# The Effects of Anti-Poverty Tax Policy on Child and Adolescent BMI and Obesity

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Working Paper prepared for:

Strong Foundations: The Economic Futures of Kids and Communities
Federal Reserve System Community Development Research Conference

Draft Date: March 8, 2017

Sources of financial support: Robert Wood Johnson Foundation Health Eating Research (66964).

Dr. Rehkopf was supported by the National Institute of Aging (K01AG047280).

**Abstract**
Background: There is substantial evidence for higher household income being associated with lower levels of child and adolescent obesity in industrialized countries. However, there is little known about whether anti-poverty policy can be expected to decrease obesity. The objective of our analysis is to determine whether increases in income due to changes in tax policy are associated with lower levels of BMI and obesity for children living in those households, and whether there are heterogeneous effects of that policy based on maternal characteristics and regional food prices.

Methods: We examined the associations of changes in both the state and federal amount of the Earned Income Tax Credit (EITC) over time on child and adolescent BMI, overweight and obesity. We examined this using longitudinal data from the National Longitudinal Survey of Youth using fixed effect regression models. Our calculation of EITC benefits were based on lagged household characteristics in order to avoid biased estimates due to selection into receiving the EITC.

Results: Increases of $1000 in the EITC were associated with decreases in child BMI percentile (-4.7, 95% CI -6.4, -3.1). While impacts were similar by gender, they were stronger for children age 2-10 (-8.0, 95% CI (-10, -5.5) as compared to children age 11 to 18 (-1.5, 95% CI -3.3, 0.22). There were some modest, but not statistically significant, differences in association by regional food prices. When controlling for year fixed effects, associations were diminished and confidence intervals included the null, although the coefficient for girls was consistent with lower BMI for girls (-2.2, 95% CI -4.7, 0.35).

Conclusions: Our findings are consistent with their being no negative impacts of the EITC on child BMI and obesity, and with beneficial impacts among some groups.

## Introduction

Despite increased medical and public health policy attention, childhood obesity remains a substantial threat to the health of the U.S. Particularly impacted are children living in poverty and in working poor households (1, 2). The causes of obesity are complex, and occur at multiple levels from macroeconomic to behavioral to genetic (3, 4). Due to the complex nature of the causes, it is likely that multiple types of interventions at multiple levels are needed to best address the problem. While interventions targeted toward specific individual-level risk factors for childhood obesity are an important part of the solution, there is currently little evidence on how changes in social and economic policy could contribute to reducing the obesity epidemic. For the most part, social and economic policies are not designed or implemented to impact health, but understanding whether these impacts exist is important for 1) a full accounting of the causes of health, and 2) as a component of the evidence for future social and economic policy decisions. The analyses we present here are focused on testing the hypothesis that a tax policy that increases income for working poor households is associated with lower levels of BMI, overweight and obesity for children living in those households.

There is associational evidence that supports this hypothesis. Environmental differences correlated with income may contribute to higher rates of child obesity in those households (5). For example, food supplies of higher caloric intake and higher levels of refined carbohydrates may differ by level of income due to differences in neighborhood (6). It has been shown that healthier food can be more expensive, with more calorie dense food generally more affordable (7), along with foods with a higher glycemic index. Similarly, the cost to participate in physical activity may be a further barrier.

However, these studies are correlational, and it is possible that the observed higher risk among lower income households may not be because of income itself. Instead, parents in poor households may have less time to ensure healthy diets and physical activity of their dependents given the increased time needed to work at low wage jobs and to deal with problems arising due to poverty (8). Other possibilities include the fact that individuals in poor households may have less knowledge about what types of diets and behaviors are best for ensuring their children maintain a healthy weight. It is also possible that genetic risk for obesity may differ by income level, although no studies have demonstrated this to be the case for the currently documented genetic risk factors for obesity (9, 10). Understanding whether low income actually causes different levels of BMI and obesity in children and adolescents has been difficult to determine because of the many potential confounding factors that may jointly determine poverty and child obesity. For instance, many 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 their children, thus making the impact of income effects on child obesity from associational studies seem larger than they really are (11, 12).

Because of these limitations, it is not known whether programs that reduce poverty through increased income may actually reduce childhood overweight and obesity. In fact, among adults, there is some evidence to suggest that increases to income heighten obesity risk among women (13). In order to address this question to inform policy for reducing childhood obesity in a sustainable and effective manner, we examine the effects of household income and labor market changes that occur due to state-to-state and federal changes over time in the Earned Income Tax Credit (EITC). The federal EITC was enacted as a modest program in 1975, with large expansions in 1986, 1990, 1993 and 2001 (14). In addition, 26 states currently provide various levels of additional tax credits, which have been implemented beginning in 1986 (15). The program is directly targeted toward the working poor, with the largest credits, up to 21% of earned income, going to households with children where combined earnings are the equivalent of one earner working full time at minimum wage. There are decreasing benefits at lower and higher income levels, with the highest level of earnings eligible households between $37,870 and $51,567 depending on number of dependent children. The maximum benefits for households without children in 2013 was $487, while with three or more children the benefit was as high as $6,044. For qualifying households income is received as a tax refund. A large literature has developed that examines the impacts of this program on expenditures, work and family structure (14, 16-23). A small body of studies have begun to examine impacts on health and child development (24-29).

Our analytic strategy involves examining the effect of this EITC benefit on child obesity in a way that allows us to reduce the extent to which individual choice and characteristics may influence our findings. We do this by using predicted EITC benefits, rather than actual benefits received, as in an intent-to-treat framework, in order to reduce bias that could occur if differentially at risk subgroups of the population were more or less likely to actually claim the credit. Secondly, we used two year lagged individual and household characteristics to predict EITC to eliminate bias that could exist from individuals changing their levels of earning, or number of children, in order to qualify for greater EITC benefits. That is, we use earnings and household size 2 years prior to the year of analysis to calculate how much benefits are received. Finally, we estimate parameters using both household and individual fixed effect models, as well as controlling for time-varying individual demographic factors that influence levels of EITC benefits, level of household earnings and number of dependents. In this way, we are examining the effects of the program changes in a way that is not dependent on individual characteristics.

In addition, we examine whether there are differences in effects by five *a priori* determined characteristics of the child, the mother and the environment: child age, maternal obesity, the metro area cost of healthy food (as a ratio to overall food prices), the metro area cost of unhealthy food (as a ratio to overall food prices), and the metro area cost of fast food (as a ratio to overall food prices). Our first hypothesis is that impacts of the EITC will be stronger at younger ages, when parental resources and control have a greater impact on eating behaviors as compared to adolescence (30, 31), and where other social interventions have been shown to have a greater impact on child development (32). Our second hypothesis is that impacts of the EITC will be worse among children with obese mother's, as genetic, social and environmental influences on obesity may overwhelm any expected benefits and exacerbate any harms of the EITC on child obesity. Our third hypothesis is that there will be more beneficial impacts of the EITC on child BMI, overweight and obesity if healthy food prices are high, because additional household income will be more impactful in reducing the barriers to access those foods (33, 34). This expectation is based on part that the monetary benefits of the EITC can be quite large, and that this has been shown to reduce the extent to which households said that their diet was limited due to financial reasons (25). Finally, we expect a similar relationship with unhealthy and fast food prices, that if relatively more costly, the EITC may reduce economic barriers to unhealthy food consumption. That is, if fast food or unhealthy food prices are already low, the EITC may have more beneficial impacts on BMI and obesity because it does not change how households will purchase fast foods. We emphasize, however, that we do not have strong support from the literature for or against any of these hypotheses, but that they are part of what should be a systematic analysis of the potential for heterogeneous impacts of social policy on child health and development, based on what are leading potential hypotheses.

