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Growing Up Poor and Childhood Weight Problems

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Abstract

This paper investigates the impact of growing up in poverty on the risk of childhood weight problems. Understanding the effect of family income on childhood weight problems is important, but has been hindered by the potential endogeneity of family income. We use matched mother-child data from the National Longitudinal Survey of Youth (NLSY) to study the effects of growing up poor on risks of childhood overweight and underweight, accounting for unobserved heterogeneity that governs both children's weight and family income. We also estimate the impacts of family income on a child's weight measured by Body Mass Index (BMI) at different points in the conditional distribution of children's weight, using a two-stage residual inclusion least absolute deviation approach. Our results show that the mean effects of poverty exposure on risks of obesity and underweight are not statistically different from zero, accounting for the endogeneity of family income. More importantly we find that growing up poor increases a child's BMI by 14.7 percent if her BMI is at the 90th quantile of her cohort's BMI distribution and reduces her BMI by 12.7 percent if her BMI is at the 10th quantile.

JEL classifications: I1 I3

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1. INTRODUCTION

In the United States the childhood underweight problem, which is defined as low weight-for-height, is not as prevalent as in developing countries. Nevertheless, existing studies show that the fraction of preadolescent children who are underweight remains about 5 percent and is disproportionately higher among the disadvantaged population (Wang et al., 2002; Gibson, 2000). However, most researchers and public health officials have devoted much of their attention to overweight problems, especially in light of the rapidly rising obesity rates among American children of all ages, both genders, and different racial and ethnic groups over the past few decades. In particular, the percentage of overweight children in elementary school, as measured by the body mass index (BMI), had more than tripled from 4 percent in 1960s to 16 percent in 2000 (Ogden et al., 2002).

The looming epidemic of childhood obesity fails to overwhelm the weight-health disparities among children from different socioeconomic groups (Anderson et al., 2003; Bhattacharya et al., 2004). The risks of underweight and overweight continue to be the highest among the most impoverished people. Food insecurity, defined as limited access to nutritionally acceptable or safe food, has been attributed to the main cause of persistent underweight and overweight epidemic among children living in poverty (Olson, 1999). In particular, low family income limits children's access to fruits, vegetables, and whole grain products, which are rapidly becoming more expensive. Consequently, these families resort to cheaper foods that incidentally have more fat and fewer nutrients (Kennedy, 1995). Both overweight and underweight are likely to be physiologically linked to imbalanced intake of the nutrients that are needed for normal child growth and development. Specifically, overweight is mainly caused by the excessive consumption of calories, while underweight is associated with iron deficiency anemia and other medical conditions caused by malnutrition (Cutler et al., 2003; Stoltzfus et al., 2004).

The prevalence of poverty among young children is staggering, with more than 20 percent of American children under the age of 13 living below the federal poverty level (National Center for

Children in Poverty, 2004; U.S. Census Bureau, 2004). Many existing studies have linked family socioeconomic status to the development of children and investigated whether the government's poverty-fighting programs can improve children's well-being (Brooks-Gunn, 1997; Haveman and Wolfe, 1995a). The weight problems associated with food insecurity among impoverished families particularly impinge on children's well-being by adversely affecting both child development and childhood morbidity rates. Childhood underweight, also known as wasting, can cause long-term developmental problems. On the other hand, overweight children are at risk of cardiovascular diseases, diabetes, and other serious health problems in childhood (National Bureau of Economic Research, 2000). However, our understanding of the relationships between poverty and childhood weight problems is very limited. Specifically, assessing the impact of family income or income maintenance programs on childhood weight problems is important, but has been hindered by the potential endogeneity of family income. The estimates of the impacts lack sufficient control for unobserved heterogeneity, such as parental abilities and attitudes, which may cause the family to have low income as well as unhealthy childhood weights.

This paper investigates the impact of living in poverty on the risks of childhood overweight and underweight. We use matched mother-child data from the National Longitudinal Survey of Youth (NLSY) to study the effects of growing up poor on risks of childhood overweight and underweight, accounting for unobserved heterogeneity that governs both children's weight and family income. We also estimate the impacts of family income on a child's weight measured by Body Mass Index (BMI) at different points in the conditional distribution of children's weight, using a two-stage residual inclusion least absolute deviation approach.

The remainder of the paper is organized as follows. A brief review of related literature is presented in Section 2. Section 3 describes the main data sets used in the empirical analysis, followed by discussions about econometric issues in estimating the effects of poverty on the risk of weight problems in Section 4. Estimation results are provided in Section 5 and conclusions are summarized in Section 6.

2. PREVIOUS RESEARCH

Family income has long been identified as one of the most critical parental inputs for the production process of children's well-being (Becker and Thomas, 1986). Numerous existing studies have also associated economic hardships with children's well-being. In particular, many researchers who study child development report that the duration and intensity of poverty in early childhood have substantially negative impacts on children's academic and cognitive achievement (Duncan et al., 1994; Smith et al., 1997). However, without controlling for family income during early childhood, the estimated effects of transitional family income on children's developmental outcomes tends to be attenuated (Yeung et al., 2002; Mayer, 1997). In addition, family income is shown to have distinct impacts on different measures of children's well-being (Haveman and Wolfe, 1995b).

A number of studies have directly assessed the impact of poverty on risks of weight problems with mixed findings. For instance, a descriptive study by the (U.S. Department of Health and Human Services, 2000) reports that 9 percent of adolescents in middle- or high-income households are overweight compared to 17 percent of adolescents living in poverty. Miller et al. (1989) find that current poverty status is associated with children's poor nutritional status, measured by heights. Other authors examine the relationships between long-term poverty and the health of children ages 12 to 18 and find the prevalence of wasting is higher among children in persistently poor families compared to children in families that are not persistently poor (Gibson, 2000; Korenman and Miller, 1994). However, Gibson (2000) reports that after controlling for race, ethnicity, and other demographic characteristics, the risk of overweight is not significantly higher among youths who live in a poor family than their non-poor counterparts.

Most of these existing empirical studies do not account for the potential endogeneity of family income, which is likely caused by the omission of unobserved family and child characteristics that govern both child outcomes and family income. A typical multivariate study in the literature involves linear or nonlinear regression of an outcome indicator, such as cognitive test scores or child weight, on measures of family income and a set of family and child characteristics (see Brooks-Gunn, 1997; Haveman and Wolfe, 1995b; Mayer, 1997). Due to the lack of control for permanent unobserved heterogeneity, this type of regression tends to yield biased results. For instance, children who grow up poor may suffer from a bad home environment and neighborhood or other characteristics that are unobservable to researchers. These unobserved inputs may contribute to the negative outcomes among these children and can independently affect children's well-being even if family financial situations are improved through income support programs like the Earned Income Tax Credit (EITC). Several authors who focus on the production process of child cognitive achievement (see Blau, 1999; Levy and Duncan, 1999; Dahl and Lochner, 2005) have, therefore, employed fixed effects or instrumental estimators to address the potential biases caused by endogeneity of family income. However, until now these corrections have not yet been applied in the studies that investigate the relationships between family income and childhood weight problems[1].

