weight. Under certain conditions *all* that matters in signing the change in caloric intake is the ratio of the price of high-energy-dense to low-energy-dense food. These predictions depend only on the convexity of indifference surfaces and would be reversed if a calorie of dense food were more expensive than a calorie of less dense food. We consider these predictions from elementary microeconomics to complement biologically based explanations.

Despite the emphasis on energy density in the literature, little direct evidence exists on the effects of changes in the prices of dense foods on weight outcomes. In previous work we showed, using linear regressions, that changes in food prices and access explain little of the variation over time in adolescent BMI in the Monitoring the Future (MTF) data (Powell *et al.* 2007a). Chou *et al.* (2004) show that fast food prices and restaurant density are correlated with adult weight outcomes, a result that may be interpreted as an effect of changes in the price of energy-dense foods. Similarly, Marcelli *et al.* (2004) find that higher fast food prices are associated with lower body weight whereas higher fast food restaurant density is associated with higher body weight. Processed (high energy density) food consumption is associated with higher weight (Keller and Lemberg 2003; MacInnis and Rausser 2005). In a related context, Lakdawalla *et al.* (2005) show that variation in the prices of selected food items, such as milk, bread, orange juice and minced beef, are correlated with micronutrient intake.

Access to supermarkets has been hypothesized in the public health literature to lead to lower BMI because supermarkets provide a greater variety and a lower price of fresh foods such as fruit and vegetables. In turn, part of the difference in BMI across racial groups may be attributable to diminished access to supermarkets in predominately minority neighbourhoods (Morland *et al.* 2002; Powell *et al.* 2007b). In our models we recover part of the effect of supermarkets in the form of a price index for fruit and vegetables, and we are also able to assess any direct effect of supermarkets (price constant) on weight.

Most of the literature estimates the determinants of one of two outcomes: the conditional mean of BMI through linear regression methods, or the probability that an individual is obese through binary response models such as logistic regression. Either of these methods may be misleading if the distribution of BMI changes in a complex manner in response to changes in one of the covariates. For example, suppose that a decrease in the price of a fast-food meal causes individuals who are already in the 95th or higher percentile of the distribution of BMI to become heavier but has no effect on the weight of others. In such a case a binary response model would (correctly) reveal that there is no change in the proportion of obese people, because the people whose weights change when the price changes are already obese. The coefficient on price in the linear regression model would be centred on some small positive value—small because most of the population's weight does not change. Or suppose that the same price decrease leads to a mean-preserving spread in the distribution of BMI. This is the worst outcome, as overweight people tend to become heavier and underweight people lighter—yet the parameter estimate in a linear regression would be centred on zero.

We start by estimating OLS and binary response models of weight outcomes. We proceed, following other papers including Kamhon and Wei-Der (2004), Quintana-Domeque (2005) and Classen (2005), to present quantile regression estimates of the BMI models in order to characterize changes in the entire distribution of conditional body weight. The results suggest that fast food and fruit and vegetable prices are highly associated with body weight among overweight adolescents but have little effect on the weight of normal-weight adolescents. Changes in access to supermarkets lead to small changes in the distribution of BMI that resemble location shifts. Finally, access to restaurants, fast food or otherwise, is neither economically nor statistically associated with adolescent weight outcomes anywhere in the BMI distribution, conditional on other food price and access measures and on demographic characteristics.

I. Data

The primary data sources are individual-level national data for eighth and tenth-grade students from the Monitoring the Future (MTF) surveys merged with data on restaurant outlets and supermarkets obtained from business lists developed by Dun and Bradstreet and external food price data obtained from the American Chamber of Commerce Research Association (ACCRA).

Monitoring the future surveys

The MTF study, which has annually surveyed nationally representative samples of high school seniors in the coterminous United States since 1975, is conducted at the University of Michigan's Institute for Social Research. Since 1991 the MTF surveys have also included 30,000 eighth and tenth-grade students annually. Located in approximately 280 schools, these eighth and tenth-grade students/schools are selected annually for the MTF survey on the basis of a three-stage sampling procedure to yield a nationally representative sample (Johnston *et al.* 2004). The data are weighted to correct for any inequalities in the selection probabilities at the various stages of sampling.

In order to cover the range of topic areas in the MTF study, eighth and tenth-graders are administered four different forms. This occurs in an ordered sequence, so as to ensure virtually identical subsamples for each form. Approximately one-third of the questions on each form are common to all forms; these include the demographic variables used in this study. Questions that relate to height and weight are included on only a subset of forms. For the seven years of data from 1997 to 2003 for eighth and tenth-grade students our sample has a total of 73,041 observations on which we have information on height and weight and non-missing information on our covariates.

BMI and overweight measures

Anthropometric information is available in the MTF and is based on self-reported measures. Using height and weight, we calculate BMI (= weight (kg)/height (m)^2). Individuals' body weight outcomes are classified on the basis of BMI for children and teens using the 2000 CDC Growth Chart. An adolescent is deemed overweight if their BMI exceeds the age and sex-specific 95th percentile. The 2000 CDC Growth Charts were developed on the basis of data collected in five cross-sectional, nationally representative health examination surveys that include the NHES II (1963–65) and III (1966–70), and NHANES I (1971–74), II (1976–80) and III (1988–94) (Kuczmarski *et al.* 2002). We create a binary indicator which is equal to unity if the respondent is overweight.

Self-reports on height and, particularly, weight are likely to contain measurement error. Wang *et al.* (2002) found under-reporting of both overweight and obesity in self-reported data of older adolescents (15–19 years). On the other hand, Strauss (1999) found that 94% of children were in the correct classification of obesity; and Goodman *et al.* (2000) found that examining self-report data among teens correctly classified 96% as obese or not obese. Cawley (2000) reports that self-reported weight is an excellent predictor of measured weight and, critically, that in a regression context the estimates are robust to whether measured or self-reported weight is used. The estimates in this paper on the covariates we are most interested in—food prices and food store availability—will be biased only if measurement error is correlated with these outcomes after conditioning on observable individual-level demographic characteristics.

Table 1 shows that the average BMI and prevalence of overweight for the full sample of students is 21.8% and 10.3%, respectively. Table 2 shows that over the 1997–2003 period both overweight and BMI trended up until 2002. Notice that the increase in overweight appears to be much larger than the increase in BMI: from 1997 to 2003 overweight increased 25%, from 8.8% to 11.0%, whereas mean BMI increased 2%, from 21.5% to 22.0%. Over the same interval the standard deviation of BMI rose roughly 10%, from 4.0% to 4.4%. These statistics suggest that BMI is more volatile over time near the threshold of overweight than away from the threshold, an observation that in part motivates our use of quantile regression methods.

Demographic measures

Demographic measures available in the student surveys include: sex, grade, age, race/ethnicity, highest level of schooling completed by father, highest level of schooling completed by mother, a rural or urban area neighbourhood designation, total student income (earned and unearned income, such as an allowance), weekly hours of work by the student, and whether the mother works part-time or full-time. The summary statistics in Table 1 show that just under one-half of the sample is male; approximately 69% of the students are white, 11% are black, 10% are Hispanic and 10% are of other racial/ethnic backgrounds. The average age of the sample is 14.7 and just under one half of the sample is in eighth grade with

TABLE 1
SUMMARY STATISTICS*

	Mean	Std dev.
Weight outcomes		
BMI	21.806	4.295
overweight	0.103	0.304
Contextual variables		
zip code per capita income (10,000 s)	2.212	0.966
zip code-level poverty rate	0.114	0.082
price of fruit and vegetables	0.720	0.105
price of a fast food meal	2.713	0.174
fast food restaurants per 10,000 capita	2.442	2.260
full service restaurants per 10,000 capita	12.831	9.632
supermarkets per 10,000 capita	0.304	0.581
Demographics		
black	0.106	0.307
hispanic	0.097	0.296
other race	0.101	0.301
white	0.696	0.460
age 12	0.001	0.031
age 13	0.207	0.405
age 14	0.256	0.436
age 15	0.236	0.425
age 16	0.275	0.447
age 17	0.024	0.153
age 18	0.001	0.036
father's education < HS	0.131	0.337
father's education = HS	0.294	0.542
father's education > HS	0.575	0.494
mother's education < HS	0.111	0.314
mother's education = HS	0.280	0.529
mother's education > HS	0.609	0.488
mother has part-time job	0.183	0.387
mother has full-time job	0.641	0.480
mother doesn't work	0.176	0.420
R's hours of work per week	3.856	7.137
R's income ($100/week)	0.228	0.267
grade 10 [omitted: grade 8]	0.513	0.500
male	0.476	0.499
family intact	0.800	0.400
rural	0.241	0.428

*$N = 73{,}041$

the remainder in tenth grade. The majority of students' parents have at least some college education (58% of fathers and 61% of mothers). Most (80%) students live with both parents, and just under one-quarter live in a rural area. Students work on average just under four hours per week. Students' weekly real (CPI-deflated; $1982–84 = 100) income, earned and unearned, is on average about $23. Approximately 64% of students' mothers work full-time, and another 18% of students have mothers who work part-time. The sample is evenly distributed across years, with about 14% in each of the seven years from 1997 to 2003.