## Methods

### Sample

We examined our question using data from the National Longitudinal Survey of Youth 1979 (NLSY1979) and the children and young adults of the National Longitudinal Survey of Youth 1979. 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. We examine data through 2004 because after 2004 there were no changes in the amount of federal EITC credits apart from adjustment for inflation. After excluding individuals missing location of residence, height or weight, or income we had 28,301 observations on 3,194 unique children and adolescents, aged 24 to 228 months old at the time of height and weight measurement.

### The Earned Income Tax Credit

The EITC is the largest anti-poverty program in the U.S. (in terms of both federal/state dollars spent and the number of families moved out of poverty). It is designed to reduce the tax burden on, and supplement the incomes of, low-wage workers in the United States. In order to qualify for the EITC, a person must have some earnings, but have an adjusted gross income below a threshold that varies by year and family size. The credit itself reduces tax liability to increase after-tax income. Since the federal and most state EITCs are refundable, filers who owe less than their calculated credit receive the difference as a cash transfer, usually as a lump sum payment after filing taxes. The amount of additional income from the EITC is substantial. The figure shows the average and maximum credit among those qualifying for the EITC by year for a household filing as married with 2 children. These changes over time reflect federal and state expansions of the EITC and are the key source of exogenous variation that we use for identification in our statistical models. The exposure in our models is based on the change in EITC benefits over a two year period of time. The range of change in state benefits over a two year period of time is from -388 to 954 dollars, the range of change in federal benefits is from -98 to 1717 dollars.

A household's qualification for and estimated benefits from the EITC for each of the years was determined using the National Bureau of Economic Research's TAXSIM program (35). This program calculates the exact qualifying value of the EITC credit using US Federal and State income tax codes. The characteristics used to determine EITC benefits were household total pre-tax income, number of dependents under 18 living in the household, marital status, state of residence and year of earnings. In order to avoid the documented selection bias of some households changing work hours in response to changes in EITC qualification rules, we used earnings and number of dependents from 2 years prior to determine EITC benefits. While this decreases precision in imputed EITC benefits qualified for, it reduces the potential for biased selection into treatment levels. Note that we use the amount of credit that an individual qualifies for, not what they actually receive. This is akin to an intent to treat analysis that preserves the quasi-experimental nature of our exposure that we argue is the most policy relevant exposure of interest. If we used the actual amount of credit received as our exposure, this would be biased because potentially healthier households would be more likely to actually receive their credit.

Child BMI percentile, overweight and obesity

Child height and weight were reported by either respondent or caregiver, and in other cases measured, depending on whether caregiver knew height and weight. When reported (not measured), height and weight were each separately adjusted for measurement error by regression calibration (36) using data from NHANES III where height and weight were both self-reported and measured (see appendix for code for calculation). Percentiles of BMI were calculated based on Centers for Disease Control and Prevention growth charts, with overweight defined as having a greater than or equal to 85$^{th}$ percentile of BMI, with obese defined as having a greater or equal to 95$^{th}$ percentile of BMI. 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, 85$^{th}$ percentile dichotomized (overweight) and 95$^{th}$ percentile dichotomized (obese). We included an indicator variable in all regression models for whether weight was measured or reported, although models were similar with and without this variable.

Analysis

Our primary modeling strategy was as follows. We first fit unadjusted generalized additive models to show the associational relationship between pretax income and EITC tax credit dollars and child BMI percentile. These models allow for a nonlinear dependence of earnings or EITC benefits on BMI percentile (37). We then present adjusted random effects models which are equivalent to cross-sectional models, with the random effects included in order to adjust for multiple measurements on the same individuals. We next present household-level fixed effect models in which children (typically siblings) living in the same household are compared to one another. These models hold constant unmeasured time-invariant differences across households such as unobserved preferences for work and obesity-related behaviors. Finally, we present child-level fixed effects models that capture within subject changes over time and hold constant unmeasured, time-invariant differences across individual children. Each of these models account for the clustered nature of the sample, and all analyses were done using sample weights so that results were more broadly generalizable to the U.S. population.

Identification relies on several attributes of the model and exposure. Most importantly, the EITC exposure we use is change in EITC generosity that results not from changes in household characteristics, but changes in the generosity of the EITC program. We use the difference between amount of EITC qualified for three years before and the amount qualified for in the year prior to the assessment of BMI. We are using the same lagged qualifying characteristics to determine the amount of EITC qualified for in each of these years, three years prior to the assessment of height and weight and in the year prior to the assessment of height and weight. For example, for the analysis of child BMI in the year 2000, we calculate the level of EITC benefits based on characteristics from the year 1997 run through the 1999 tax schedule, minus the level or EITC benefits from characteristics of the year 1995 run through the 1997 tax schedule. In addition, further supporting identification, the EITC exposure depends on the change in EITC qualification, i.e. difference between amount of EITC qualified for two years earlier and the amount qualified for in the year prior to the assessment of BMI (such as due to policy changes in the EITC schedule). The regression model we used for examining the effects of income was as follows:

$$y_{\mathrm{it}} = \beta_1 \mathrm{EITC}_{\mathrm{it}} + \beta_2 x_{\mathrm{it}} + u_i + e_{\mathrm{it}}$$

Where $y_{\mathrm{it}}$ is either a continuous measure of BMI percentile or a dichotomous measure of 85th percentile of BMI (overweight) or 95th percentile of BMI for individual (or household) $i$ at time $t$,

$\beta_1$ is the parameter estimate of the association between thousands of dollars of EITC credit and the outcome, $\beta_2$ is a vector of parameter estimates for control variables $x_{it}$, $u_i$ is a normally distributed random error, or an individual or household fixed effect and $e_{it}$ is the remaining individual idiosyncratic error. The use of a random effects assumption is equivalent to a cross-sectional analysis that takes into account the multiple measures of the same individual, while the individual-level fixed effect models implies that we are examining within subject change over time.

Control variables $x_{it}$ were currently married, currently divorced, number of dependents, mother's IQ (as percentile on the Armed Services Qualifying Examination), mother's level of education (as less than high school, high school diploma, some college, 4-year college degree), child age in months, child age in months squared, census region, the Rosenberg Self-Esteem scale (38), the Rotter Locus of Control Score (39), the Pearlin Mastery scale (40), mother's depression, mother's health status (SF12), Hispanic ethnicity of the child, race of the child, number of dependents in the household, pretax earnings (and 2nd-5th polynomials of income) and wave of data collection (as a linear term and as a squared term). The polynomials for pretax earnings were included to account for the non-linear benefit structure of the EITC. Year as a linear and squared term was included in order to account for secular non-linear changes in obesity over time, which was increasing over this time period. We also examine models with two other specifications for year (or wave of data). First, we include instead an indicator for wave 10 (year 1994), as this is when the largest increase in EITC occurred. Next, we fit a model using fixed effects for year.