This paper also draws from past studies that focus on the impact of other determinants of childhood nutritional status. Several authors have reported that family structure is related to childhood obesity (see Wolfe et al., 1994; Lissau and Soerensen, 1994). Jeffery and French (1996) also report that the inclusion of diet and exercise behaviors helps explain the BMI measures among adult women but fails to reduce the magnitude of correlations between family income and weight status. Fullerton et al. (2004) find that children who live in the southern states in the United States, also known as the "stroke belt," are 20 percent more likely to die from stroke than children living in other parts of the country. The authors partly attribute this high mortality rate to poverty and lifestyles, especially dietary habits. According to Mokdad (2004), the states that are included in the stroke belt also have the highest obesity rates in the United States. These environmental factors and family characteristics will be controlled in the empirical analysis in this study.

[1]A notable exception is Anderson et al., 2003, who use both fixed effects and instrumental variable methods to assess the effects of maternal employment on childhood risk of overweight.

3. DATA

The main data are matched mother-child samples from the National Longitudinal Survey of Youth (NLSY79). These data are ideal for studying the effects of family income on children's risk of weight problems. The NLSY contains a comprehensive set of variables for 6,283 women and 11,340 children who were born to them. In particular, biannual measures of height, weight, and home environment are collected from 1986 to 2002 for the children. The NLSY contains detailed measures of a set of demographic, educational, and socioeconomic variables for their mothers annually from 1979 through 1994 and biannually thereafter.

The main measure of weight healthiness is the Body Mass Index (BMI), which is calculated as weight in kilograms divided by height in meters squared. Two common definitions have been adopted in the previous studies about obesity and underweight. One of them uses the absolute measure of BMI and categorizes a person as obese with a BMI greater than 30 kg/m^2 and underweight with a BMI less than 18.5 kg/m^2. The problem with this approach is that children's body fatness changes during different stages of growth and, additionally, boys and girls vary in their body fatness as they grow. The Centers for Disease Control and Prevention (CDC) has recently endorsed the use of relative BMI measures to assess weight status in children, and specifically has produced sex-specific BMI percentiles for children aged 2 to 20 to address the shortcomings of absolute measures of BMI. This measure of child weight utilizes age- and gender- specific growth charts published by the CDC (Centers for Disease Control, 2000). A child is categorized as underweight if her BMI percentile below the 5th percentile and overweight if her BMI percentile is greater than or equal to the 95th percentile. These definitions have been adopted by numerous studies to define childhood and adolescent overweight and underweight (see Anderson et al., 2003). Nevertheless, this approach still has shortcomings, especially considering that the cut-off points for obesity or underweight remain arbitrary as both weight problems are a matter of degree. Consequently, both binary indicators of weight status and continuous measures of BMI are used in our empirical analyses.

While the probability that overweight preschool-aged children will become obese adults is over 30 percent, overweight in children younger than age 2 is only weakly associated with increased risk for adult obesity (Whitaker et al., 1997). This study focuses on the weight measures of children aged 3 to 12. The rationale for omitting adolescents is that the body changes during puberty render BMI a less appropriate measure of nutritional status.

Among all observations of NLSY79 children, there were 28,592 records between 3 to 12 years old that provided valid BMI measures.[2] The sample size is further reduced down to 25,934 after excluding 2,658 cases where children were born prior to the first interview that their mothers gave to the NLSY79. Therefore, the remaining children are not missing family income, geographical identifier, and other crucial variables during early childhood. The final sample size used in the empirical analysis is 25,476 children years after 458 observations were further dropped due to missing state identifiers. This estimation sample contains 7,746 children who matched to 3,883 NLSY79 women. The NLSY79 mother-child data contains sampling weights that can be used to make comparisons between the full NLSY79 sample and the national population in the same age range. The sample used in this paper is very close to the full sample for the interested age range. Therefore, all regressions in this study utilize this weight information.

Another crucial element of analysis in this study is poverty and family income measure. Numerically, the poverty cutoffs used in this study are the same as the official poverty thresholds published each year by the Census Bureau. To determine whether a family is poor, however, the official poverty measure uses pre-tax money income to assess its available financial resources. This approach has been questioned by many researchers, particularly because it defeats the purpose of the U.S. government's major anti-poverty programs, such as the Earned Income Tax Credit (EITC) and food

[2]For BMI values being computed to be valid, the weight and height measures must be present as well as biologically plausible. An observation is defined as an outlier if any measure for weight-for-age, height-for-age, or weight-for-height is a biologically implausible value (BIV) according to an algorithm provided by the 2000 CDC growth charts (Centers for Disease Control, 2000).

stamps (see Joint Center for Poverty Research, 1999; Formby et al., 2005). Both these cash and in-kind transfers do not count as pre-tax income and, therefore, cannot move families out of poverty. The poverty status in the empirical analysis is defined using the poverty thresholds, which are determined by disposable incomes (after-tax and transfer) required to meet minimum livelihood needs, which vary by family size and composition. The detailed information is presented in the Appendix. We also use the poverty guidelines, which are issued by the U.S. Department of Health and Human Services, as an alternative measure of poverty, and the estimation results are not statistically different.[3] Note that a child's weight status is determined by her lifetime net calorie accumulation, which is a function of the historical family inputs. We intend to take advantage of the longitudinal nature of the data and construct variables to measure permanent poverty exposure and other family inputs and environmental variables, such as portion of child's life with grandparent present, average number of children living in mother's household since birth, portion of child's life with both parents present, and percentage of child's life living in the South. Table 1 provides descriptive statistics of the data. Note that the over-sampled black, Hispanic, and low income white individuals are excluded in the empirical estimation. Additionally, the sampling weights are applied when reporting summary statistics and estimating empirical models. Based on the weighted sample 10.0 percent of children are underweight while 14.0 percent are overweight. In average, they have spent 18.8 percent of their childhood in poverty and 15.8 percent of their families are still living in poverty.

4. ESTIMATION STRATEGY

We estimate models of the following form:

$$\text{Weight}_i = \alpha + Y_i\,\beta + \mathbf{X}_i\,\gamma + \varepsilon_i, \tag{1}$$

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[3]The main differences between the federal poverty thresholds and the poverty guidelines are that the latter vary by family size but not by family composition and ignore economies of scale (U.S. Department of Health and Human Services, 2005).