TABLE 2
SUMMARY STATISTICS OVER TIME FOR SELECTED VARIABLES*

	Overweight	BMI	Super-markets	Prices		Restaurant density	
				Fruit + veg	Fast food	Fast food	Full serve
1997	0.088	21.549	0.306	0.668	2.791	2.010	12.580
	0.000	20.686	0.182	0.659	2.775	1.832	11.361
	0.283	4.050	0.432	0.069	0.216	1.617	9.192
1998	0.092	21.644	0.278	0.702	2.778	2.172	12.646
	0.000	20.831	0.000	0.696	2.757	1.979	10.745
	0.289	4.182	0.436	0.068	0.168	1.965	9.485
1999	0.098	21.726	0.335	0.705	2.769	2.107	12.329
	0.000	20.877	0.000	0.664	2.760	1.904	10.270
	0.298	4.288	0.986	0.129	0.152	1.955	9.201
2000	0.106	21.805	0.290	0.694	2.693	2.060	11.661
	0.000	20.877	0.000	0.682	2.701	1.966	10.249
	0.308	4.227	0.632	0.065	0.140	1.700	7.445
2001	0.116	21.947	0.298	0.677	2.647	2.656	13.540
	0.000	20.903	0.000	0.675	2.637	2.384	11.581
	0.320	4.475	0.449	0.079	0.151	2.860	11.639
2002	0.110	21.987	0.333	0.814	2.659	2.952	14.223
	0.000	21.090	0.000	0.796	2.645	2.695	12.279
	0.313	4.420	0.507	0.109	0.148	2.776	11.054
2003	0.110	21.996	0.289	0.784	2.648	3.129	12.870
	0.000	21.090	0.000	0.770	2.623	2.716	11.425
	0.313	4.396	0.421	0.100	0.152	2.354	8.679
Total	0.103	21.806	0.304	0.720	2.713	2.442	12.831
	0.000	20.877	0.000	0.702	2.702	2.202	11.157
	0.304	4.295	0.581	0.105	0.174	2.260	9.632

*Each cell contains mean, median and standard deviations.

Restaurant and supermarket outlet density measures

Data on restaurant outlets and supermarkets were obtained from a business list developed by Dun and Bradstreet (2007). This list was obtained through the use of Dun and Bradstreet MarketPlace software. MarketPlace uses the following sources to help update its database quarterly: telecenters to update and verify their data; Yellow Page directories, which are matched against its database to identify new businesses; news and media sources, which are monitored daily to identify businesses that have merged, been acquired, closed or claimed bankruptcy; government registries to identify business registration information; and websites, including its own, where businesses have the ability to review and update their own information. Dun and Bradstreet assigns to each business a unique numerical identifier to ensure validity of its data over time (Dun and Bradstreet 2005). MarketPlace allows sorting by multiple criteria such as zip code and Standard Industry Classification (SIC) codes, with SIC code, searches for specific types of business available at varying levels of specificity. This study drew on the primary SIC code listing in creating the list of outlets used for our analyses.

Information on restaurant and supermarket outlets available in the Dun and Bradstreet data-set was pulled by zip code for the years 1997–2003. The outlet density data were linked to the individual-level data by the students' school zip code. While this might be a good proxy for the student's home zip code at lower grade levels (in this case grade 8), high schools are likely to draw their student population from beyond their own zip codes. If a child lives in a different zip code from that of their school, the extent to which neighbouring zip codes are similar will help to mitigate this potential source of error for differing access between time spent near and around school and time spent around home. Information on the total number of restaurants (SIC code 5812) was pulled at the 4-digit SIC code level, and the subset number of fast food restaurant (SIC code 581203) outlets was pulled at the 6-digit SIC code level. From these data we define two restaurant outlet density variables: the per capita (per 10,000 persons) number of fast food restaurants and of full service (total restaurants minus fast food restaurants) restaurants. Information was also pulled from the database on overall number of supermarket outlets (SIC code 541101) at the 6-digit SIC code, level. Table 1 shows that there are 2.5 fast food and 13 non-fast food outlets per 10,000 people, and roughly 3 supermarkets per 100,000 people. Table 2 reveals that the per capita number of supermarkets and non-fast-food restaurants remained fairly constant over the 1997–2003 period, while the per capita number of fast food restaurants trended upwards, increasing by 56%.

Neighbourhood economic measures

Per capita income and poverty rates at the zip code level were obtained from the 2000 US Census and matched at the zip code level to the MTF data for each of the years 1997–2003.

Food price measures

Food and fast food price data were obtained from the American Chamber of Commerce Researchers Association (ACCRA) Cost of Living Index reports, which contain quarterly information on prices across more than 300 US cities annually. The ACCRA collected 62 different prices across a range of products. Price data collection was based on establishment samples that reflect a mid-management standard of living. For consistency, national brands are stipulated where possible; otherwise, 'lowest price', i.e. the average of the lowest prices found in all stores surveyed, was used. These price data were matched to the MTF sample based on the closest city match available in the ACCRA data using school zip code geocode data. Price data were drawn from quarters I and II, as these reflect the time frame of the MTF surveys. From the items provided in the ACCRA data we created two prices indices: a fruit and vegetables price index and a fast food price index.

The fruit and vegetables price index is based on the food prices available for this food category (potatoes, bananas, lettuce, sweet peas, tomatoes, peaches and frozen corn). ACCRA reports weights for each item based on expenditure shares derived from the Bureau of Labor Statistics (BLS) Consumer Expenditure Survey. These weights are used to compute a weighted fruit and vegetables price based on the seven food items noted above. The fruit and vegetables price is also deflated by the BLS Consumer Price Index (CPI) (1982–1984 = 100) and, as shown in Table 1, has an average real price of 72 cents. Table 2 reveals that the real price of fruit and vegetables trended upwards, increasing by 17% over the 1997–2003 period.

The fast food price index is based on the following three items included in the ACCRA data: a McDonald's quarter-pounder with cheese, a thin crust regular cheese pizza at Pizza Hut and/or Pizza Inn, and fried chicken (thigh and drumstick) at Kentucky Fried Chicken and/or Church's Fried Chicken. The fast food index is computed as an average of these three food prices since they have equal weights. The fast food price also is deflated by the

CPI. Table 1 shows that the average real fast food price is \$2.71. Table 2 shows that the real fast food price trended downwards over the 1997–2003 period, by roughly 5%.

II. Analytical Framework

(a) Theory

In this section we present a simple model to ground our empirical work. We show that, putting aside any changes in food expenditures caused by changes in food prices, changes in relative prices change caloric intake in a manner that can be predicted solely by the relative cost of purchasing a calorie from high or low-energy-dense, food. If the price of a calorie of dense food is lower (higher) than the price of a calorie of less dense food, increases in the price of dense food decrease (increase) calories. This result depends only on the convexity of indifference curves and not on any mechanism related to the physiological effects of energy-dense foods.