Heterogeneity of effects

We also examine whether there were differences in impacts over 5 *a priori* determined characteristics of the child, the mother and the environment: child age, maternal obesity, the metro area cost of healthy food, the metro area cost of unhealthy food, and the metro area cost of fast food. Child age was *a priori* divided into two categories 2-10 and 11-18, corresponding generally to pre and post-puberty, as well as ages when parents have more and less control over their child's diet and exercise patterns. Maternal obesity was based on the traditional definition of obesity, with greater than or equal to a BMI of 30 defined as obese. Metro area food prices were based on the ACCRA cost of living index data for metropolitan areas (41). The ACCRA Cost of living Index 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 (42). We created three cost indexes were: healthy food (bananas, lettuce, sweet peas, peaches), unhealthy food (sugar and shortening) and fast food (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). Healthy food, unhealthy food and fast food ratios are ratios of average cost of bundle of food as compared to average cost of a general food summary in order to create equivalent measures for general food prices in the metropolitan statistical area.

**Results**

Table 1 shows the differences between the populations that qualified for an Earned Income Tax Credit Refund as compared to those who did not qualify, among the entire NLSY sample population. The education of the primary subject's mother and grandmother were both slightly higher among those who did not qualify for the credit. Earnings, wealth and mom's test scores were also substantially higher. These differences illustrate the challenge of identifying the causal effects of the earned income tax credit policy through approaches that rely solely on conditioning on covariates, without using changes in benefits that are not linked to individual characteristics.

Figure 1 shows the non-linear change in earned income tax credit benefits over time, the key source for identifying the effects of the EITC on child body mass index.

Supplemental Figures 1a and 1b show the unadjusted relationship between pretax household earnings and child BMI percentile, for girls and boys. These figures show the previously identified relationship where higher pretax earnings are associated with generally lower levels of BMI. While this is a close to linear association for boys, for girls the highest level of BMI is not among the very poorest families, but among those households earning around $20,000 per year. Prior work on cardiovascular biomarkers in the National Health and Nutrition Examination data reported some similar findings in adults (43).

Table 2 shows regression coefficients for changes in the earned income tax credit qualifications and child BMI percentile, overweight and obesity. Due to prior literature suggesting differences by gender (13), all analyses were run stratified by gender. The table shows the coefficients from three different types of models, for three outcomes in three populations. The first column shows results from random effect models, the second column from household fixed effect models, the third column of data from individual fixed effect models. The first three rows of coefficients are for models with a dependent variable of Body Mass Index percentile. The coefficients can be interpreted as the difference in BMI percentile associated with an increase in $1000 of EITC benefits. 95% confidence intervals are shown in parentheses. Rows 4 through 6 show regression coefficients for the relationship between an increase in $1000 of EITC income and the log odds of the child being obese. Rows 7 through 9 of data show the same format of coefficient, but for obesity. For BMI percentile, there is a meaningful and statistically significantly lower level of BMI percentile associated with a greater amount of household EITC earnings, with both boys and girls showing a similar difference. An increase in EITC income is associated with decreased overweight and obesity in the full population. Notably, coefficients from the three types of models were very similar, suggesting that there are few unmeasured individual level confounders of the changes in EITC generosity over time that form the basis for our identification strategy. For household fixed effect models, for every $1000 increase in the EITC we find a 4.7 BMI percentile decrease (95% CI -6.4, -3.1) and for child fixed effect models we find a 4.4 BMI percentile decrease (95% CI -5.8, -3.0).

Table 3 shows three a priori specified effect stratifications of earned income tax credit dollars on child BMI percentile and obesity, by age, by mother's obesity, and by metro area food prices. Since our prior analyses did not find differences in coefficients by gender, we do not further stratify these models by gender. Supplemental Figure 2 shows the differences in the distribution of food costs for both those that do not qualify for the EITC (shown in blue) and those who do qualify for the EITC (shown in red). Supplemental Figure 2 shows that while food prices differ markedly by U.S. location, there is little difference in food prices for those who do and do not qualify for any EITC refund. The results presented in table 3 show that there are difference in the association of increases in EITC refund with BMI percentile, overweight and obesity depending on age. For all outcomes, the only differences that were substantial and for which confidence intervals did not cross the null were for children ages 2-10 as compared to children 11-18. Thus the primary results shown previously in table 2 are largely driven by the age 2-10 population. Effects were not found to differ by level of mom's obesity, with equal benefits for those children in households with an obese or a non-obese mother. Finally, we examined differences in effect by three types of food price ratios: healthy food, unhealthy food and fast food. While differences were not marked, there was a qualitatively greater impact in areas with the highest level of healthy food prices, and in areas with the lowest relative levels of fast food prices. Results were generally similar for all three types of models (random effect, household fixed effect and child fixed effect).

Table 4 compares our primary findings with different model specifications for controlling for year of data. Column 1 repeats the analyses controlling for wave and wave-squared. Supplemental Figure 3A shows that the majority of increase in EITC occurred in wave 10 (1994), and Supplemental Figures 3B-D show that there were lower levels of BMI, overweight and obesity in that year, thus our second model controls for an indicator variable for wave 10. Finally, model 3 controls for fixed effects for wave. As wave 10 is our primary source of identification, results are attenuated in model 2. Results are further attenuated in model 3, as the temporal changes in the generosity of the EITC are the primary source of identification in the model. Results for models 2 and 3 are generally consistent with their being no negative impact of the EITC on child obesity, and the coefficient for girls for BMI include the null, but are generally consistent with our primary findings in model 1.

**Discussion**

We find that increases in the EITC benefits are associated with decreased levels of BMI, overweight and obesity among boys and girls, with the most substantial differences in children ages 2 to 10. While our inference from these findings is not as strong as would be the evaluation of a randomized Earned Income Tax Credit policy, our analytic approach that uses temporal and spatial difference in EITC benefit structure allows us to examine the effects of the policy that are not dependent on individual characteristics. Our findings suggest that the EITC policy may have meaningful benefits for reducing child BMI under the age of 10 in working poor populations. There is, however, an important caveate to these findings, since our identification is based on temporal changes in the EITC. When we control for year fixed effects, all of our estimates include the null, although the direction of coefficients are similar to our primary models. It is also critical to understand that the impacts we estimate are from all of the changes that are induced by EITC policy, including the EITC benefits themselves, the changes to earned income, and the changes to labor market participation. Our analysis does not estimate the more theoretical effect of income *per se*.

While our study is the first to examine the impact of the EITC policy on child BMI, there have been other studies of impacts on other health outcomes. Prior studies have examined how changes in EITC policies predict specific health outcomes, such as infant health (27, 44, 45) adult biomarkers (28), adult obesity (46), and self-assessed health (28). Most of these studies suggest that EITCs are health promoting (27, 28, 44) but there are exceptions that reveal deleterious health effects of the EITC (45, 46).