Table 1
Descriptive Statistics
(25,476 children years)

Variables	Unweighted		Weighted	
	Mean	S.D.	Mean	S.D
Household Characteristics				
Gross family income ($10,000)	4.788	4.081	5.573	4.422
Net family income	4.157	2.999	4.752	3.182
If under federal poverty threshold	0.229	0.420	0.158	0.364
If under 0.5 federal poverty threshold	0.075	0.263	0.051	0.219
Food stamp recipient	0.221	0.415	0.148	0.355
Urban	0.762	0.426	0.722	0.448
Living in South	0.384	0.486	0.343	0.475
Family size	4.448	1.456	4.368	1.313
# of female adults in HH	1.140	0.436	1.100	0.360
# of college graduates in HH	0.296	0.618	0.394	0.696
# of children in HH	2.567	1.182	2.484	1.105
Grandmother present in HH	0.068	0.251	0.047	0.212
Mother's Characteristics				
Age	33.097	4.755	33.947	4.713
Black	0.290	0.454	0.144	0.352
Non-white Hispanic	0.208	0.406	0.074	0.261
AFQT score	36.100	26.897	45.362	27.243
Married	0.637	0.481	0.720	0.449
High school dropout	0.164	0.370	0.114	0.318
High school	0.692	0.462	0.698	0.459
College education or more	0.144	0.351	0.188	0.391
BMI at age of 22	24.059	4.796	23.555	4.597
Obese at age of 22	0.111	0.314	0.095	0.294
Underweight at age of 22	0.048	0.214	0.056	0.230
Child's Characteristics				
Age in months	87.193	30.784	88.601	30.850
Boy	0.507	0.500	0.511	0.500
BMI	17.182	3.504	17.145	3.397
BMI percentile specific to age and gender	56.195	33.661	55.925	33.321
Firstborn	0.390	0.488	0.411	0.492
% of childhood spent in poverty	0.283	0.352	0.188	0.298
% of childhood living in urban area	0.784	0.370	0.753	0.383
% of childhood when both parents present	0.653	0.407	0.744	0.366
Underweight	0.105	0.306	0.100	0.300
Overweight	0.138	0.345	0.140	0.347

where $Weight_i$ is a measure of children's weight status, Y_i represents family's poverty status, and $\mathbf{X}_i$ is a vector of other characteristics that determine the weight outcomes. The coefficients β's are estimated effects of poverty on child weight outcomes.

The first set of regressions uses binary indicators of obesity and underweight as dependent variables $Weight_i$ and, in turn, β's represent the effect of poverty exposure on these indicators for weight status. Many observed characteristics, such as race, ethnicity, family structure, and education affect the extent of poverty exposure. However, poverty is not randomly distributed even conditional on these observed characteristics due to unobserved heterogeneity. These unobservable characteristics may be correlated with the increased risk of growing up poor as well as growing up unhealthy. Leaving these unobservables in ε_i is likely to yield biased estimates. For instance, highly motivated mothers tend to earn more as well as to engage their children in healthy activities. If this is the case, even after controlling for the available observable inputs, the coefficient estimates would deviate from the true effect of net family income and poverty status on childhood weight problems. This study employs the following methods to address the potential bias caused by these omitted variables. First, two alternative differencing methods are used to exploit the longitudinal and family-based nature of the data. Specifically, sibling fixed-effects approach exploits and "differences out" within-family unobserved characteristics that might influence both family and children's weight status, while child fixed-effects approach applies first difference to difference out both child-specific and within-family unobservable characteristics. In addition, sibling differences in weight outcomes can be related to variations in the extent of poverty exposure during their earlier ages and, in turn, can also help in identifying the longer-term impacts of lagged family income. Contrasting these two types of across children variations, as in a difference-in-difference approach, would better control for the children's differences in unobserved characteristics. However, there are also important disadvantages associated with these differencing methods. For child-specific differencing, the biannual changes in the explanatory variables tend to exhibit attenuated variation and, in turn, yield imprecise estimates. On the other hand, the main disadvantage of the sibling fixed-effect approach is that its benefits would occur only to families with multiple children, and it is not clear that the added precision due to the increased variation of explanatory variables would offset the loss in precision from the smaller sample sizes.

Considering the strengths and weaknesses of the fixed-effect estimators discussed above, we also exploit instrumental variables to help identify the effects of poverty on weight status. Properly selected instrumental variables, which are correlated with family income but not directly related to weight outcomes, can help control for both unobserved heterogeneity and measurement error in income without making strong assumptions about its invariability or sacrificing sample size. In particular, we exploit the fact that the disposable family income is determined by family characteristics as well as characteristics of tax code and welfare policies. The first set of instrumental variables include state-level variables that are likely to be related to household earnings, such as the unemployment rate, median earnings for full-time employed women, percentage of working women employed in managerial or professional occupations, and average wage for a manufacturing worker. The second set of instruments include variables that characterize the generosity of state-level welfare policies, such as percentage of state population receiving Aid to Families with Dependent Children (AFDC) or Temporary Assistance for Needy Families (TANF), AFDC/TANF maximum amount paid, and food stamp guarantee. The fact that nearly two percent of NLSY households moved to a different state annually, along with the cross-sectional differences in these state-level policy environments yield considerable variations in household income shocks over a child's early life. These variations can facilitate the identification of our empirical models. While unlikely to be correlated with idiosyncratic shocks to the child's health production process, these variables are potentially exogenous sources that might determine the cash transfers at-risk families can receive. We also exploit the time-varying policy parameters for the federal EITC schedule regarding phase-in rate, phase-out rate, maximum earning, and maximum benefits. The dramatic, non-linear changes of the EITC program throughout the time span when the NLSY was collected can help identify the effect of disposable family income.[4]

As discussed in the Data section, we use both binary and continuous measures of weight status. Probit specification is adopted when *Weight* variable in equation (1) is binary variables for overweight or underweight. The quantile regression method is employed when a continuous weight measure is the dependent variable. The latter specification is used to estimate the effects of a set of explanatory variables on the quantiles of the BMI distribution. Least square regression, an alternative estimator, is inadequate to estimate change of weight distributions in response to various family income levels. One of quantile regression's appealing features is its ability to estimate quantile-specific effects of the impact of family income not only on the center but also on the tails of the weight distribution. Without accounting for the potential endogeneity of net family income, the conventional quantile regression also yields inconsistent estimates. Therefore, this paper employs the two-stage least absolute deviation (2SLAD) estimator, which is analogous to the two-stage least squares estimator (2SLS) while in the second stage of 2SLAD quantile regressions are conducted. Unlike 2SLS, the 2SLAD estimator is consistent under more restrictive conditions due to its nonlinear nature (Amemiya, 1982; Powell, 1983). We propose to use two-stage residual inclusion which gives consistent estimates, given that the instruments are valid (Rivers and Vuong, 1988; Blundell and Smith, 1989; Tera, 2005).

5. RESULTS

5.1 Probit Estimates

Column 1 in Table 2 provides the results from a probit model that estimates the effect of exposure to poverty, measured by the portion of childhood spent in poverty, on the probability of a child being overweight. This model, like all other models reported in this paper, includes covariates such as survey

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[4] Dahl and Lochner (2005) have provided more detailed discussion about using the changes of EITC in the 1980s and 1990s as identification sources for their study, which estimates the causal effect of income on children's academic achievements.