In a framework drawing on Lakdawalla and Philipson (2002) and on MacInnis and Rausser (2005), consider a consumer in a discrete-time environment who chooses in each period t an amount of energy-dense food f_{dt}, an amount of energy-light food f_{lt} and consumption of a composite commodity x_t. It is convenient to measure food consumption in calories, so f_{dt} and f_{lt} denote the number of calories drawn from energy-dense and -light foods in period t. In the interest of simplicity we abstract from physical activity, thus ignoring perverse outcomes in which changes in caloric intake are more than offset by changes in activity (see Lakdawalla and Philipson 2002). Assuming enough structure so that the problem may be represented recursively, in period t the value V of weight W is

$$V_t(W_t) = \max_{f_{dt}, f_{lt}, x_t} U(f_{dt}, f_{lt}, x_t | W_t) + \beta V_{t+1}(W_{t+1}), \tag{1}$$

where $U(\cdot)$ denotes the period return.[1] This utility derives in part from the health and gastronomic effects of consumption of various foods and is separable from utility deriving from consumption of a composite commodity x_t. Maximization is subject to a law of motion for weight,

$$W_{t+1} = g(f_{dt} + f_{lt} | W_t), \tag{2}$$

where $g'(\cdot) > 0$ and we assume that changes in weight depend solely on total calories consumed and not (conditional on calories), on the proportion of calories consumed in the form of energy-dense foods. The individual faces a budget constraint which, in the interest of simplicity, binds each period,

$$M \geqslant p_{dt} f_{dt} + p_{lt} f_{lt} + x_t, \tag{3}$$

where p_d and p_l denotes the prices of dense and light foods.

Solving the above problem in two steps illuminates the effects of changes in food prices, holding food expenditures constant. In a first step, the consumer chooses high and low-energy foods, given expenditures on food E. Dropping time subscripting, this problem may be expressed as

$$\begin{aligned} &\max_{f_d, f_l} U(f_d, f_l, M - E) + \beta V(W) \\ &\text{s.t. } E = p_d f_d + p_l f_l. \end{aligned} \tag{4}$$

In a second step the consumer chooses E and x, given the solution to the problem above.

Consider a change in the price of energy-dense foods. The effect on weight is

$$\frac{\partial W}{\partial p_d} = \frac{\partial W}{\partial C}\left(\frac{\partial f_d^*}{\partial p_d} + \frac{\partial f_l^*}{\partial p_d}\right), \tag{5}$$

where $C = (f_d + f_l)$ denotes total caloric consumption and $\partial W/\partial C > 0$ by assumption. If we consider compensated changes in price, then the following proposition holds.

Proposition 1 A compensated increase in the price of energy-dense foods decreases (increases) body weight if the relative price of consuming a calorie of energy-dense foods is lower (higher) than energy-light foods.

Proof. Calories decrease when p_d increases if $\partial(f_d^* + f_l^*)/\partial p_d < 0$, or equivalently if $\partial f_d^*/\partial p_d < -\partial f_l^*/\partial p_d$. For compensated price changes, it can be shown that

$$\frac{\partial f_d^*/\partial p_d}{\partial f_l^*/\partial p_d} = -\frac{p_l}{p_d}, \tag{6}$$

where f^* denote Hicksian demands, and where this expression follows from totally differentiating the value function with respect to p_d, holding value constant and substituting in the first-order conditions, completing the proof.

Figure 1 illustrates this proposition for the case where high-energy-dense foods are cheaper per calorie than low-density foods. Holding the utility generated from the consumption of the food items constant, all that matters in signing the change in calories is the price ratio. Generally, however, when the price of a food type changes, consumption of the composite commodity changes, which in turn may affect the marginal rate of substitution between high-density and low-density foods, and not in an easily predictable fashion.

The result above clarifies the condition under which total calories rise when the relative price of dense foods falls: calories will rise only if the cost of obtaining a calorie from energy-dense food is lower than the cost of obtaining a calorie from less dense food. As noted earlier, it has been well established that a calorie can be purchased at a lower price if the food chosen is energy-dense. It follows that, ignoring income effects, the model predicts that decreases in the price of energy-dense foods will increase body weight. In a hypothetical world in which a calorie is more expensive if obtained from dense food, we would instead predict that a decrease in the price of dense food would decrease body weight.

Finally, we note that broadly interpreting food prices as full prices, including both monetary costs and the time of preparation and other non-pecuniary costs, allows us to draw the conclusion that technologies which reduce the price of prepared meals relative to the price of home-cooked meals tend to increase body weight through a substitution effect. We assume in drawing this conclusion that prepared meals are more energy-dense than home-cooked meals and that a calorie is more expensive to obtain from a home-cooked meal. In this sense, this simple model formalizes part of the argument presented by Cutler *et al.* (2003), that technological changes have decreased the cost of mass-produced (and typically energy-dense) food and the resulting changes in consumption patterns have contributed to higher levels of obesity.

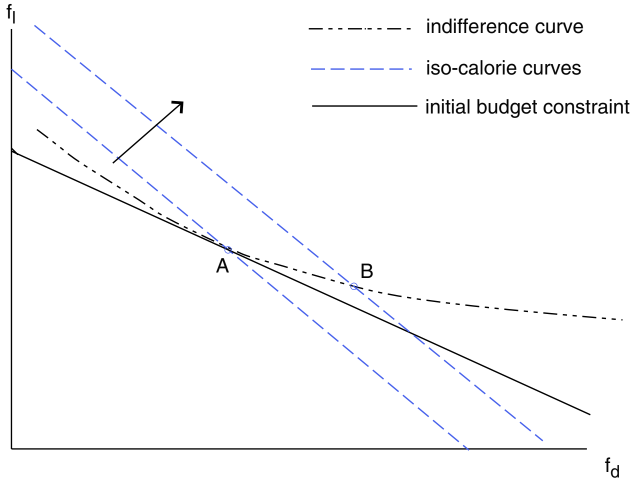

FIGURE 1. Decrease in the price of relatively cheaper food increases calories.
The figure shows high and low-energy-dense food space (f_d, f_l), measured in calories, and an initial consumption bundle **A** for prices $p_d < p_l$. When the price of high-density food falls and is compensated, the new bundle **B** has more (fewer) calories if the price of high-density food is less (more) per calorie than that of low-density food.

(b) Empirical considerations

The model above informs our empirical work in several ways. Both optimal weight and food demands depend on the function $g(\cdot)$ and on taste parameters, both of which will generally vary across individuals. Further, taste for calories and for the proportion of calories from dense foods may depend on current weight. A regression of W on f_d and f_l suffers from endogeneity owing to, generally, reverse causation and omitted variables. For these reasons, the partial correlations between food consumption and weight do not recover the causal effect of food consumption on weight, and we do not present estimates of these correlations. Further, we do not have detailed data on food consumption patterns and we do not attempt to estimate the food demand relations directly.

We therefore attempt only to estimate the reduced-form effect of changes in food prices on body weight. Consider a reduced form for the weight W_{ist} of individual i in region s at time t,

$$W_{ist} = X_{ist}\beta + Z_{st}\delta + P_{st}\alpha + \phi_t + u_{ist}, \tag{7}$$

where X denotes individual-level influences on body weight, Z denotes regional influences on body weight other than prices and food store access, P denotes a vector of observations on food prices and restaurant and food store densities, ϕ are year effects, u is a disturbance term, and β, δ and α are vectors of parameters to be estimated. Estimation of (7) using single-equation methods allows us to interpret the estimates of α causally if the disturbance term is uncorrelated with prices and food outlet access, conditional on X and Z. Generally, we require that food outlet densities and food prices vary as a result of supply rather than demand-side shocks, conditional on other observables. We reduce the dependence of prices and densities on demand-side shocks by including demand shifters such as measures of neighbourhood socioeconomic status (local area per capita income and poverty rates) in Z.

However, a complication arises from consideration of equation (5). If individuals in the same region are subject to the same price shock, there is no reason to expect the change in weight to be equal across individuals. Demand slopes may vary, and a given change in food consumption will generally lead to different changes in weight, depending on genetics and initial weight. Statistically, the parameters α in equation (7) may vary across individuals. We address this issue using quantile regression methods described below.