There are two studies that are most closely related to this current study, although there are important differences in the analytic approach and intent of these studies. Prior work has shown that there were detrimental effects of income instrumented by the EITC on women's BMI (13), and no impacts on childhood BMI (47). These analyses differed in intent and modeling approach from our analysis as they both used an instrumental variable approach to identify income effects on BMI among adults, rather than the EITC policy. The prior study on child BMI also used changing returns to income, based on demographic characteristics set at birth, in order to further instrument income. We use a nearly identical study sample of NLSY data, and similarly operationalize BMI outcomes – the primary difference is the focus on income in general, in the prior work, while we focus on the EITC policy in the current analysis. As compared to the paper in adults, there could also be differences in the effects of EITC dollars by age. This is suggested by our stratified analysis that shows benefits under the age of 10 and no benefits between ages 10 to 18.

There are several limitations inherent to our analysis. No data that we are aware of asks participants if they actually received the earned income tax credit that they qualify for. However, a comprehensive past estimate of the amount of individuals who qualify actually get the credit are from 80-86% (20), with more recent estimates suggesting this level of benefit uptake is even higher. The effect of this small amount of measurement error is an underestimate of the potential impact of income on BMI, overweight and obesity. Child height and weight were also not measured in all children, and prior work has shown that whether children were measured or not is not independent of other demographic factors, such as socioeconomic status.

We did not directly test the mechanisms through which increased EITC benefits may be associated with lower BMI and overweight and obesity. While only speculation, evidence suggests that many parents spend this cash transfer on housing, cars/car repairs, paying off bills, child care and/or children's items (e.g., learning/enrichment items, clothing, etc) (48). Many of these expenditures could have long-term and/or indirect benefits. Investments in cars/car repair and child care can increase earnings by making it easier for parents to work. Investing in new housing may improve access to healthy food and/or outdoor activity. Paying off debt may also be critical for having enough money to afford food and basic necessities throughout the year. Somewhat suggestive of the role of food prices is our stratified analysis that there are some differences in the effectiveness of EITC that appear to be dependent on food prices. Most clearly, the association seems to be greater (and more beneficial) in areas with higher healthy food prices, suggestive that additional income allows individuals to overcome the barriers to purchase healthy food. Less clear are our findings that EITC income increases seem to matter more in areas with the lowest fast food prices. This may be the result of spending on healthier food as a substitute, although other types of data and study design will be needed to further test this speculation.

Whatever the mechanisms may be, our findings are particularly informative for understanding how social and economic policy may impact childhood obesity. While the magnitudes of effect we estimate in this analysis are small relative to the overall burden of obesity, they are suggestive of there being no negative impacts, and of benefits for some groups of the population. In addition, given the fact that other studies appear to show benefits for some other health outcomes, there appear to be some efficiency in this program in terms of multiple benefits for children and families.

Table 1. Household, maternal and child characteristics, Children and Young Adults of the National Longitudinal Survey of Youth 1979, age 2-18, 1986-2004.

| | Total Population (n=3194) | EITC qualify (n=1816) | EITC non-qualify (n=2595) |
|---|---|---|---|
| Mother and Household characteristics | | | |
| Education of mom (years) | 13 | 12 | 13 |
| Education of Grandmother (years) | 11 | 11 | 12 |
| Pretax earnings (year 2000 dollars) | 55,000 | 15,000 | 69,000 |
| Wealth (year 2000 dollars) | 150,000 | 83,000 | 170,000 |
| Mom's AFQT score | 52 | 38 | 45 |
| Mom Married (%) | 63 | 26 | 84 |
| Mom Divorced (%) | 23 | 43 | 11 |
| Mom foreign born (%) | 6.2 | 6.7 | 5.9 |
| Number of siblings | 3.5 | 4.0 | 3.4 |
| Mom's BMI ($m/kg^2$) | 26 | 27 | 26 |
| Northeast (%) | 13 | 9.4 | 15 |
| Midwest (%) | 28 | 25 | 29 |
| South (%) | 40 | 47 | 36 |
| West (%) | 20 | 20 | 20 |
| Child characteristics | | | |
| Age (in months) | 115 | 123 | 112 |
| Female (%) | 50 | 50 | 49 |
| Black (%) | 26 | 42 | 18 |
| Latino (%) | 18 | 21 | 18 |
| BMI percentile | 57 | 59 | 56 |
| Child overweight (%) | 30 | 32 | 28 |
| Child obese (%) | 14 | 16 | 13 |

Means and percents are average among observations, for which there were 28,301 in the total population, 9,589 in the EITC qualified population, and 18,712 in the EITC non-qualified population. All values account for sample weights.

Table 2. Analysis of Change in qualified for EITC dollars with BMI percentile and overweight and obesity: Regression coefficients (and 95% confidence intervals) for EITC benefits with body mass index (percentile), overweight (>=85th percentile) and obese (>=95th percentile) among children and adolescence age 2-18, Children and Young Adults of the National Longitudinal Survey of Youth, 1986-2004.

| | Random Effect | Household Fixed Effects | Child Fixed Effect |
|---|---|---|---|
| Body Mass Index Percentile | | | |
| Total | -4.3 (-6.0, -2.8) | -4.7 (-6.4, -3.1) | -4.4 (-5.8, -3.0) |
| Girls | -4.9 (-7.0, -2.7) | -5.4 (-7.7, -3.2) | -5.3 (-7.3, -3.2) |
| Boys | -3.8 (-6.0, -1.7) | -4.1 (-6.3, -1.9) | -3.7 (-5.6, -1.7) |
| Overweight | | | |
| Total | -0.024 (-0.047, -0.0014) | -0.025 (-0.049, -0.0014) | -0.024 (-0.047, -0.00035) |
| Girls | -0.031 (-0.063, 0.000097) | -0.034 (-0.067, -0.0011) | -0.039 (-0.071, -0.0088) |
| Boys | -0.018 (-0.050, 0.014) | -0.018 (-0.050, 0.014) | -0.010 (-0.040, 0.020) |
| Obese | | | |
| Total | -0.020 (-0.037, -0.0017) ) | -0.019 (-0.038, -0.0014) | -0.018 (-0.036, -0.00023 |
| Girls | -0.0096 (-0.033, 0.014) | -0.011 (-0.036, 0.014) | -0.013 (-0.036, 0.0094) |
| Boys | -0.032 (-0.055, -0.0077) | -0.029 (-0.055, -0.0047) | -0.024 (-0.047, -0.00030) |

Table notes:
Random effect models include a random effect for each child. Household fixed effect include a fixed effect for each household. Child fixed effect include a fixed effect for each child. All models include the following covariates: indicator variable for measurement method of weight, mother's IQ, mother's level of education, child age in months, child age in months squared, census region, race, Hispanic ethnicity, mother U.S. born, Rosen scale, Rotter scale, Pearlin scale, mother's depression, mother's health status (SF12) and wave of data (as linear and quadratic terms). All terms except indicator for type of weight measure, maternal level of education, age in months, age in months squared, wave and wave squared drop out of the fixed effect models because they are not time-varying. Sample sizes are 26,291 observations among 5,906 individuals in 2,693 households for the total population; 12,959 observations among 2,893 individuals in 1,983 households among girls; 13,332 observations among 3,013 individuals in 2,031 households among boys. Coefficients are for $1000 of Earned Income Tax Credit Benefits.