Table 2
Estimated Effect of Poverty on Child's Risk of Overweight with Probit
(Robust standard errors are in parentheses)

	(1)		(2)		(3)		(4)	
Pct of child's life spent in poverty	0.0228	(0.0115)	-0.0476	(0.0146)	-0.0514	(0.0145)	-0.0472	(0.0152)
Black	—		0.0404	(0.0097)	0.0326	(0.0095)	0.0263	(0.0102)
Non-white Hispanic	—		0.0202	(0.0113)	0.0203	(0.0111)	0.0224	(0.0111)
Mother high school graduate	—		-0.0088	(0.0122)	-0.0040	(0.0122)	-0.0058	(0.0124)
Mother college or more	—		-0.0365	(0.0173)	-0.0289	(0.0170)	-0.0326	(0.0172)
Mother's AFQT score	—		-0.0005	(0.0002)	-0.0006	(0.0002)	-0.0005	(0.0002)
Pct child's life with both parents present	—		-0.0337	(0.0118)	-0.0346	(0.0115)	-0.0290	(0.0121)
Mother obese at age of 21	—		—		0.0906	(0.0112)	0.0900	(0.0113)
Mother underweight at age 21	—		—		-0.0924	(0.0181)	-0.0936	(0.0179)
Child was firstborn	—		—		—		-0.0169	(0.0085)
Portion of child's life living in South	—		—		—		0.0216	(0.0089)
Avg. # children in HH since birth	—		—		—		-0.0082	(0.0050)
Pct child's life with grandmother present	—		—		—		0.0352	(0.0205)
Sample size	25,476		25,476		25,476		25,476	
Pseudo R-Squares	0.0271		0.0365		0.0511		0.0534	

Notes: (1) The dependent variable is a binary indicator for overweight; (2) Point estimates provided above are marginal effects of the corresponding parameters; (3) All specifications include an intercept term, indicators for weight and height information being self-reported, child age, child age squared, child gender, mother's age in years, education levels of the mother's parents, and year dummies with year 1986 being omitted; (4) All standard errors are robust and clustered on mother's ID; (5) The estimation is weighted using the child's sampling weights.

year indicators, child's age, child's age squared, mother's age, and binary variables that indicate whether the child's height and weight were reported by the child's mother. We find that the percentage of a child's life spent in poverty is positively and significantly correlated with the probability of being overweight. The estimated marginal effect suggests that a 10 percentage point increase in the exposure to poverty is linked to a 0.2 percentage point increase in children's likelihood of being overweight. However, as we add more demographic and socioeconomic characteristics the estimated effect of poverty on risk of overweight turns negative while remaining statistically significant. It appears that the positive correlation between poverty status and the risk of overweight is spurious due to strong correlations between poverty status and many of omitted variables in model (1). For instance, if black and Hispanic families have higher poverty rates than white families and black and Hispanic children are more susceptible to obesity due to genetic disadvantages, the exclusion of racial and ethnic indicators will overestimate the effect of poverty on overweight. Similarly, we include other family characteristics that may be either correlated with children's weight outcomes or the family poverty status.

In model (2) we add mother's education level, AFQT score, and marriage history. The results show that increasing a mother's education level from less than high school to college will reduce her child's risk of being overweight by about 3 percentage points. A mother's AFQT score and average marriage status since child birth are negatively and significantly associated with children's risk of being overweight. Indicators for maternal weight problems are added to model (3) and we find that there is a strong positive intergenerational correlation. In particular, a mother being overweight at age 21 is likely to increase her child's risk of being overweight by 9 percentage points. This correlation may be attributed to hereditability of obesity as well as unobserved family heterogeneity, such as certain dietary patterns. More controls for family composition and residing regions are included in model (4). Among these additional covariates, birth order, number of children, and presence of grandparent may serve as proxy for resource allocation constraints within family (Anderson et al., 2003). The estimated marginal effects imply that the presence of grandparents is positively associated with child overweight; being firstborn or having multiple siblings in household is negatively associated with the risk of being overweight. More importantly, it appears there is evidence to suggest an increased risk of overweight among Southern residents. Specifically, children who have spent all their life in the South increase their likelihood of being overweight by more than 2 percentage points when compared to children who have never lived in the South.

In Table 3 we present the probit results from four models that estimate the impact of poverty on risks of underweight. Similar to Table 2, Column 1 presents the estimated marginal effects of poverty without an extensive set of covariates. The results indicate that children who have spent all of their life in poverty increase their risk of being underweight by nearly 2 percentage points, compared to children whose family has never been poor. As more controls for family characteristics are included in models (2) through (4), we find that the simple model underestimates the impact of poverty. In model (4), the point estimate for the effect of poverty on risk of underweight is 3.1 percentage points. However, most of these additional covariates fail to be statistically significant except for the measures of maternal weight outcomes. Specifically, a mother who was underweight at age 21 is likely to increase her child's probability of being underweight by 4.4 percentage points and this result is statistically significant.

Controlling for a set of demographic and family characteristics, in Tables 2 and 3, we find that a child who has spent a greater portion of her childhood in poverty is more likely to be underweight but less likely to be overweight. In the following section, we present results from estimations that account for unobserved heterogeneity that may be correlated with children's weight outcomes as well as family poverty status.

5.2 Linear Probability, Fixed Effects, and IV Regression

To simplify computations, we apply fixed effects and IV methods to a linear probability model, in which the dependent variable is a binary indicator of weight problems. In column 1 of Tables 4 and 5, we report the estimates from a linear probability model that has the same specification as model (4) in Tables 2 and 3 respectively. The marginal effects of corresponding covariates are not different statistically.

Table 3
Estimated Effect of Poverty on Child's Risk of Underweight with Probit
(Robust standard errors are in parentheses)

	(1)		(2)		(3)		(4)	
Pct of child's life spent in poverty	0.0192	(0.0093)	0.0260	(0.0126)	0.0297	(0.0124)	0.0310	(0.0126)
Black	—		-0.0041	(0.0080)	0.0005	(0.0080)	0.0006	(0.0083)
Non-white Hispanic	—		0.0086	(0.0086)	0.0091	(0.0085)	0.0094	(0.0086)
Mother high school graduate	—		0.0114	(0.0097)	0.0092	(0.0096)	0.0086	(0.0098)
Mother college or more	—		0.0143	(0.0139)	0.0113	(0.0138)	0.0091	(0.0140)
Mother's AFQT score	—		-0.0001	(0.0002)	-0.0001	(0.0002)	-0.0001	(0.0002)
Pct child's life both parents present	—		0.0064	(0.0098)	0.0081	(0.0096)	0.0076	(0.0099)
Mother obese at age of 21	—		—		-0.0520	(0.0105)	-0.0521	(0.0105)
Mother underweight at age of 21	—		—		0.0441	(0.0127)	0.0442	(0.0126)
Child was firstborn	—		—		—		0.0091	(0.0067)
Portion of child's life living in South	—		—		—		0.0024	(0.0067)
Avg. # children in HH since birth	—		—		—		0.0012	(0.0035)
Pct of child's life grandmother present	—		—		—		-0.0053	(0.0140)
Sample size	25,476		25,476		25,476		25,476	
Pseudo R-Squares	0.036		0.0364		0.0426		0.0429	

Notes: (1) The dependent variable is a binary indicator for underweight; (2) Point estimates provided above are marginal effects of the corresponding parameters; (3) All specifications include an intercept term, indicators for weight and height information being self-reported, child age, child age squared, child gender, mother's age in years, education levels of the mother's parents, and year dummies with year 1986 being omitted; (4) All standard errors are robust and clustered on mother's ID; (5) The estimation is weighted using the child's sampling weights.