(c) Empirical models for BMI and overweight

We begin by estimating reduced-form equations for body mass of the form (7) by ordinary least squares.[2] In X_i we include controls for race, age, grade, respondent's income and hours of work, parental education, family structure, mother's work status and urban residence. In Z_s we include per capita income in region s and, as a measure of income dispersion and absolute deprivation, the proportion of individuals below the poverty line. In P_s we include the mean price of a fast food meal, the price of a bundle of fruit and vegetables, and local density of restaurants and supermarkets as discussed in Section I.

We consider the price and accessibility of a fast food meal as a proxy for the price of energy-dense food, and similarly the price of fruit and vegetables as a proxy for less energy-dense, more healthful, food. In these and all subsequent models we include a full set of year dummies. These dummies nonparametrically remove common trends in weight outcomes and the covariates. All regression estimates and summary statistics are calculated using sampling weights to correct for the complex design of the MTF survey.

Determinants of mean BMI may differ from determinants of overweight. We model overweight status using probit regressions of the form

$$(8) \qquad \Pr(W_{ist} > k_i | X_{ist}, Z_{st}, P_{st}) = \Phi(X_{ist}\beta + Z_{st}\delta + P_{st}\alpha + \phi_t),$$

where k_i denotes the age and sex-specific cutoff for overweight status as defined by the CDC for individual i and $\Phi(\cdot)$ denotes the standard normal distribution function.

(d) Quantile regression models for the distribution of BMI

As emphasized in Section II(b), different individuals' weights may respond differently to changes in incentives. These heterogeneous changes may not be fully captured by either OLS or probit specifications. One approach to this problem is a random coefficients model, which we do not pursue because we are most interested in how individuals of different weights respond to changes, and in particular how changes in food prices and access affect adolescents who are near or above the threshold for overweight. We want to know which individuals, defined in terms of their weight adjusted for height and demographic characteristics, are being affected, and by how much, when policy-relevant variables change.

A quantile regression model for the τth quantile of the distribution of W can be written

$$(9) \qquad q_\tau(W_{ist} | X_{ist}, Z_{st}, P_{st}) = X_{ist}\beta^\tau + Z_{st}\delta^\tau + P_{st}\alpha^\tau + \phi_t^\tau.$$

For example, for $\tau = 50$, this equation specifies a conditional median function for BMI. We are most interested in how the parameters α change as we move across quantiles. This function and the determinants of other conditional quantiles may be estimated using linear programming methods. We estimate these models, and elasticities calculated from the parameter estimates, using the algorithms in Stata 9.2.

III. Empirical Results

(a) OLS models for BMI

Table 3 displays OLS estimates of mean BMI for male and female respondents, pooled, and stratified by sex. In each case we present estimates for specifications with and without the regional contextual variables (prices, food outlet densities and income measures). We focus on the effects of the food price and access measures, the effects of local income and its distribution and the effects of maternal employment.

The estimates of the parameters on the demographic covariates are generally of the anticipated signs. Hispanic and, particularly, black female respondents have higher BMI than white respondents with the same observed characteristics. Higher parental education, which may in part proxy (unobserved) household income, is associated with lower BMI. However, the respondent's own income is related positively to BMI for male respondents and negatively for females.

Compared with respondents whose mothers do not work, respondents whose mothers have part-time jobs are lighter whereas those whose mothers have full-time jobs are heavier. These effects vary across the sex of the respondent, with males but not females experiencing greater weight when their mothers work full time, and females' but not males' weights decreasing when their mothers work part-time. These results are not necessarily consistent with previous findings that maternal employment increases child obesity (Anderson *et al.* 2003; Fertig *et al.* 2005), but they are somewhat difficult to interpret since we are unable to condition on household income.

Higher zip code income predicts lower BMI. The proportion of individuals in the zip code area in poverty, conditional on income, is marginally statistically significantly associated with BMI. The point estimates weakly suggest more poverty may be slightly associated with greater weight ($t = 1.69$ in the pooled model). The effect is also economically small, implying moving an individual to a zip code with a 10 percentage point higher poverty rate would increase BMI by 0.063 units.

The price of fruit and vegetables is positively and statistically significantly associated with BMI, whereas the price of fast food is negatively associated with BMI, but with only a marginally statistically significant point estimate. The price effect of fruit and vegetables is particularly strong for female respondents. Neither fast food nor full service restaurant densities are statistically or economically significantly associated with BMI. Higher supermarket density, however, is highly associated with lower BMI ($t = 3.42$ in the pooled model).

Contrasting the models that do and do not include the contextual variables, note first that the contextual variables, although often individually statistically significant, explain a very small amount of the variation in BMI, for example in the pooled model without the contextual variables $R^2 = 0.0613$, and with the contextual variables $R^2 = 0.0631$. Notable changes in the estimates on other parameters include somewhat smaller effects of race—suggesting that part of the difference in weight between whites and minorities can be attributed to differences in prices, supermarket access and neighbourhood incomes—and the effects of parental education and intact households also fall when conditioning on contextual variables, similarly suggesting that part of these effects are in fact due to either neighbourhood incomes, access or prices.

(b) Probit models of overweight

The probit estimates displayed in Table 4 are in most cases similar to the OLS estimates of BMI in terms of signs and statistical significance, with the exception that the price of

TABLE 3
OLS ESTIMATES OF MEAN BMI

	Full sample		Males		Females	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
price of fruit & veg		0.6364		0.3741		0.8640
		(2.72)		(1.05)		(2.99)
price of fast food		− 0.2555		− 0.2346		− 0.2583
		(− 1.90)		(− 1.21)		(− 1.50)
fast food restaurant density		− 0.0049		0.0032		− 0.0121
		(− 0.46)		(0.16)		(− 0.89)
full service restaurant density		0.0011		0.0037		− 0.0012
		(0.40)		(0.69)		(− 0.33)
supermarket density		− 0.1123		− 0.1346		− 0.0863
		(− 3.99)		(− 4.23)		(− 1.95)
per capita income		− 0.1535		− 0.1131		− 0.1915
		(− 5.59)		(− 2.93)		(− 5.49)
poverty rate		0.6286		0.4237		0.6764
		(1.69)		(0.85)		(1.34)
black	1.1416	1.0164	0.4386	0.3556	1.7538	1.5980
	(17.82)	(15.15)	(4.86)	(3.80)	(19.09)	(16.42)
hispanic	0.6734	0.5926	0.4654	0.4087	0.8658	0.7688
	(7.92)	(7.17)	(4.02)	(3.55)	(7.47)	(6.88)
other race	− 0.0646	− 0.0680	0.0028	0.0023	− 0.1382	− 0.1432
	(− 0.97)	(− 1.02)	(0.03)	(0.02)	(− 1.66)	(− 1.70)
grade10	0.7041	0.7523	0.9350	0.9816	0.3869	0.4360
	(4.94)	(5.30)	(5.37)	(5.62)	(1.60)	(1.81)
father < HS	0.4570	0.4449	0.3738	0.3644	0.5243	0.5109
	(6.51)	(6.35)	(3.38)	(3.31)	(5.55)	(5.39)
father > HS	− 0.4615	− 0.4080	− 0.3943	− 0.3588	− 0.5201	− 0.4532
	(− 9.58)	(− 8.48)	(− 5.87)	(− 5.29)	(− 8.20)	(− 7.14)
mother < HS	0.1454	0.1168	0.2354	0.2167	0.0777	0.0418
	(1.78)	(1.42)	(1.75)	(1.61)	(0.76)	(0.40)
mother > HS	− 0.2072	− 0.1722	− 0.2417	− 0.2156	− 0.1713	− 0.1280
	(− 4.83)	(− 3.99)	(− 3.78)	(− 3.34)	(− 2.81)	(− 2.11)
intact family	− 0.2629	− 0.2454	− 0.2671	− 0.2545	− 0.2572	− 0.2357
	(− 5.28)	(− 4.92)	(− 3.61)	(− 3.42)	(− 3.91)	(− 3.62)
Rural	0.3089	0.2253	0.4310	0.3692	0.1794	0.0792
	(5.92)	(4.21)	(5.78)	(4.83)	(2.53)	(1.09)
R's hours work	0.0090	0.0090	0.0048	0.0046	0.0147	0.0150
	(2.41)	(2.41)	(0.93)	(0.89)	(2.66)	(2.72)
R's income	0.0974	0.1010	0.3464	0.3481	− 0.3307	− 0.3169
	(0.96)	(1.00)	(2.57)	(2.59)	(− 2.28)	(− 2.19)
mother part-time job	− 0.1118	− 0.1201	− 0.0240	− 0.0309	− 0.1866	− 0.1971
	(− 1.75)	(− 1.88)	(− 0.24)	(− 0.30)	(− 2.31)	(− 2.43)
mother full-time job	0.1207	0.0961	0.1997	0.1820	0.0567	0.0266
	(2.37)	(1.88)	(2.69)	(2.45)	(0.84)	(0.39)
male	0.8059	0.8100				
	(19.71)	(19.87)				
R^2	0.0613	0.0631	0.0497	0.0509	0.0636	0.0664