Table 3. Analysis of stratified analysis by Age, Maternal Obesity and Metro Area Food Price domains: Analysis of change in EITC dollars with BMI percentile and overweight and obesity: Regression coefficients (and 95% confidence intervals) for EITC benefits with body mass index (percentile), overweight (>=85$^{th}$ percentile) and obese (>=95$^{th}$ percentile) among children and adolescence age 2-18, Children and Young Adults of the National Longitudinal Survey of Youth, 1986-2004.

| | Random Effect | Household FE | Child FE |
|---|---|---|---|
| By Age | | | |
| BMI percentile | | | |
| age 2-10 | -8.0 (-10,-5.5) | -9.4 (-12, -6.7) | -9.3 (-12, -6.5) |
| age 11-18 | -1.5 (-3.3, 0.22) | -1.5 (-3.4, 0.33) | 0.0087 (-.022, .040) |
| Overweight | | | |
| age 2-10 | -0.061 (-.094, -.030) | -0.081 (.12, -0.045) | -0.065 (-0.10, -0.028) |
| age 11-18 | 0.016 (-.017, 0.049) | -0.0085 (-.033, 0.016) | -0.0078 (-.034, 0.018) |
| Obesity | | | |
| age 2-10 | -0.031 (-.055, -.0058) | -0.035 (-.063, -.0072) | -0.031(-0.060,-0.0021) |
| age 11-18 | -1.4 (-2.8, 0.06) | 0.019 (-0.0084, 0.047) | -0.0077 (-0.028, 0.013) |
| | | | |
| By Mom obesity | | | |
| BMI percentile | | | |
| Mom's BMI <30 | -5.2 (-7.1, -3.1) | -5.5 (-7.5, -3.3) | -5.8 (-7.7, -3.9) |
| Mom's BMI >=30 | -4.3 (-6.7, -1.8) | -4.9 (-7.5, -2.3) | -4.8 (-7.0, -2.5) |
| Overweight | | | |
| Mom's BMI <30 | -0.025 (-.052, 0.0030) | -0.024 (-.0522, .0030) | -0.029 (-.049, -.0087) |
| Mom's BMI >=30 | -0.027 (-.021, -0.0010) | -0.033 (-.076, .011) | -0.035 (-.073, 0.0037) |
| Obesity | | | |
| Mom's BMI <30 | -0.029 (-0.049, -.0087) | -0.028 (-.049, -.0065) | -0.028 (-.054, -.0011) |
| Mom's BMI >=30 | 0.0051 (-.029, 0.040) | -0.00050 (-.038, .037) | -0.0067 (-0.40, 0.026) |
| | | | |
| By Metro Area specific food price domains relative to general food costs (BMI percentile only) | | | |
| *Healthy food ratio* | | | |
| Lowest tertile | -2.7 (-6.9, 1.6) | -2.3 (-6.8, 2.2) | -2.7 (-6.6, 1.2) |
| Highest tertile | -5.5 (-7.6, -3.4) | -5.2 (-7.9, -3.5) | 5.7 (-7.7, -3.7) |
| | | | |
| *Unhealthy food ratio* | | | |
| Lowest tertile | -5.3 (-9.6, -1.0) | -5.4 (-10, -0.92) | -2.7 (-6.6, 1.2) |
| Highest tertile | -4.4 (-6.5, -2.2) | -4.4 (-6.6, -2.2) | -4.3 (-6.3, -2.3) |
| | | | |
| *Fast food ratio* | | | |
| Lowest tertile | -6.7 (10, -3.0) | -7.0 (-11, -3.2) | -7.1 (-10, -3.9) |
| Highest tertile | -3.8 (-5.9, -1.7) | -4.0 (-6.2, -1.8) | -3.9 (-5.9, -1.9) |

Table notes:

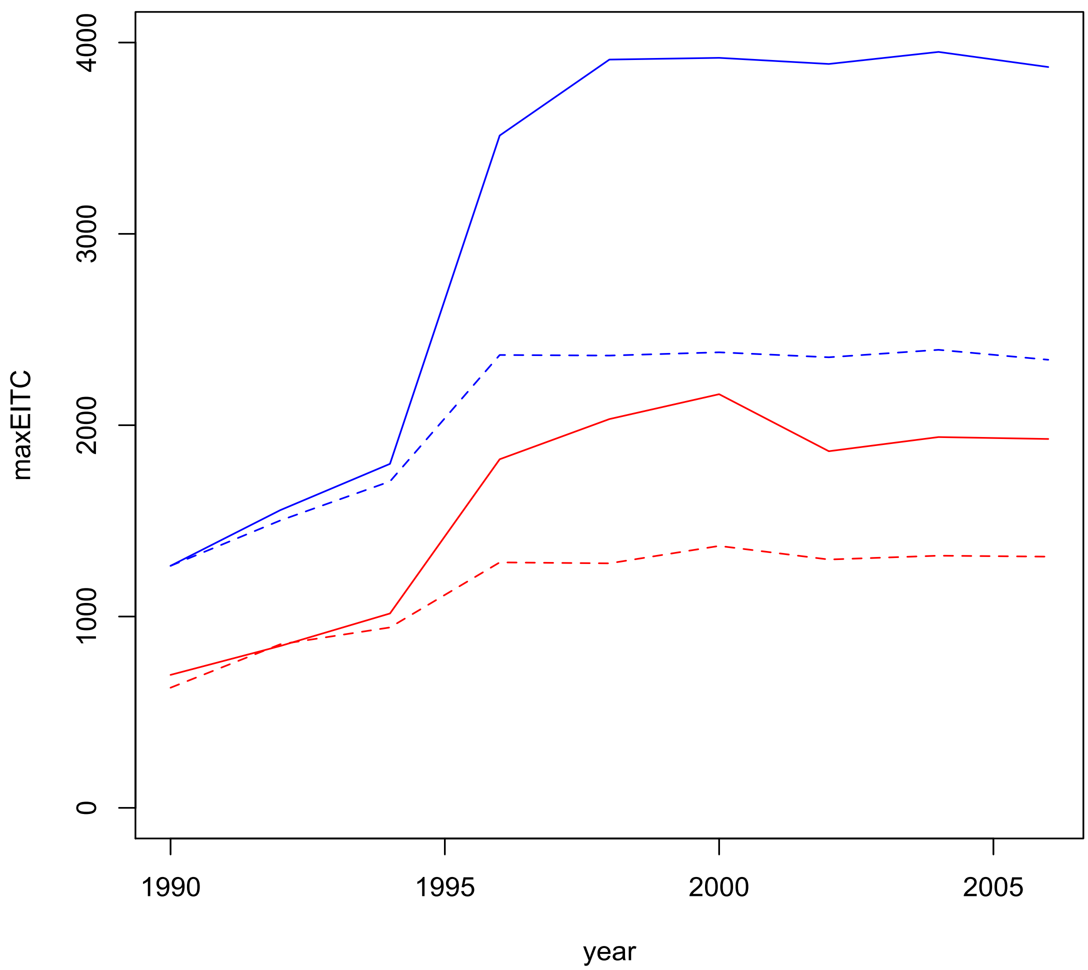
Random effect models include a random effect for each child. Household fixed effect include a fixed effect for each household. Child fixed effect include a fixed effect for each child. All models include the following covariates: indicator variable for measurement method of weight, mother's IQ, mother's level of education, child age in months, child age in months squared, census region, race, Hispanic ethnicity, mother U.S. born, Rosen scale, Rotter scale, Pearlin scale, mother's depression, mother's health status (SF12) and wave of data (as linear and quadratic terms). All terms except indicator for type of weight measure, maternal level of education, age in months, age in months squared, wave and wave squared drop out of the fixed effect models because they are not time-varying. Sample sizes are 26,291 observations among 5,906 individuals in 2,693 households for the total population; 12,959 observations among 2,893 individuals in 1,983 households among girls; 13,332 observations among 3,013 individuals in 2,031 households among boys. Coefficients are for $1000 of Earned Income Tax Credit Benefits. Healthy food, unhealthy food and fast food ratios are ratios of average cost of bundle of food as compared to average cost of a general food summary in order to create equivalent measures for general food prices in the metropolitan statistical area.