Table 4
Estimated Effect of Poverty on Child's Risk of Overweight with Heterogeneity Control
(Robust standard errors are in parentheses)

	(1) Linear Prob		(2) LP child FE		(3) LP sibling FE		(4) Instrument	
Pct child's life in poverty	-0.0487	(0.0161)	0.0849	(0.0597)	0.0378	(0.0969)	0.1570	(0.1851)
Pct child's life both parents present	-0.0314	(0.0135)	-0.0732	(0.0526)	-0.0462	(0.0709)	-0.0530	(0.0751)
Pct child's life living in South	0.0215	(0.0086)	0.0959	(0.0095)	0.0215	(0.0113)	0.0207	(0.0094)
Avg. # children in HH since birth	-0.0087	(0.0052)	-0.0243	(0.0219)	0.0150	(0.0370)	-0.0202	(0.0114)
Sample size	25,476		17,730		8,320		25,476	

Notes: (1) The dependent variable in column 1 is a binary indicator of child being overweight; (2) The dependent variable in column 2 is the difference between the current value and lagged value for the binary indicator of child being overweight; (3) The dependent variable in 3 is the difference of two siblings' overweight indicators; (4) All specifications in (1) and (2) include an intercept term, indicators for weight and height information being self-reported, child age, child age squared, child gender, mother age and year dummies with year 1986 being omitted; (5) Estimations in columns 1 and 4 are weighted using the child's sampling weights while those in 2 and 3 are weighted using family average weights.

Table 5
Estimated Effect of Poverty on Child's Risk of Underweight with Heterogeneity Control
(Robust standard errors are in parentheses)

	(1) Linear Prob		(2) LP child FE		(3) LP sibling FE		(4) Instrument	
Pct child's life spent in poverty	0.0323	(0.0138)	0.0990	(0.0526)	0.0732	(0.0709)	0.1147	(0.1405)
Pct child's life both parents present	0.0084	(0.0102)	-0.0736	(0.0468)	0.0728	(0.0640)	0.0417	(0.0574)
Pct of child's life living in South	0.0023	(0.0062)	0.0617	(0.0922)	0.0231	(0.1191)	0.0020	(0.0070)
Avg. # children in HH since birth	0.0010	(0.0036)	0.0409	(0.0200)	-0.0171	(0.0240)	-0.0035	(0.0084)
Sample size	25,476		17,730		8,320		25,478	

Notes: (1) The dependent variable in column 1 is a binary indicator of child being underweight; (2) The dependent variable in column 2 is the difference between the current value and lagged value for the binary indicator of child being underweight; (3) The dependent variable in 3 is the difference of two siblings' underweight indicators; (4) All specifications in (1) and (2) include an intercept term, indicators for weight and height information being self-reported, child age, child age squared, child gender, mother age and year dummies with year 1986 being omitted; (5) Estimations in columns 1 and 4 are weighted using the child's sampling weights while those in 2 and 3 are weighted using family average weights.

Estimated from the child fixed-effects estimator for overweight and underweight equations are presented in column 2 of Tables 4 and 5. The sibling-fixed effects estimates and IV results are reported in columns 3 and 4 of these tables. The point estimates from these fixed effects and IV models suggest that the results obtained via naive probit or linear probability regressions might be biased downward. In particular, after controlling for unobserved heterogeneity, we find that extensive poverty exposure increases a child's risk of being obese. The IV regression yields the largest effect estimates: Growing up poor increases a child's risk of being overweight by 15 percentages points when compared to children who have never been poor. However, as predicted in Section 4, we find that the estimators with controls for unobserved heterogeneity tend to yield greater standard errors in both overweight and underweight equations. Therefore, the estimated effects of poverty on probability of being underweight or overweight are not statistically different from zero, accounting for the endogeneity of the family income. The results on other covariates of interest obtained from the simple linear probability model appear to hold when controls for unobserved heterogeneity are applied. For instance, growing up in the South is associated with an increased risk of being overweight by 2 percentage points and this finding remains unchanged across different specifications.

5.3 OLS and Quantile Regressions

We report OLS and quantile regressions in Table 6. A baseline regression model without controls for unobserved heterogeneity suggests that a child growing up poor is likely to have 2.7 percent lower BMI than others that have never been exposed to poverty, and this finding is statistically significant. However, an IV regression indicates that on average the exposure to poverty has no significant impacts on children's weight measures. As we focus on the impact of poverty on children's BMI conditional on different BMI quantiles, the results become more interesting. According to the baseline quantile regression estimates, growing up poor has similar impacts on a child's BMI measures no matter whether her weight is located in upper 5th quantile or lower 5th quantile. This finding is consistent with the baseline OLS estimates as they suggest that growing up poor will uniformly reduce a child's BMI by

Table 6
Estimated Effect of Income on Child's Log(BMI)
(Robust standard errors are in parentheses)

		Quantile Regression				
	OLS	5th (13.2kg/m^2)	10th (13.8 kg/m^2)	Median (16.3 kg/m^2)	90th (21.6 kg/m^2)	95th (23.9 kg/m^2)
Baseline Model						
Percentage of child's life spent in poverty	-0.0272	-0.0259	-0.0203	-0.0242	-0.0392	-0.0227
	(0.0094)	(0.0088)	(0.0068)	(0.0057)	(0.0112)	(0.0135)
(Pseudo)R-squared	0.2224	0.0571	0.0643	0.1108	0.1940	0.2183
Instrument						
Percentage of child's life spent in poverty	0.0096	-0.0991	-0.1270	0.0231	0.1471	0.0844
	(0.0084)	(0.0476)	(0.0597)	(0.0140)	(0.0421)	(0.0399)
(Pseudo)R-squared	0.2208	0.0565	0.0640	0.1104	0.1935	0.2181

Notes: (1) The dependent variable is log(BMI); (2) Specification is the same as that in column 4 in Table 2; (3). Child's sample weights are applied to all estimations; (4) The standard errors for OLS are robust and clustered on the mother's ID; (5) The standard errors for quantile regressions are clustered on mother's ID using bootstrapping methods with 100 replications.

more than 2 percent. After controlling for unobserved heterogeneity with a 2SLAD procedure, however, we find that poverty has varying effects for children whose weights are located at different positions of distribution. For children whose weights are in lower 5th and 10th quantiles, persistent exposure to poverty can reduce their BMI by as much as 9.9 percent and 12.7 percent, respectively. Growing up poor actually increase the risk of being overweight among children whose weights are near the top quantiles of distribution. Particularly, for a child whose weight is in the vicinity of the 90th quantile, persistent poverty in childhood is likely to increase her BMI by 14.7 percent, which is great enough to move her from being at risk of overweight to being overweight.

