The Joint Impact of Income Supplementation and Food Prices

on Child and Adolescent Overweight

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Abstract

Our analysis examines the independent and joint effects of income supplementation and food prices on child overweight from the ages of 2 to 18. We examine the effects of supplementation using variation from the national expansions and changing benefits structures of the Earned Income Tax Credit (EITC). We examine the effects of prices using regional and temporal variation of baskets of unhealthy, healthy and fast food. We then examine whether there are interactions between income supplementation and local food pricing in determining onset of childhood overweight. These questions are examined using individual fixed effect regression models among children of participants of the National Longitudinal Survey of Youth 1979 from 1990 to 2006. In aggregate we find that higher EITC benefits are associated with increased child overweight. However, among individual living in areas with the highest prices for healthy food, receipt of larger EITC benefits results in lower levels of overweight.

Introduction

The burden of child obesity is disproportionately borne by low-income families and disadvantaged communities. Many have posited that this reflects effects of both family poverty and community characteristics. It is argued that family poverty increases the risk of child obesity because poor families cannot afford healthier food options (e.g. fruits, vegetables) and so rely on less healthy options (e.g., energy dense high fat, high carbohydrate foods).(1) However, moving beyond evidence of correlation to estimates of causal effects has been difficult because there are many potential confounding factors that may jointly determine poverty and child obesity. For instance, many difficult to measure parental characteristics (e.g., parents' knowledge, preferences, behaviors, or own childhood exposures) could simultaneously lead families into poverty and increase the risk of obesity among children, thus making estimates of income effects on child obesity seem larger than they really are (i.e., causing upward confounding bias).(2, 3)

In recent years, many population health researchers have tried to estimate causal effects of various exposures with actual and natural experiments. Researchers have estimated the health consequences of natural income experiments such as lottery winnings and changes in U.S. social security payments.(4, 5) Researchers have also examined how actual incomes experiments (e.g., the Negative Income Tax experiment from 1968-1979) impact health outcomes.(6) However, most of these analyses have not considered how these effects could vary by context. A lack of geographic/temporal variation in the (natural) experiment or a lack of data on local contextual factors have made it impossible for many of these researchers to take a multi-level approach. Our proposed research bridges this gap by focusing on exogenous, policy driven income variation, but further considering how this income variation may interact with contextual factors (i.e., local food prices). Such an analysis should reveal important insights into how resources may or may not affect child overweight in different environments.

methods

We examined our question using data from the children and young adults of the National Longitudinal Survey of Youth 1979 (NLSY79). The NLSY79 is a nationally representative survey of U.S. men and women who were 14-22 in 1979. The NLSY79 Children and Young Adults is a separate survey of all children of NLSY79 females that began in 1986, and has collected data every 2 years since then for all children from birth to age 21. County of residence was determined using geocoded location of residence. After excluding individuals missing location of residence, height, weight or household income, there were with a total of 22,704 observations for our analysis.

A family's qualification for and estimated benefits from the EITC for each of the years 1990 to 2008 was determined using the National Bureau of Economic Research's (NBER) TAXSIM program.(7) This program calculates the exact value of the EITC credit using US Federal and State income tax codes. The characteristics used to determine EITC benefits were family total pre-tax income, number of dependents under 18 living in the household, marital status and year of earnings.[1]

Our specific food price data are calculated from the ACCRA Cost of living Index which offers the broadest geographic coverage of any pricing data with metropolitan area specific prices on a range of foods, such as fruits and vegetables, which do not have Universal Product Codes.(8) We created three cost indexes: healthy food (bananas, lettuce, sweet peas, peaches), unhealthy food (sugar and shortening) and fast food

[1] Planned analysis also include state of residence that will allow for another source of EITC variation.

(McDonald's quarter-pounder with cheese, a 12" thin crust regular cheese pizza and a fried chicken drumstick and thigh at Kentucky Fried Chicken and/or Church's Fried Chicken.).

The model we used for examining interaction between EITC benefits and food costs was as follows:

$$y_{it} = \beta_1 EITC_{it} + \beta_2 x_{it} + \beta_3 \text{Food cost}_{it} + \beta_4 EITC*\text{Food cost}_{it} + u_i + e_{it}$$

Where y_{it} is a dichotomous measure of 85th percentile of BMI [2] (overweight) for individual i at time t, β_1 is the parameter estimate of the association between dollars of EITC and overweight, β_2 is a vector of parameter estimates for control variables x_{it}, U_i is a normally distributed individual fixed effect [3] and e_{it} is the remaining individual variance. Additionally, β_3 reflects the association between local food price indices and overweight and β_4 reflects the interaction between local prices and the effect of EITC dollars on overweight. The use of individual-level fixed effect models means that we are examining within subject change over time. The parameters from our model can thus be best interpreted as reflecting the effects of changes in EITC and food costs over time.

results

The table below shows the results from three fixed effect models examining within individual variation between our predictors of interest and overweight. We find that overall in this population of children, higher levels of EITC benefits are associated with increased probability of becoming overweight. We also find that higher healthy food

[2] We calculated BMI as percentile of BMI for age (in months) and gender based on CDC growth charts, and fit each model using three outcomes: continuous BMI percentile, 85th percentile dichotomized (overweight) and 95th percentile dichotomized (obese). Results were generally much weaker for the continuous BMI percentile measure, and similar for overweight and obese, suggesting greater importance of income transfers and prices at the upper end of the BMI distribution. In this brief abstract we present results only for overweight.

[3] Hausman tests as compared to random effects models were generally rejected.

prices are associated with increased probability of becoming overweight. Unexpectedly, we also find that higher fast food prices are also associated with increased probability of becoming overweight. These associations with prices, however, differ depending on level of EITC benefits received. Most notably, among individual living in areas with the highest prices for healthy food – receipt of greater EITC benefits results in lower levels of becoming overweight. These results point to the importance of contextualizing income effects on obesity and, more generally, of recognizing that the impacts of policies on children are likely to depend on local environments.

Table. Fixed effect regression estimates of the association of food prices and earned income tax credits (in dollars) on overweight (85th percentile of BMI), NLSY79 children age 2-18, 1990-2006.[4]

Predictor variable	coefficient (standard error)
Unhealthy food prices	
Middle tertile	-0.17 (0.31)
Upper tertile	-0.28 (0.36)
EITC	0.36 (0.17)**
EITC X middle tertile	-0.25 (0.20)
EITC X upper tertile	-0.13 (0.22)
Healthy food prices	
Middle tertile	0.62 (0.35)*
Upper tertile	0.15 (0.37)
EITC	0.40 (0.16)**
EITC X middle tertile	-0.24 (0.20)
EITC X upper tertile	-0.36 (0.21)*
Fast food prices	
Middle tertile	0.84 (0.38)**
Upper tertile	0.37 (0.41)
EITC	0.35 (0.15)**
EITC X middle tertile	-0.19 (0.19)
EITC X upper tertile	-0.23 (0.20)

[4] Table notes: All models also include year (as a linear term), indicator variables for 4 census regions, level of maternal education in years, age in months, age in months squared, currently married and currently divorced. All models were fit using NLSY79 sampling weights. EITC benefits are in thousands of dollars. * indicates $p<0.10$, ** indicates $p<0.05$.

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