Notes
$N = 73{,}041$ (male $N = 34{,}451$, female $N = 38{,}590$). Standard errors adjusted for clustering at zip code level and heteroskedasticity robust. All models include a constant and age and year dummies. *t*-ratios are in parentheses.

TABLE 4
PROBIT MODELS OF OVERWEIGHT STATUS

	Full sample		Males		Females	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
price of fruit & veg		0.0229		0.0402		0.0104
		(1.54)		(1.59)		(0.61)
price of fast food		– 0.0189		– 0.0205		– 0.0168
		(– 2.02)		(– 1.43)		(– 1.58)
fast food restaurant density		– 0.0009		– 0.0009		– 0.0008
		(– 1.18)		(– 0.63)		(– 1.04)
full service restaurant density		0.0002		0.0004		0.0001
		(1.15)		(0.97)		(0.51)
supermarket density		– 0.0062		– 0.0101		– 0.0025
		(– 2.39)		(– 2.89)		(– 0.86)
per capita income		– 0.0134		– 0.0161		– 0.0117
		(– 5.22)		(– 4.35)		(– 4.13)
poverty rate		0.0215		0.0059		0.0231
		(0.86)		(0.15)		(0.80)
black	0.0543	0.0449	0.0207	0.0130	0.0806	0.0692
	(9.97)	(8.29)	(2.57)	(1.65)	(11.56)	(9.40)
hispanic	0.0337	0.0272	0.0326	0.0268	0.0345	0.0277
	(5.84)	(4.90)	(3.83)	(3.20)	(4.71)	(4.05)
other race	0.0066	0.0069	0.0078	0.0083	0.0050	0.0051
	(1.44)	(1.49)	(1.08)	(1.14)	(0.95)	(0.94)
grade10	0.0045	0.0083	0.0318	0.0362	– 0.0258	– 0.0220
	(0.54)	(1.01)	(2.70)	(3.07)	(– 2.28)	(– 2.00)
father $<$ *HS*	0.0165	0.0157	0.0182	0.0175	0.0146	0.0138
	(3.78)	(3.63)	(2.45)	(2.38)	(2.70)	(2.60)
father $>$ *HS*	– 0.0260	– 0.0218	– 0.0282	– 0.0238	– 0.0240	– 0.0201
	(– 8.02)	(– 6.86)	(– 5.22)	(– 4.43)	(– 6.26)	(– 5.37)
mother $<$ *HS*	0.0085	0.0069	0.0172	0.0158	0.0023	0.0006
	(1.64)	(1.34)	(1.84)	(1.70)	(0.41)	(0.11)
mother $>$ *HS*	– 0.0162	– 0.0136	– 0.0221	– 0.0189	– 0.0108	– 0.0088
	(– 4.99)	(– 4.25)	(– 4.09)	(– 3.51)	(– 2.86)	(– 2.40)
intact family	– 0.0124	– 0.0111	– 0.0220	– 0.0209	– 0.0050	– 0.0036
	(– 3.62)	(– 3.28)	(– 3.81)	(– 3.62)	(– 1.27)	(– 0.95)
rural	0.0228	0.0159	0.0333	0.0255	0.0132	0.0074
	(6.54)	(4.49)	(5.78)	(4.38)	(3.13)	(1.78)
R's hours work	0.0000	0.0000	– 0.0001	– 0.0002	0.0002	0.0003
	(0.11)	(0.10)	(– 0.39)	(– 0.46)	(0.84)	(0.95)
R's income	0.0029	0.0031	0.0159	0.0161	– 0.0149	– 0.0144
	(0.49)	(0.53)	(1.77)	(1.82)	(– 1.88)	(– 1.85)
mother part-time job	– 0.0078	– 0.0081	– 0.0034	– 0.0038	– 0.0108	– 0.0107
	(– 1.74)	(– 1.80)	(– 0.42)	(– 0.48)	(– 2.41)	(– 2.42)
mother full-time job	0.0055	0.0041	0.0112	0.0093	0.0013	0.0005
	(1.58)	(1.17)	(1.94)	(1.61)	(0.35)	(0.13)
male	0.0697	0.0698				
	(24.12)	(24.36)				

Notes
$N = 73{,}041$ (male $N = 34{,}451$, female $N = 38{,}590$). Dependent variable indicates respondent is overweight. Standard errors adjusted for clustering at zip code level and heteroskedasticity robust. All models include a constant and age and year dummies. *t*-ratios are in parentheses.

fruit and vegetables is not statistically significant. The magnitudes of the point estimates are larger in these models, however. A \$1 increase in the price of a fast food meal decreases the prevalence of obesity by about two percentage points. A \$1 increase in the price of fruit and vegetables reduces obesity by about four percentage points among males and one percentage point in females (but are not precisely estimated, with $t = 1.5$ for the full sample). The restaurant density measures have very small and statistically insignificant effects, whereas one more supermarket per 10,000 people reduces obesity by about one percentage point among males ($t = 2.89$) but by only a quarter of percentage point among females ($t = 0.86$).

In Table 7 below these estimates, along with several other selected estimates, are presented in terms of elasticities. Although often not statistically significant when stratified by sex, notice that the elasticities of overweight to changes in the contextual variables are much higher than the analogous BMI elasticities. This result suggests that changes in these variables do not induce shifts in the distribution of BMI but rather affect individuals at different points in the distribution of BMI differently; in particular, individuals near the overweight threshold seem to react more to changes in incentives than other adolescents.

(c) Quantile regressions for the distribution of BMI

Given the argument presented in Section II that different individuals can be expected to respond differently to changes in food prices and access, and given the suggestive evidence from the OLS and probit estimates that individuals near the overweight threshold exhibit more elastic responses than other individuals, we now turn to the quantile regression estimates. The quantile estimates allow us to characterize complex changes in the conditional distribution of BMI as the price and access measures change.

Tables 5 and 6, for males and females, display quantile regression estimates for selected quantiles between the 5th and 95th quantiles. Graphs of the parameter estimates for selected quantiles are also displayed in Figures 2 and 3. Consider first the estimates for males displayed in Table 5 and graphically in Figure 2. Food prices have negligible effects for most respondents but large effects for respondents at risk of overweight. The effect of the price of fruit and vegetables is roughly zero for males at the median, is equal to the OLS estimate at about the 60th quantile, and rises to over five times the OLS estimate at the 95th quantile. The effect of the price of a fast food meal increases in magnitude as we consider adolescents at higher points in the conditional distribution of BMI. Above the 90th quantile the effect is more than four times as large as the OLS estimate, suggesting that a \$1 increase in the price of a fast food meal decreases BMI by approximately one unit. Increases in supermarket density affect all respondents, but somewhat more so those who are heavier. In contrast, the restaurant density measures both hover around zero.