5.4 Estimates for Subgroups

To investigate if the relationship between poverty and childhood weight problems differs by gender, maternal education, or race and ethnicity, equation (1) is estimated separately for individual subgroups. Estimates for overweight and underweight equations are provided in Tables 7 and 8, respectively. We find that controlling for unobserved heterogeneity, the poverty status has almost no effects on the risk of being overweight among children whose mothers have college or higher education. This finding might be partly due to the fact that only a small fraction of college-educated mothers live in poverty. Nevertheless, mothers with higher education may tend to provide more health inputs to their children, such as preparing nutritionally balanced meals, which can offset the negative impact of poverty to some extent. Overall, growing up poor has the greatest effect on increasing the risk of being overweight among Hispanic children and among girls. The effect of poverty on risk of underweight is most sizable among white children, females, and children whose mothers only receive high school education or less.

5.5 Identification of Empirical Models and Sensitivity Analysis

In this paper we employed a set of instrumental variables in linear probability and quantile regression models to identify the casual relationship between family income and childhood weight

Table 7
Estimated Effects of Poverty on Risk of Overweight for Subgroups
(Robust standard errors are in parentheses)

	(1) Overweight %		(2) Probit		(3) Child Fixed Effects		(4) Sibling Fixed Effects		(5) IV	
Education										
HS or less	0.1503	(0.3574)	-0.0644	(0.0398)	0.0441	(0.1118)	0.2194	(0.2042)	0.1292	(0.1794)
College or more	0.1452	(0.3523)	-0.0414	(0.0159)	0.0090	(0.0698)	0.0002	(0.1005)	0.0073	(0.2736)
Race										
White	0.1192	(0.3240)	-0.0512	(0.0218)	0.0829	(0.0858)	0.1011	(0.1331)	0.1632	(0.2031)
Black	0.1765	(0.3813)	-0.0288	(0.0274)	0.0044	(0.0820)	0.0864	(0.1241)	0.1115	(0.1839)
Hispanic	0.1685	(0.3743)	-0.0319	(0.0341)	0.2104	(0.1053)	-0.1407	(0.1666)	0.2547	(0.2570)
Gender										
Girls	0.1386	(0.3455)	-0.0649	(0.0203)	0.2102	(0.0868)	0.0905	(0.1243)	0.2464	(0.1954)
Boys	0.1533	(0.3603)	-0.0300	(0.0213)	0.0374	(0.0835)	-0.0061	(0.1239)	0.0956	(0.3054)

Notes: (1) The dependent variable is a binary indicator for overweight; (2) Point estimates provided above are marginal effects of the corresponding parameters; (3) All specifications are similar to the one used in column 4 in Table 2 except that corresponding grouping variables are dropped; (4) All standard errors are robust and clustered on mother's ID; (5) Estimations in columns 2 and 5 are weighted using the child's sampling weights while those in 3 and 4 are weighted using family average weights.

Table 8
Estimated Effects of Poverty on Risk of Underweight for Subgroups
(Robust standard errors are in parentheses)

	(1) Underweight %		(2) Probit		(3) Child Fixed Effects		(4) Sibling Fixed Effects		(5) IV	
Education										
HS or less	0.1048	(0.3063)	0.0572	(0.0251)	0.2370	(0.1019)	0.2341	(0.1325)	0.3026	(0.1551)
College or more	0.1045	(0.3059)	0.0271	(0.0145)	0.0674	(0.0605)	0.0377	(0.0818)	0.1895	(0.1417)
Race										
White	0.1079	(0.3103)	0.0400	(0.0190)	0.1775	(0.0749)	0.1420	(0.1052)	0.2057	(0.1622)
Black	0.1043	(0.3057)	0.0233	(0.0168)	-0.1546	(0.0727)	-0.0081	(0.0931)	0.0164	(0.1130)
Hispanic	0.1027	(0.3035)	0.0171	(0.0192)	0.1088	(0.1035)	-0.1808	(0.1323)	-0.2156	(0.1707)
Gender										
Girls	0.1026	(0.3034)	0.0306	(0.0160)	0.1168	0.0735	0.0918	(0.1095)	-0.0027	(0.1469)
Boys	0.1065	(0.3085)	0.0309	(0.0174)	0.0825	(0.0745)	0.0583	(0.0862)	0.2667	(0.2442)

Notes: (1) The dependent variable is a binary indicator for Underweight; (2) Point estimates provided above are marginal effects of the corresponding parameters; (3) All specifications are similar to the one used in column 4 in Table 2 except that corresponding grouping variables are dropped; (4) All standard errors are robust and clustered on mother's ID; (5) Estimations in columns 2 and 5 are weighted using the child's sampling weights while those in 3 and 4 are weighted using family average weights.

problems. The identification of these models requires that these instruments are strong predictors of family income but not childhood weight problems. To test the overidentification restrictions of these instruments, we conduct the Hansen-Sargan test, which fails to reject the null hypothesis that the instruments are valid, i.e., uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. The results are reported in Appendix Table A2. The instruments are highly predictive of poverty status (F-statistic of 184.94 in the first stage). In addition, we also conduct a set of indirect tests to check whether these proposed instruments are correlated with omitted determinants of child health among the poor. Specifically, we run regressions to test if these instrumental variables are correlated with state-level free lunch program participation rates, and percentage of families that are unable to provide balanced meals using the1999 Current Population Survey (CPS) data. We find no strong correlations between chosen instruments and the characteristics that might capture the unobserved determinants of children's weight.

To check the robustness of our findings, we also consider alternative measures for the exposure to poverty, such as family's poverty status in last year, percent of childhood spent in deep poverty (family living below half the poverty threshold), average family net income since birth, and family net income in last year. Implementing the fullest specification, we obtain estimates for overweight and underweight equations. We present estimates corresponding to risk of overweight, risk of underweight, and quantile regressions in Appendix Tables A4 through A6, respectively. As expected, when half the poverty threshold is used to define poverty status in fixed-effects models, we find the impact of poverty exposure on risk of being overweight increases. As shown in column 2 of Table A4, for instance, a 10 percentage point increase in the average exposure to deep poverty in the past is linked to an increase of 1.5 percentage points in children's likelihood of being overweight, almost doubling the estimate from a similar model that is based on 100 percent of the poverty threshold. Different from IV models, as discussed in Section 4, the identification of child fixed-effects models depends on variations of poverty status over time, and these results may be driven by children who had the most volatile economic environment. Moreover, when poverty status or family income is based on last year we find that estimated effects generally decline while their standard errors increase, indicating that the short term effects of poverty on weight problems are not significantly different from zero.