Table 4. Analysis of Change in qualified for EITC dollars with BMI percentile and overweight and obesity for household fixed effect models with different controls for study year: Regression coefficients (and 95% confidence intervals) for EITC benefits with body mass index (percentile), overweight (>=85th percentile) and obese (>=95th percentile) among children and adolescence age 2-18, Children and Young Adults of the National Longitudinal Survey of Youth, 1986-2004.

| | Model 1<br>Wave and wave-squared | Model 2<br>Indicator for wave 10 | Model 3<br>Fixed effect for wave |
|---|---|---|---|
| Body Mass Index Percentile | | | |
| Total | -4.7 (-6.4, -3.1) | -1.6 (-3.4, 0.26) | -1.2 (-3.0, 0.66) |
| Girls | -5.4 (-7.7, -3.2) | -2.36 (-4.9, 0.14) | -2.2 (-4.7, 0.35) |
| Boys | -4.1 (-6.3, -1.9) | -0.59 (-3.0, 1.8) | -0.28 (-2.7, 2.2) |
| Overweight | | | |
| Total | -0.025 (-0.049, -0.0014) | -0.014 (-0.040, 0.012) | -0.0052 (-0.031, 0.021) |
| Girls | -0.034 (-0.067, -0.0011) | -0.022 (-0.058, 0.013) | -0.019 (-0.055, 0.017) |
| Boys | -0.018 (-0.050, 0.014) | -0.0010 (-0.036, 0.034) | 0.0055 (-0.030, 0.041) |
| Obese | | | |
| Total | -0.019 (-0.038, -0.0014) | -0.020 (-0.040, 0.00032) | -0.011 (-0.031, 0.0092) |
| Girls | -0.011 (-0.036, 0.014) | -0.0077 (-0.035, 0.020) | -0.0049 (-0.032, 0.022) |
| Boys | -0.029 (-0.055, -0.0047) | -0.023 (-0.051, 0.0045) | -0.017 (-0.045, 0.011) |

Table notes:
Household fixed effect include a fixed effect for each household. All models include the following covariates: indicator for type of weight measure, maternal level of education, age in months, age in months squared. Model 1 is identical to the household fixed effect model shown in table 2, but is shown here again for comparison with the other model specifications. Model 2 controls for an indicator for wave 10 of the data (1994). Model 3 includes wave fixed effects. Sample sizes are 12,959 observations among 2,893 individuals in 1,983 households among girls. Coefficients are for $1000 of Earned Income Tax Credit Benefits.

Figure. Maximum (blue) and mean among those qualifying (red) income benefits from the Earned Income tax Credit over time among household with 2 or more dependents (solid line) or 1 dependent (dashed line), NLSY analysis sample, 1986-2006.




Maximum (blue) and mean among those qualifying (red) income benefits from the Earned Income tax Credit over time among households with 2 or more dependents (solid line) or 1 dependent (dashed line), NLSY analysis sample based on predicted income, 1990-2006, in year 2000 dollars.

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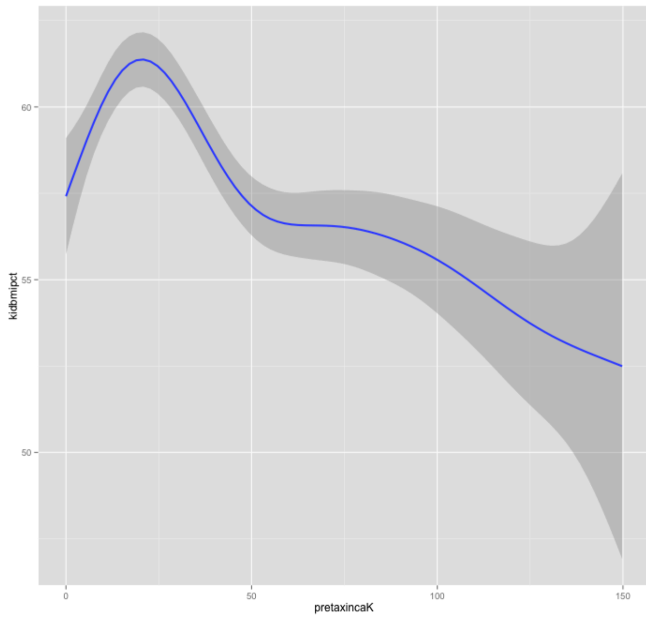
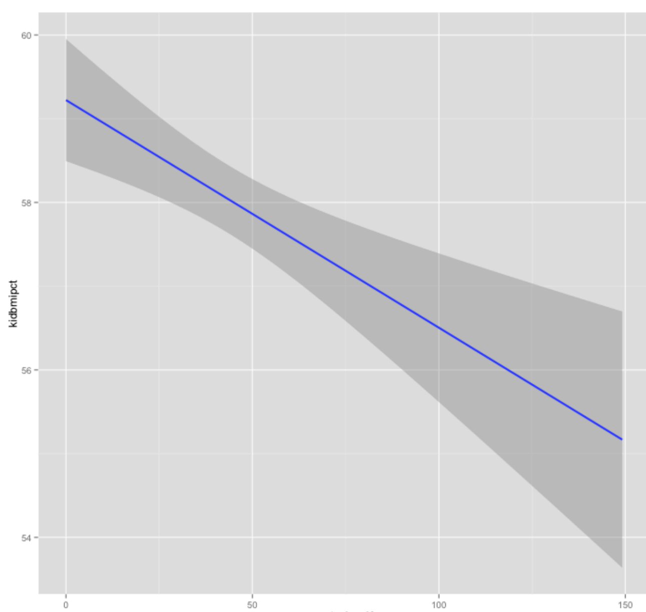
Supplemental Figure 1. Unadjusted association between household pretax income (figures 2a and 2b) and earned income tax credit benefits (figures 2c and 2d) with child body mass index percentile, among children and adolescence age 2-18, Children and Young Adults of the National Longitudinal Survey of Youth, 1986-2004.