Table 6 shows that female adolescents exhibit similar patterns. An increase in the price of fruit and vegetables increases the BMI of all females, but the effect is more than twice as large at the 95th percentile as it is at the median. Similarly, increases in the price of a fast food meal decrease the BMI of female adolescents in the top quartile of the conditional BMI distribution much more so than elsewhere in the distribution. Restaurant density has very little effect on any conditional quantile. Increases in supermarket density decrease female's BMI. Unlike food prices, though, the effect of supermarkets is well approximated as a location shift.

Higher neighbourhood income is associated with lower male and female BMI, and the magnitude of the effect increases with BMI quantile. Holding income constant, increases in neighbourhood poverty rates are associated with decreases in BMI at the 5th and 10th

TABLE 5
BMI QUANTILE REGRESSIONS: MALES

Variables	5	10	25	50	75	90	95
price of fruit & veg	− 0.5318	− 0.5132	− 0.0305	0.0392	0.8270	0.5889	2.0402
	(− 1.69)	(− 2.11)	(− 0.12)	(0.13)	(1.66)	(0.82)	(2.29)
price of fast food	0.1236	0.1104	0.0291	− 0.1548	− 0.4975	− 1.0279	− 0.9421
	(0.70)	(0.83)	(0.20)	(− 0.91)	(− 1.69)	(− 2.39)	(− 1.80)
fast food resaurant density	0.0170	0.0120	− 0.0052	− 0.0114	0.0115	− 0.0253	− 0.0007
	(1.39)	(1.23)	(− 0.46)	(− 0.79)	(0.43)	(− 0.65)	(− 0.02)
full service restaurant density	0.0031	0.0050	0.0046	0.0055	0.0038	0.0111	− 0.0015
	(1.11)	(2.19)	(1.62)	(1.44)	(0.50)	(1.08)	(− 0.15)
supermarket density	− 0.1057	− 0.1265	− 0.1216	− 0.1425	− 0.2164	− 0.2043	− 0.1819
	(− 3.66)	(− 3.40)	(− 3.32)	(− 3.33)	(− 3.10)	(− 2.37)	(− 1.90)
per capita income	0.0277	0.0022	− 0.0184	− 0.0922	− 0.1812	− 0.4038	− 0.3789
	(0.79)	(0.08)	(− 0.62)	(− 2.62)	(− 2.91)	(− 4.40)	(− 3.35)
poverty rate	− 0.4548	− 0.3361	0.1858	0.3806	1.3226	− 0.0799	0.8813
	(− 1.04)	(− 0.99)	(0.51)	(0.87)	(1.76)	(− 0.07)	(0.68)
black	0.1534	0.3150	0.3528	0.3876	0.4504	0.5875	0.5263
	(1.60)	(4.27)	(4.51)	(4.19)	(2.82)	(2.62)	(1.98)
hispanic	− 0.1161	0.0996	0.0878	0.3272	0.7509	0.6887	0.8234
	(− 1.15)	(1.32)	(1.10)	(3.48)	(4.67)	(2.96)	(2.88)
other race	− 0.3086	− 0.2612	− 0.1418	− 0.1089	0.2143	0.3302	0.3349
	(− 3.42)	(− 3.77)	(− 1.99)	(− 1.28)	(1.45)	(1.56)	(1.32)
grade10	1.2840	1.1402	1.0370	1.0542	1.1463	1.3437	0.5235
	(7.77)	(8.93)	(7.83)	(6.77)	(4.22)	(3.79)	(1.29)
father < HS	− 0.0468	0.0883	0.2163	0.1987	0.5821	0.4221	0.5016
	(− 0.47)	(1.13)	(2.66)	(2.04)	(3.46)	(1.73)	(1.68)
father > HS	− 0.0403	− 0.0537	− 0.1450	− 0.3796	− 0.7106	− 0.7115	− 0.7563
	(− 0.63)	(− 1.07)	(− 2.72)	(− 5.94)	(− 6.39)	(− 4.36)	(− 3.70)
mother < HS	− 0.2385	− 0.0922	0.0351	− 0.0316	0.0817	0.8170	1.0149
	(− 2.20)	(− 1.11)	(0.40)	(− 0.29)	(0.44)	(2.96)	(2.92)
mother > HS	− 0.0352	− 0.0319	− 0.1321	− 0.1859	− 0.3732	− 0.4325	− 0.4329
	(− 0.56)	(− 0.64)	(− 2.51)	(− 2.94)	(− 3.41)	(− 2.69)	(− 2.19)
intact family	− 0.1187	− 0.0829	− 0.0622	− 0.1619	− 0.4737	− 0.3889	− 0.4820
	(− 1.75)	(− 1.56)	(− 1.11)	(− 2.43)	(− 4.08)	(− 2.31)	(− 2.40)
rural	− 0.1500	0.0060	0.1728	0.2020	0.6188	0.6494	0.4834
	(− 2.27)	(0.11)	(3.18)	(3.13)	(5.54)	(3.93)	(2.34)
R's hours work	0.0023	0.0019	0.0012	− 0.0002	− 0.0029	0.0073	0.0031
	(0.54)	(0.56)	(0.36)	(− 0.05)	(− 0.40)	(0.67)	(0.25)
R's income	0.1007	0.2286	0.2552	0.4005	0.4476	0.2189	0.3205
	(0.85)	(2.45)	(2.69)	(3.68)	(2.37)	(0.76)	(0.98)
mother part-time job	0.0022	0.0710	− 0.0263	− 0.0230	− 0.1201	− 0.0823	− 0.0671
	(0.02)	(1.02)	(− 0.36)	(− 0.27)	(− 0.81)	(− 0.38)	(− 0.25)
mother full-time job	0.1014	0.1780	0.1907	0.2111	0.3194	0.1550	0.1162
	(1.39)	(3.18)	(3.23)	(3.00)	(2.64)	(0.89)	(0.55)

Notes
$N = 34{,}451$. All models include a constant and age and year dummies. *t*-ratios are in parentheses.

quantiles and with increases in BMI at higher quantiles. For females, then, higher poverty rates are associated with reductions in weight for underweight respondents and increases in weight for those at risk of becoming overweight, suggesting that alleviating poverty may