6. CONCLUSIONS

This paper set out to test the hypothesis that persistent poverty exposure is negatively related to child weight outcomes. In particular, our primary research question is whether there is a causal relationship between exposure to poverty and pre-adolescent obesity. Mixed evidence is found about the effect of poverty on childhood weight problems, both overweight and underweight. Simple probit models without controls for unobserved heterogeneity indicate that growing up poor is likely to be associated with reduced risk of being overweight by 4.7 percentage points and increased risk of being underweight by 3.1 percentage points. Both results are statistically significant. Once correcting for unobserved heterogeneity, we find that the estimated effects of poverty exposure on overweight change signs, and the estimates on underweight increase by a factor of 2. Accounting for unobserved heterogeneity, the magnitudes of these estimated effects are greater than those cross-sectional results reported by Gibson (2000), Koreman and Miller (1994), and Hofferth and Curtin (2005). However, none of these estimates remain statistically significant, and we have to reject the hypothesis that poverty is causally related to weight problems over the whole sample.

We do find that poverty status is causally related to weight problems for children in the tail ends of the weight distribution and the mean effects of family income produced by OLS fail to characterize the change of BMI distribution induced by family income. Quantile regressions with appropriate controls for unobserved heterogeneity suggest that there are variations in the impacts of poverty exposure along the conditional distribution of child weights. Specifically, we conclude that children who are at risk of underweight, that is, located at the lower end of the conditional distribution of BMI due to genetics or other underlying factors not directly correlated with income, are likely to be moved into being underweight as a result of extensive exposure to poverty in early childhood while those who are located at the upper end of the conditional distribution of BMI are subject to increased risk of being overweight when growing up poor. In other words, improved economic status can only mitigate the propensity to weight problems marginally among impoverished children. The predisposition to weight problems can be attributed to factors suggested by other authors (see Cawley, 2006), such as access to grocery stores and exercise-friendly neighborhoods. One limitation of the study is that we do not control for the food expenditures in a family. The strong and positive effects of living in the southern states on the risk of overweight indicate that the persistence of eating habits, which are proxied by residing regions, is independent of poverty status. It is possible that families do not always purchase more healthy foods when there is a positive exogenous income shock, which can also help explain the lack of causality between family income and weight problems.

These findings have important policy implications concerning our ongoing fight against obesity epidemics and other childhood malnutrition problems. In particular, income transfers are likely to have an ambiguous effect on risks of weight problems among the majority of impoverished children. When aimed at low income and minority children, policy interventions should focus on promoting access to publicly provided health care (such as Medicaid and SCHIP), healthy foods, and exercise-friendly areas in low income neighborhoods.

Appendix
Technical Notes

A.1 DEFINITION OF POVERTY

The main poverty definition used in this study is the "federal poverty thresholds," which are estimated and published each year by the Census Bureau. This measure was originally developed by the Social Security Administration in 1964. Survey data in the early 1960s indicated that families spent approximately one third of their income on food. Therefore, the poverty line was calculated from the estimated annual costs of a minimal food budget designed by the U.S. Department of Agriculture (USDA) and then multiplied by three, a method that continues today (U.S. House of Representatives, Committee on Ways and Means, 1996). The poverty line varies by family size and by whether the individuals are over or under age 65, because food costs are expected to differ. It is revised yearly based on inflationary changes in the Consumer Price Index. It is approximately 25 to 30 percent higher in Alaska and Hawaii because of higher food costs.

A.2 INCOME MEASURES

The gross family income variable includes parents' wages and salary income, income from self-employment, payments received from interest, rental income, food stamps, AFDC, SSI benefits, child support, alimony, veteran benefits, disability benefits, educational benefits, unemployment insurance, and other sources. This income measure also includes total amount of money received by parents from individuals living outside the household and from relatives who reside in the same household. Following Dahl and Lochner (2005), we use multiple imputation procedures to replace missing values of total gross income, which are caused by invalid individual income components or missed interviews. The first method involves regressing family total gross income on mother's age, age squared, schooling years, schooling years squared, and marital status among families that have nonmissing gross income for more than 8 periods. Among these families, the remaining missing gross income will be replaced by predicted values if these predicted values are nonnegative and less than 300,000 2002 dollars.

The second approach involves imputing missing values for major components of family income, such as (1) self-earned income, educational benefits, unemployment insurance; (2) spouse-earned income, educational benefits, unemployment insurance; (3) partner's income; (4) money received from outside household; (5) child support and alimony; (6) other sources of income such as interest, rental; and (7) welfare income. Similar to method 1, for each income component, a separate regression is performed on a set of family characteristics among families that have nonmissing values for more than 4 periods. The predicted values will be used to replace the missing values. If the gross family income for a certain year remains missing after the first two procedures, we use year, race, marital status, and mother's age specific median value to replace the income components before summing them together for the imputed total gross family income.

Appendix Table A1
First Stage Regression Results
(Dependent variable is pct of child's life spent in poverty)

	Point Estimates	S.E.
Average EITC phase-in rate	0.1111	(0.3061)
Average EITC phase-out rate	3.8974	(2.8672)
Average EITC max earnings	0.1768	(0.1341)
Average EITC max benefits	-0.2010	(0.1173)
Average state AFDC/TANF max benefits	0.0049	(0.0011)
Average state food stamp guarantee	-0.2809	(0.1281)
Average state per capita income	0.0540	(0.0105)
Average state unemployment rate	1.2571	(0.1472)
Average state wage rates for manufacturing workers	0.0085	(0.0025)
Average state AFDC/TANF participation rate	-0.2270	(0.1526)
Average wage rates for female workers	-0.1654	(0.0223)
Average percentage for female workers holding professional position	0.2525	(0.0846)
Average poverty rates among female-headed households	-0.0184	(0.0223)
Black	0.0556	(0.0044)
Hispanic	0.0172	(0.0054)
Mother HS or less	-0.1400	(0.0044)
Mother college or more	-0.1092	(0.0061)
Mother AFQT score	-0.0016	(0.0001)
Pct of childhood when both parents present	-0.4005	(0.0041)
Mother overweight at age 21	0.0130	(0.0043)
Mother underweight at age 21	-0.0245	(0.0054)
Firstborn	0.0031	(0.0033)
Pct of childhood living in the South	-0.0015	(0.0048)
Average number of children present in household	0.0561	(0.0017)
Pct of childhood when grandparent present in household	0.0449	(0.0075)
Weight self-reported	-0.0023	(0.0039)
Height self-reported	-0.0026	(0.0043)
Child age	0.0048	(0.0032)
Child age squared	0.0000	(0.0002)
Boy	0.0008	(0.0025)
Mother age	-0.0076	(0.0006)
Highest grade completed by grandmother	-0.0035	(0.0005)
Year 1988	-0.0229	(0.0163)
Year 1990	-0.0261	(0.0193)
Year 1992	-0.0382	(0.0218)
Year 1994	-0.0420	(0.0243)
Year 1996	-0.0356	(0.0277)
Year 1998	-0.0451	(0.0317)
Year 2000	-0.0413	(0.0345)
Year 2002	-0.0376	(0.0356)
Intercept	1.5254	(0.2949)