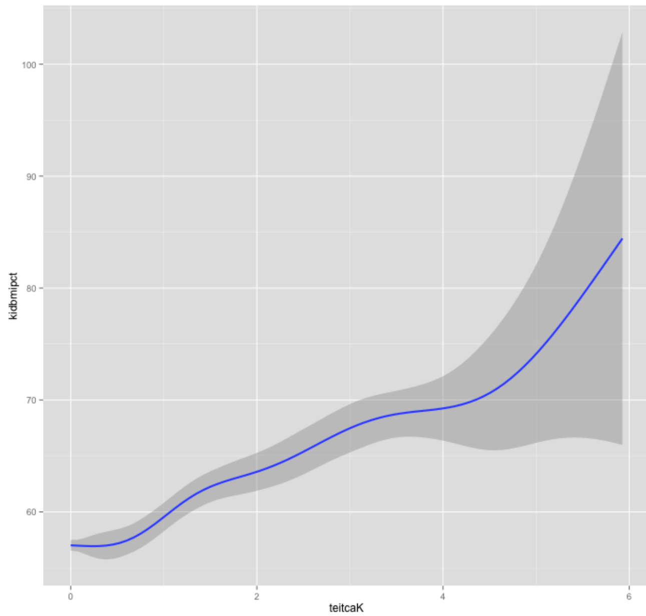
Supplemental Figure 1a. Girls BMI percentile and household Pretax income (in thousands)



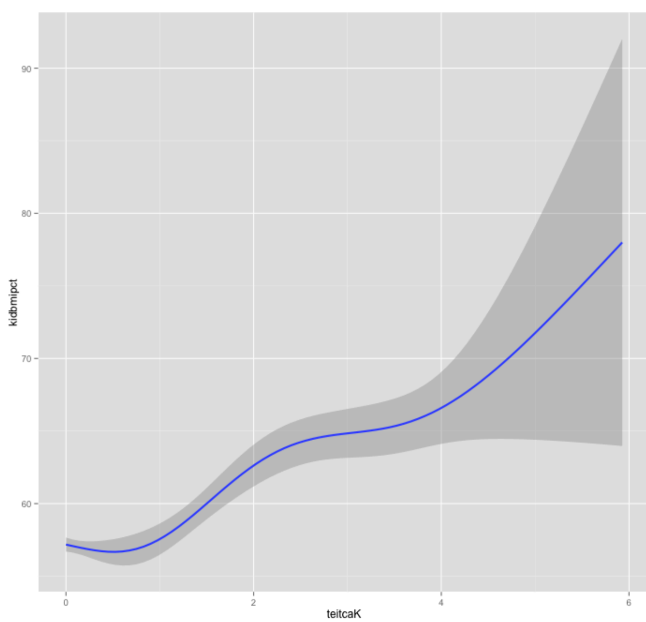

Supplemental Figure 1b. Boys BMI percentile and household Pretax income (in thousands)



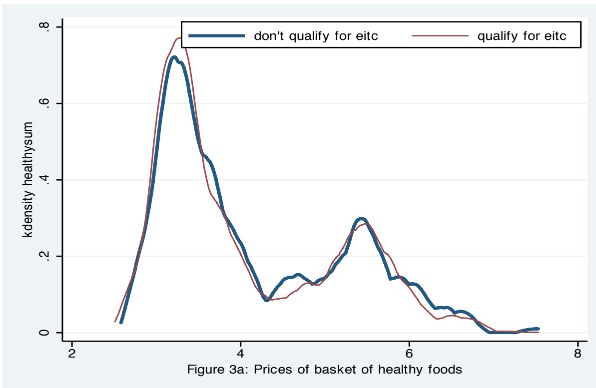
Supplemental Figure 1c. Girls BMI percentile and household Earned Income tax credit dollars (in thousands)

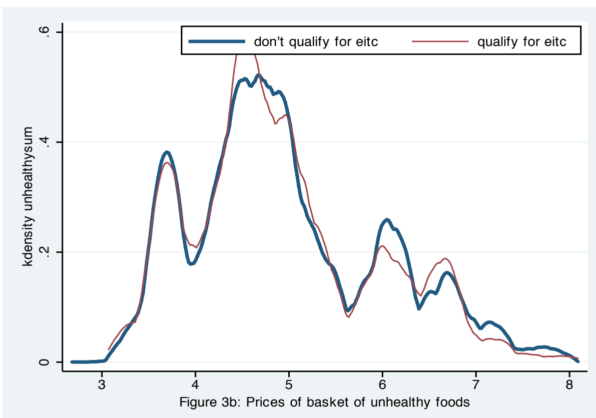



Supplemental Figure 1d. Boys BMI percentile and household Earned Income tax credit dollars (in thousands)



Supplemental Figure 2. Distribution of Healthy food costs (figure 2a), Unhealthy food costs (figure 2b) and Fast food costs (figure 2c) for those who don't qualify for Earned Income Tax Credit benefits (blue line) and those who do qualify for Earned Income Tax Credit benefits (red line) for households part of the National Longitudinal Survey of Youth, 1979-2004.



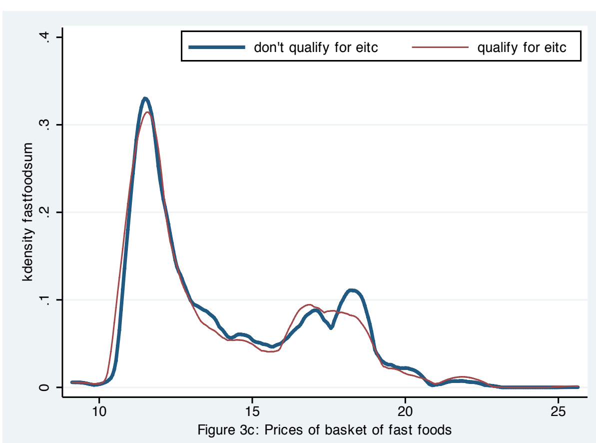
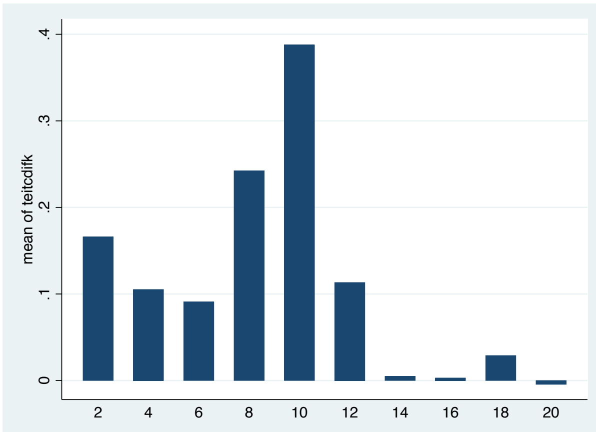