TABLE 6
BMI QUANTILE REGRESSIONS: FEMALES

Variables	5	10	25	50	75	90	95
price of fruit & veg	0.5177	0.3872	0.4003	0.9407	0.8545	1.4270	2.3597
	(1.90)	(1.71)	(1.83)	(4.06)	(2.01)	(2.03)	(2.38)
price of fast food	0.0003	− 0.1187	0.0865	− 0.1074	− 0.5713	− 1.0876	− 0.3661
	(0.00)	(− 0.91)	(0.67)	(− 0.80)	(− 2.35)	(− 2.68)	(− 0.62)
fast food restaurant density	− 0.0042	− 0.0072	− 0.0036	− 0.0073	− 0.0070	0.0030	− 0.0188
	(− 0.34)	(− 0.53)	(− 0.32)	(− 0.62)	(− 0.34)	(0.09)	(− 0.40)
full service restaurant density	0.0010	− 0.0011	0.0013	− 0.0023	− 0.0068	− 0.0101	− 0.0029
	(0.32)	(− 0.28)	(0.43)	(− 0.73)	(− 1.28)	(− 1.25)	(− 0.26)
supermarket density	− 0.1885	− 0.1335	− 0.0833	− 0.0636	− 0.0432	− 0.1479	− 0.0702
	(− 4.59)	(− 3.74)	(− 2.29)	(− 1.54)	(− 0.55)	(− 1.34)	(− 0.44)
per capita income	− 0.0305	− 0.0446	− 0.0641	− 0.1183	− 0.2201	− 0.3951	− 0.5987
	(− 0.96)	(− 1.67)	(− 2.37)	(− 4.12)	(− 3.99)	(− 4.14)	(− 4.12)
poverty rate	− 0.7218	− 0.2408	0.2060	0.8553	1.6371	1.9810	1.5665
	(− 1.74)	(− 0.71)	(0.63)	(2.52)	(2.64)	(1.89)	(1.02)
black	0.5340	0.6760	0.8897	1.3461	2.1862	3.1140	3.2648
	(6.23)	(9.64)	(12.75)	(18.54)	(16.44)	(13.78)	(9.76)
hispanic	0.4016	0.4263	0.5034	0.6337	0.8495	1.3554	1.1446
	(4.46)	(5.79)	(6.95)	(8.34)	(6.11)	(5.68)	(3.30)
other race	− 0.1749	− 0.2271	− 0.2165	− 0.1970	− 0.2776	− 0.0765	0.0211
	(− 2.13)	(− 3.30)	(− 3.24)	(− 2.82)	(− 2.19)	(− 0.36)	(0.07)
grade10	0.8742	0.7174	0.6896	0.8801	0.0241	− 0.5749	− 1.2940
	(4.23)	(4.30)	(4.31)	(5.36)	(0.08)	(− 1.04)	(− 1.86)
father < HS	0.2230	0.2801	0.3651	0.5009	0.8079	0.9266	0.7568
	(2.64)	(4.02)	(5.31)	(6.94)	(6.11)	(4.12)	(2.28)
father > HS	− 0.1822	− 0.1727	− 0.1717	− 0.3627	− 0.5244	− 1.0664	− 1.2666
	(− 3.19)	(− 3.56)	(− 3.57)	(− 7.12)	(− 5.58)	(− 6.59)	(− 5.45)
mother < HS	− 0.2693	− 0.1568	− 0.0972	0.0548	0.1259	0.1630	0.4359
	(− 3.04)	(− 2.12)	(− 1.34)	(0.72)	(0.89)	(0.67)	(1.20)
mother > HS	0.0135	0.0164	− 0.0242	− 0.0686	− 0.2317	− 0.4637	− 0.6519
	(0.24)	(0.34)	(− 0.51)	(− 1.35)	(− 2.48)	(− 2.90)	(− 2.82)
intact family	− 0.0926	− 0.1705	− 0.1852	− 0.2025	− 0.2382	− 0.4651	− 0.5518
	(− 1.50)	(− 3.34)	(− 3.70)	(− 3.82)	(− 2.48)	(− 2.81)	(− 2.36)
rural	− 0.1321	− 0.1078	− 0.0244	− 0.0399	0.0192	0.4757	0.4912
	(− 2.12)	(− 2.08)	(− 0.48)	(− 0.74)	(0.20)	(2.86)	(2.03)
R's hours work	0.0083	0.0083	0.0100	0.0148	0.0196	0.0274	0.0304
	(1.69)	(2.10)	(2.63)	(3.68)	(2.67)	(2.17)	(1.54)
R's income	− 0.4242	− 0.2724	− 0.1423	− 0.1910	− 0.2458	− 0.8339	− 0.8166
	(− 2.95)	(− 2.42)	(− 1.31)	(− 1.70)	(− 1.21)	(− 2.45)	(− 1.58)
mother part-time job	0.2016	0.1115	0.0116	− 0.1254	− 0.1760	− 0.6712	− 0.8522
	(2.62)	(1.71)	(0.18)	(− 1.85)	(− 1.43)	(− 3.26)	(− 2.86)
mother full-time job	0.1305	0.0573	0.0889	0.0628	0.0964	0.0639	− 0.0546
	(2.03)	(1.06)	(1.67)	(1.13)	(0.95)	(0.37)	(− 0.22)

Notes
$N = 38{,}590$. All models include a constant and age and year dummies. t-ratios are in parentheses.

decrease the probability of both underweight and overweight. In contrast, variation in poverty rates (income constant) have little effect on the distribution of male BMI.

The effects of the demographic variables on the distribution of BMI also often vary substantially across quantiles. The OLS estimates suggest that mother's part-time

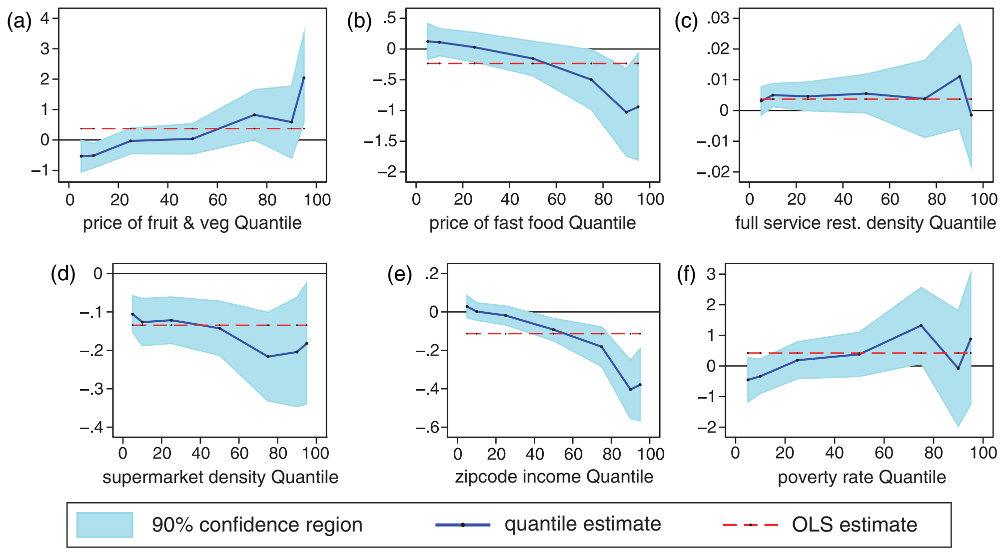

FIGURE 2. Selected quantile regression estimates: males.
Effects of selected covariates on quantiles of the conditional distribution of BMI. The dashed lines denote the OLS estimate. The solid lines and the shaded areas represent the quantile estimates and their 90% confidence regions.

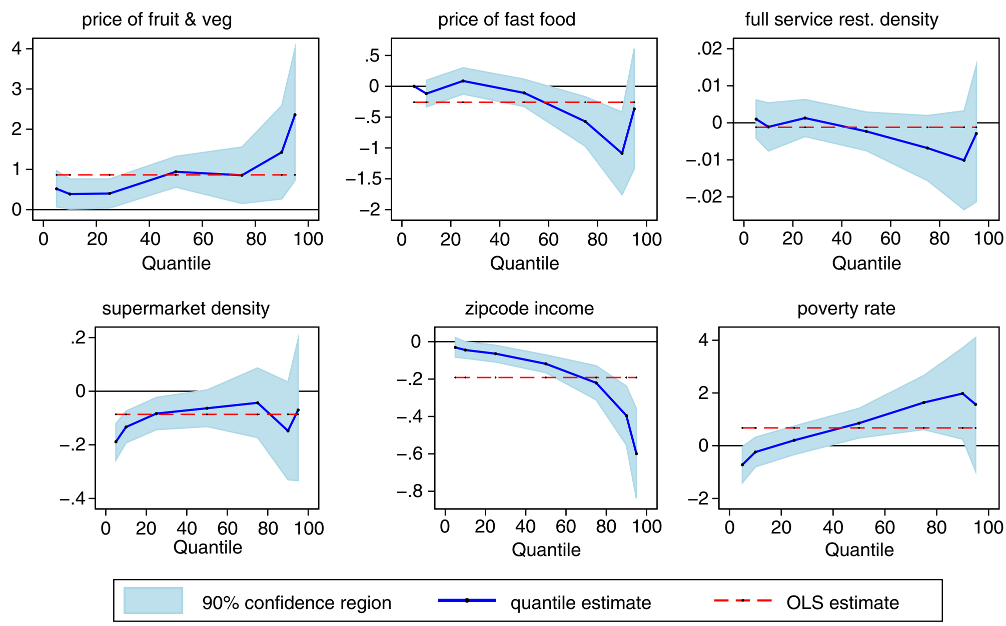

FIGURE 3. Selected quantile regression estimates: females.
Effects of selected covariates on quantiles of the conditional distribution of BMI. The dashed lines denote the OLS estimate. The solid lines and the shaded areas represent the quantile estimates and their 90% confidence regions.

employment reduces female BMI but not male, whereas full-time employment increases male BMI but not female. The estimates also differ when the quantiles are decomposed. Mother's full-time employment increases the BMI of males in the interquartile range more so than in either tail. Mother's full-time employment increases BMI among underweight females (at the 5th quantile) but does not otherwise statistically affect female BMI. Mother's part-time employment serves as a protective factor for adolescent females: it both substantially increases the BMI of underweight girls and markedly reduces the BMI of overweight girls. The same pattern obtains for males but is nowhere statistically significant. Parental education also has differential effects across the BMI distribution. For example, having a mother with less than a high school education reduces BMI among already underweight adolescents and increases BMI among those who are overweight or at risk of becoming overweight (though the latter effect is not statistically significant for females). Both male and female respondents with mothers who have greater than high school education have statistically significantly lower BMI in the upper half of the distribution.