Table A2
Specification Test for the Instrumental Variables for Poverty Exposure

	Weight Measures (Dependent variable)		
	Overweight	Underweight	Log(BMI)
Overidentification test	$\chi^2(12)$ p-value= 0.4442	$\chi^2(12)$ p-value= 0.1010	$\chi^2(12)$ p-value=0.6246
Exogeneity test	F(1,25446) p-value= 0.0665	F(1,25446) p-value= 0.0912	F(1,25446) p-value= 0.0977
Power of instruments	F(13, 25462) = 184.94		

Table A3
Correlations between Instruments and Child Health Inputs
(Based on state level data from CPS and CDC)

	Instruments					
	Poverty Rates Female Heads	Per Capita Income	Unemployment Rate	Average Female Wage	% Women Professional	Max TANF Benefits
Average child care copayment	-0.1437 (0.3145)	0.0278 (0.8462)	0.1296 (0.3645)	-0.1066 (0.4564)	0.1754 (0.2182)	-0.2866 (0.0415)
Average daily serving of fruits and vegetables	-0.0632 (0.6596)	0.4158 (0.0024	-0.1707 (0.2310)	0.5996 (0.1175)	-0.3496 (0.0119)	0.2111 (0.1370)
Free lunch participation among poor children	0.0977 (0.4954)	-0.3651 (0.0084)	0.0432 (0.7635)	-0.5804 (0.4933)	0.167 (0.2414)	-0.106 (0.4590)

Notes: (1) Significance levels for corresponding correlations are provided in parentheses.

Table A4
Estimated Effects of Poverty on Risk of Overweight with Different Poverty Measures
(Robust standard errors are in parentheses)

	(1) Probit		(2) Child Fixed Effects		(3) Sibling Fixed Effects		(4) IV	
In poverty last year	-0.0323	(0.0085)	0.0186	(0.0098)	—	—	0.1104	(0.1746)
Pct of child's life spent in deep poverty	-0.0789	(0.0222)	0.1507	(0.0797)	0.1860	(0.1208)	0.1510	(0.3072)
In deep poverty last year	-0.0407	(0.0109)	0.0300	(0.0129)	—	—	0.0301	(0.2613)
Avg family net income since child birth ($10,000)	-0.0001	(0.0007)	0.0013	(0.0012)	-0.0006	(0.0012)	0.0138	(0.0089)
Family net income last yr ($10,000)	-0.0013	(0.0012)	0.0001	(0.0015)	—	—	-0.0016	(0.0096)

Notes: (1) The dependent variable is a binary indicator for overweight; (2) Point estimates provided above are marginal effects of the corresponding parameters; (3) All specifications are similar to the one used in column 4 in Table 2 except that corresponding grouping variables are dropped; (4) All standard errors are robust and mother's on child ID; (5) Estimations in columns 2 and 5 are weighted using the child's sampling weights while those in 3 and 4 are weighted using family average weights.

Table A5
Estimated Effects of Poverty on Risk of Underweight with Different Poverty Measures
(Robust standard errors are in parentheses)

	(1) Probit		(2) Child Fixed Effects		(3) Sibling Fixed Effects		(4) IV	
In poverty last year	0.0164	(0.0071)	0.0012	(0.0092)	—	—	0.0626	(0.1275)
Pct of child's life spent in deep poverty	0.0145	(0.0174)	0.0055	(0.0722)	0.0106	(0.0822)	0.3074	(0.2355)
In deep poverty last year	0.0050	(0.0102)	-0.0069	(0.0129)	—	—	-0.0812	(0.1947)
Avg family net income since child birth ($10,000)	-0.0004	(0.0003)	0.0001	(0.0004)	0.0006	(0.0008)	0.0006	(0.0054)
Family net income last yr ($10,000)	0.0000	(0.0012)	0.0003	(0.0017)	—	—	0.0033	(0.0071)

Notes: (1) The dependent variable is a binary indicator for Underweight; (2) Point estimates provided above are marginal effects of the corresponding parameters; (3) All specifications are similar to the one used in column 4 in Table 2 except that corresponding grouping variables are dropped; (4) All standard errors are robust and clustered on mother's ID; (5) Estimations in columns 2 and 5 are weighted using the child's sampling weights while those in 3 and 4 are weighted using family average weights.

Table A6
Estimated Effect of Income on Child's BMIPCT
(Robust standard errors are in parentheses)

	OLS		Quantile Regression					
			10th quantile (13.8 kg/m^2)		Median (16.3 kg/m^2)		90th quantile (21.6 kg/m^2)	
A. Baseline Model								
In poverty last year	-0.0165	(0.0048)	-0.0103	(0.0042)	-0.0173	(0.0037)	-0.0256	(0.0256)
Pct of child's life spent in deep poverty	-0.0520	(0.0129)	-0.0113	(0.0099)	-0.0482	(0.0482)	-0.0606	(0.0169)
In deep poverty last year	-0.0235	(0.0064)	-0.0016	(0.0064)	-0.0211	(0.0054)	-0.0434	(0.0100)
Avg family net income since child birth ($10,000)	0.0001	(0.0003)	0.0005	(0.0002)	0.0002	(0.0002)	-0.0004	(0.0004)
Family net income last yr ($10,000)	-0.0006	(0.0007)	-0.0003	(0.0006)	-0.0003	(0.0005)	-0.0009	(0.0009)
B. Instrument								
In poverty last year	0.0217	(0.0916)	-0.0233	(0.0832)	0.0374	(0.0701)	0.0434	(0.1343)
Pct of child's life spent in deep poverty	-0.0928	(0.1638)	-0.2300	(0.1379)	-0.0161	(0.1179)	0.0681	(0.2351)
In deep poverty last year	0.0783	(0.1362)	0.0913	(0.1181)	0.1442	(0.0972)	-0.1003	(0.2034)
Avg family net income since child birth ($10,000)	0.0021	(0.0037)	-0.0027	(0.0031)	0.0001	(0.0027)	0.0098	(0.0050)
Family net income last yr ($10,000)	-0.0023	(0.0052)	-0.0067	(0.0041)	-0.0024	(0.0038)	0.0041	(0.0073)

Notes: (1) The dependent variable is log(BMI); (2) Specification is the same as that in column 4 in Table 2; (3). Child's sample weights are applied to all estimations; (4) The standard errors for OLS are robust and clustered the on mother's ID; (5) The standard errors for quantile regressions are clustered on the mother's ID using bootstrapping methods with 100 replications.

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