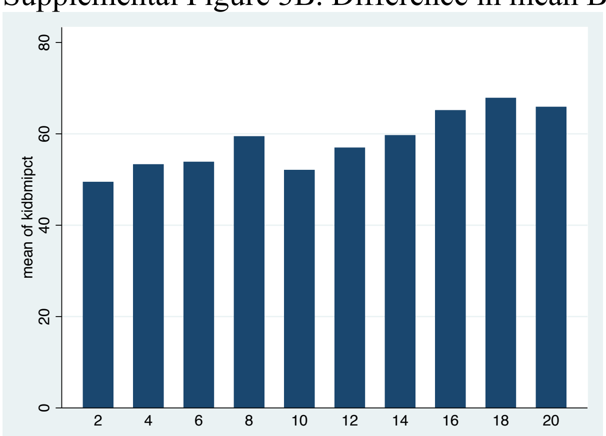

Table notes. All data in year 2000 dollars from ACCRA cost of living data, specific to Metropolitan Statistical Areas.

Supplemental Figure 3. Mean differences in EITC benefits by wave, and BMI, overweight and obesity by wave among children and adolescence age 2-18, Children and Young Adults of the National Longitudinal Survey of Youth, 1986-2004.

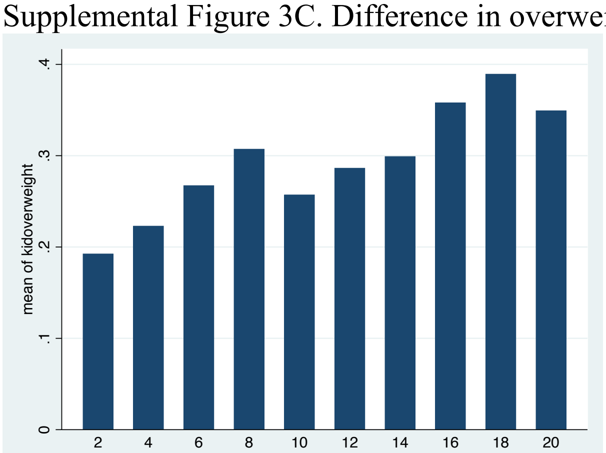
Supplemental Figure 3A. Two-year Difference in Total EITC benefits by wave.



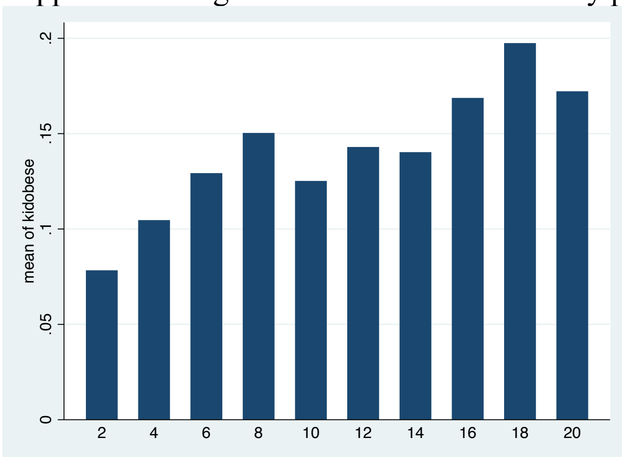

Supplemental Figure 3B. Difference in mean BMI by wave.




Supplemental Figure 3C. Difference in overweight prevalence by wave.



Supplemental Figure 3D. Difference in obesity prevalence by wave.



## Appendix: Regression Calibration

```
/*height*/
/*mom report*/
if htMeas=2 & hisp=1 & sex=1 then rcheight=36.05004+(height*-0.21110)+(height*height*0.00977)
if htMeas=2 & hisp=1 & sex=2 then rcheight=39.93579+(height*-0.42641)+(height*height*0.01274)
if htMeas=2 & black=1 & sex=1 then rcheight=27.75345+(height*0.2223041)+(height*height*0.00493)
if htMeas=2 & black=1 & sex=2 then rcheight=23.18317+(height*0.43286)+(height*height*0.00268)
if htMeas=2 & other=1 & sex=1 then rcheight=26.57263+(height*0.088471)+(height*height*0.00768)
if htMeas=2 & other=1 & sex=2 then rcheight=23.93771+(height*0.179814)+(height*height*0.00705)
/*child self-report*/
if htMeas=3 & hisp=1 & sex=1 then rcheight=74.226355+(height*-0.95685)+(height*height*0.012593)
if htMeas=3 & hisp=1 & sex=2 then rcheight=104.837578+(height*-1.8534)+(height*height*0.018712)
if htMeas=3 & black=1 & sex=1 then rcheight=22.29194+(height*0.72696)+(height*height*-0.0008855)
if htMeas=3 & black=1 & sex=2 then rcheight=63.29834+(height* 0.498508)+(height*height*0.0079630)
if htMeas=3 & other=1 & sex=1 then rcheight=71.36133+(height*-0.992027)+(height*height*0.013785)
if htMeas=3 & other=1 & sex=2 then rcheight=105.3449+(height*-2.06811)+(height*height*0.022186)
/***weight***/
/*mom report*/
if wtMeas=2 & hisp=1 & sex=1 then rcweight=1.979896+(weight*0.976196)+(weight*weight*0.0001861)
if wtMeas=2 & hisp=1 & sex=2 then rcweight=4.856150+(weight*0.853504)+(weight*weight*0.0013711)
if wtMeas=2 & black=1 & sex=1 then rcweight=5.40424+(weight*0.839770)+(weight*weight*0.0011734)
if wtMeas=2 & black=1 & sex=2 then rcweight=1.22577+(weight*1.021120)+(weight*weight*0.0000791)
if wtMeas=2 & other=1 & sex=1 then rcweight=2.65184+(weight*0.9322821)+(weight*weight*0.0004832)
if wtMeas=2 & other=1 & sex=2 then rcweight=1.93299+(weight*0.948483)+(weight*weight*0.0007236)
/*child self-report*/
if wtMeas=3 & hisp=1 & sex=1 then rcweight=-19.07018+(weight*1.3121)+(weight*weight*-0.001148)
if wtMeas=3 & hisp=1 & sex=2 then rcweight=17.34292+(weight*0.72869)+(weight*weight*0.0012346)
if wtMeas=3 & black=1 & sex=1 then rcweight=38.087592+(weight*0.51386)+(weight*weight*0.001437)
if wtMeas=3 & black=1 & sex=2 then rcweight=-94.45333+(weight*2.29872)+(weight*weight*-0.004077)
if wtMeas=3 & other=1 & sex=1 then rcweight=9.554425+(weight*0.9058396)+(weight*weight*0.0001336)
if wtMeas=3 & other=1 & sex=2 then rcweight=-9.471714+(weight*1.13840)+(weight*weight*-0.0003437)
```