Several other variables shown in the OLS and probit models to reduce body weight on average have effects that, like food prices, are concentrated in the upper range of the conditional distribution for either males or females. These include the racial dummies and the indicator for an intact family.

(d) Policy implications

Table 7 displays selected estimates expressed as elasticities, which makes the magnitude of the effects more readily interpretable. The results underscore the finding that changes in food prices have much larger effects on overweight individuals than they do on individuals of normal or lower weight. Most of the variation in body weight that occurs in response to food prices happens above roughly the 80th percentile, reconciling the small OLS elasticities with the substantial elasticities at the 90th and higher quantiles and with the large probit elasticities. Restaurant density has negligible effects throughout the distribution. Finally, supermarket access has effects that are similar to a location shift in the distribution of BMI: more supermarkets reduce weight by roughly the same amount throughout the distribution.

TABLE 7
EFFECT OF A 1% INCREASE IN SELECTED VARIABLES ON WEIGHT OUTCOMES

			BMI quantile:		
	Mean BMI	Overweight	50	90	95
Males					
price of fruit and vegetables	0.012%	0.216	0.001	0.015	0.049**
price of fast food	– 0.029	– 0.416	– 0.020	– 0.100**	– 0.085*
fast food restaurant density	0.000	– 0.016	– 0.001	– 0.002	– 0.002
full service restaurant density	0.002	0.038	0.003	0.005	0.005
supermarket density	– 0.002***	– 0.023***	– 0.002	– 0.002**	– 0.002*
Females					
price of fruit and vegetables	0.029***	0.117	0.033***	0.039**	0.059**
price of fast food	– 0.033	– 0.718	– 0.014	– 0.112***	– 0.034
fast food restaurant density	– 0.001	– 0.031	– 0.001	0.000	– 0.002
full service restaurant density	– 0.001	0.020	– 0.001	– 0.005	– 0.001
supermarket density	– 0.001**	– 0.018	– 0.001	– 0.002	– 0.001

Notes
Elasticities calculated from OLS, probit and quantile regressions presented in Tables 3–6.
1% signicance***, 5% significance**, 10% significance*.

Most of these effects seem fairly small, and even the larger effects on high-risk adolescents often fail to achieve statistical significance. Nonetheless, whether or not these effects are considered 'large' depends on the context. Consider the implications of the probit estimates for a town with 10,000 adolescents in its population. Unconditionally, we would expect slightly over 1000 to be overweight. The estimates suggest that a tax that increased the price of a meal at a fast food restaurant by $1 would reduce the number of overweight adolescents by (10,000)(0.0189) = 189. Reducing the price of the basket of fruit and vegetables to half its mean would lift about (10,000)(0.720)(0.5)(0.0229) = 82 adolescents out of overweight status. And opening one new supermarket per 10,000 capita would reduce the weight of an additional (10,000)(0.0062) = 62 adolescents to below the overweight threshold.

Consider the effects of changes in policy-alterable variables on the outcomes of overweight adolescents at the 95th percentile of the conditional distribution of BMI (see Table 7). A subsidy that decreases the price of fruit and vegetables by 10% would decrease their BMI by about 0.5% (0.49% for male and 0.59% for female respondents); for example, a 5 ft 6 in. adolescent who weighs 200 pounds (BMI = 32.3) could expect to be one pound lighter in the presence of the tax. Similarly, an 0.85% reduction in an adolescent male's BMI in response to a tax-induced 10% rise in the price of a fast food implies that a 200 pound male's weight would fall by about 1.7 pounds in response to the tax.

Are these effects 'large' for policy purposes? The answer depends on both the costs of implementing policies that reduce body weight and on the social benefits of weight reduction. In no case should we expect moderate taxes to have dramatic effects on adolescent body weight, even for the very overweight adolescents whose body weights are most responsive to changes in prices and other incentives. Further, benefits from taxing foods must be weighed against the costs of taxation, including possibly higher rates of certain nutritional deficiencies.

IV. Conclusions

Are decreases in the price of energy-dense foods, such as fast food meals, responsible for increases in adolescent overweight? Would taxing fast food or subsidizing fruit and vegetable consumption be effective policy instruments to reduce obesity? We present estimates of the causes of adolescent body weight focusing on the prices of, and access to, high-energy-dense and low-energy-dense foods. We show in a simple rational choice model that a decrease in the relative price of energy-dense foods tends to increase BMI if the price of a calorie of energy-dense food is lower than the price of a calorie of less energy-dense foods. If the price per calorie of energy-dense foods were higher than that of less dense foods, we would expect the opposite. This behavioural explanation complements physiological mechanisms that have previously been proposed to explain the relationship between relative food prices and body weight.

We use large repeated cross-sections of adolescents drawn from the Monitoring the Future surveys to investigate the determinants of the distribution of BMI. The results show that, as predicted, the price of energy-dense food (proxied by fast food prices) is negatively associated with weight, whereas the price of less energy-dense foods (proxied by the prices of fruit and vegetables) is positively associated with weight outcomes. Restaurant access is not statistically or economically associated with BMI, whereas higher supermarket density is associated with lower body weight and probability of overweight. Local per capita income is negatively associated with BMI, but (conditional on incomes) poverty rates have little effect on BMI or overweight. Our estimates are limited in that we use self-reported height and weight data, and we treat food price and restaurant and food store density as exogenously assigned conditional on observable characteristics. Demand-driven variation in prices and densities that remains after conditioning on observable characteristics will bias our estimates.

Quantile regression estimates indicate that OLS models of BMI may be misleading. For policy purposes we are most interested in the outcomes of individuals at risk, i.e. those near or above the weight at which they are considered obese and whose weight damages health and other outcomes. Food prices have small effects on most of the population, but larger effects on individuals above the 80th or so quantile of the conditional distribution of BMI. For example, for males and females the effects of fruit and vegetable prices and fast food meal prices at the 90th or 95th quantile are three to five times greater than the OLS estimates. OLS estimates of the effects of food prices and access may be misleadingly small because they average the negligible effects on individuals below the 80th quantile with the much larger effects in the top quintile.

From a policy perspective, if taxes, subsidies, zoning regulations and similar economic incentives were used to address obesity, our results suggest that taxing fast food might be effective. However, as noted earlier, the desirability of such taxes hinges not only on their likely effect on body weight but also on a variety of distributional and other considerations, including potential adverse effects on nutritional deficiencies such as anaemia. Our results also show that subsidizing fruit and vegetable consumption, either directly through price subsidies or indirectly through encouraging supermarket construction, may reduce adolescent overweight. On the other hand, our results suggest that policies that affect restaurant outlet density would not be effective in changing adolescent body weight.

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NOTES

1. We assume away addictive effects of food consumption. See Cawley (1999) for a discussion of the implications of addictive caloric consumption.
2. In these models we do not include zip code fixed effects for two reasons. First, we wish specifications to be consistent across estimators, and fixed effects are difficult or impossible to include in the nonlinear probit and quantile regressions to follow. Second, there is substantially less variation in the price and access measures left over to identify the effects of interest when cross-regional variation is removed. However, we did estimate the OLS models with zip code effects and found that, generally, the price and access measures effects were imprecisely estimated, but the point estimates sometimes fell and sometimes increased. These estimates are available from the authors on request.

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