

Socio-economic, behavioural and environmental factors predicted body weights and household food insecurity scores in the Early Childhood Longitudinal Study-Kindergarten

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(Received 4 July 2007 – Revised 1 October 2007 – Accepted 19 November 2007 – First published online 14 February 2008)

Recent increases in obesity prevalence among children in developed countries are of policy concern. While significant positive associations between households' food insecurity status and body weights have been reported for adults, it is known from the energy physiology literature that energy requirements depend on BMR, anthropometric measures and physical activity. It is therefore important to model the bi-directional relationships between body weights and households' food insecurity scores especially for children that have evolving nutrient and energy requirements. The present paper estimated dynamic random effects models for children's body weights and BMI, and households' food insecurity scores using longitudinal data on 7635 children in the USA enrolled in 1st, 3rd and 5th grades (1999–2003) of the Early Childhood Longitudinal Study-Kindergarten. The main findings were, first, physical exercise and numbers of siblings were significantly ($P < 0.05$) negatively associated with body weights, while households' food insecurity score was not a significant predictor. Moreover, children's body weights were significantly lower in households with higher parental education and incomes; time spent watching television and in non-parental care were positively associated with weights. Second, models for households' food insecurity scores showed that poverty and respondents' poor emotional and physical health significantly increased food insecurity. Moreover, households with children who were taller and heavier for their ages faced significantly higher food insecurity levels. Overall, the results showed that household food insecurity was unlikely to exacerbate child obesity in the USA and it is important that children receive balanced school meals and perform higher physical activity.

Anthropometric measures: Children: Food insecurity: Longitudinal data: Poverty

The early literature in nutrition research emphasised the importance of adequate energy, protein, and micronutrient intakes for child health and developed standards for children's growth patterns^(1–5). While information on the consequences of energy and nutrient deficiencies was compiled in less developed countries, it was recognised that dietary intakes may be inadequate for low-income groups in developed countries. Children from such households may require nutritious foods such as those high in Ca, Fe, and vitamins A and C for maintaining immunological functions and growth⁽⁶⁾. With the burgeoning obesity epidemic in countries such as the USA, however, policy discussion has acquired a different emphasis. Recent research has investigated whether households' food insecurity status and entitlement programmes such as food stamp benefits may be contributing to the obesity epidemic^(7–11). The hypothetical links between food shortages and obesity are that temporary shortages may encourage consumption of energy-dense foods, and that weight gain may be an 'adaptive response' to food shortages⁽⁷⁾.

Further, much of the research investigating links between food insecurity and body weights has focused on adult populations, where significant positive associations have been

reported^(8,9). Typically, the time frame for the studies is short, and cross-sectional data or longitudinal observations spanning a few years are employed. Such analyses seldom incorporate the principles of energy physiology implying that, for a given level of physical activity, heavier individuals have higher energy requirements^(12–16). While positive associations between food insecurity levels and body weight could be due to higher food insecurity leading to overweight, it is plausible that being overweight in poor households exacerbates food insecurity. Moreover, obese individuals are likely to suffer from hypertension, diabetes mellitus and CVD. If such individuals lose their employment and start receiving food stamps, then one would observe positive associations between food stamps receipt and obesity because the underlying causality runs from obesity to food stamps receipt via reductions in hours worked.

The inter-relationships between food insecurity levels and body weights are simpler to analyse among children because inadequate intakes of energy and micronutrients can diminish growth and increase morbidity⁽¹⁷⁾. Children in food-insecure households in developed countries may have poor micronutrient status though severe undernutrition is rare. Evidence on

Abbreviation: ECLS-K, Early Childhood Longitudinal Study-Kindergarten.

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inter-relationships between households' food insecurity status and children's body weights has been ambiguous. While some researchers have reported positive associations between food insecurity and body weights⁽¹⁰⁾, others have found insignificant or negative associations^(18,19). However, these studies have not analysed longitudinal data to afford insights into the dynamic inter-relationships between food insecurity levels and children's body weights. Moreover, combining height and weight as the BMI can complicate modelling of relationships^(17,20,21). Econometric models can address bi-directionalities in the inter-relationships between children's weight and households' food insecurity scores, while tackling important aspects such as dependence of children's current weight on the respective previous levels.

The Early Childhood Longitudinal Study-Kindergarten (ECLS-K) started following over 19 000 children in the USA enrolled in kindergarten in 1998⁽²²⁾, and data from kindergarten, and 1st, 3rd, and 5th grades are available. Children's heights and weights and households' food insecurity levels were longitudinally measured. Previous research has employed indicator or categorical variables to approximate households' food insecurity status and there have been no systematic attempts to model the effects of children's growth on households' food insecurity levels. If, for example, households with children that are taller for their ages report higher food insecurity, then child growth may be compromised by policies focusing exclusively on the links between food insecurity and obesity. Such issues are important from a policy standpoint, and joint modelling of children's anthropometric measures and households' food insecurity levels using econometric techniques can provide useful insights.

Experimental methods

Subjects

The ECLS-K is an ongoing longitudinal study that started in 1998 by observing 19 684 children in kindergarten enrolled in 1277 schools and their parents (sometimes referred to as 'respondents' due to complicated living arrangements)⁽²²⁾. Children and the households were observed in kindergarten and 1st, 3rd and 5th grades. The multi-stage sampling study design ensured a nationally representative sample. However, there was attrition due to families relocating and from changing schools; 11 479 children remained in the ECLS-K from kindergarten and through 5th grade. Only identifiers for children were retained in the data and the analyses were approved by the Human Subjects Committee of the University of Houston.

Socio-demographic and economic variables

Extensive information was compiled in ECLS-K on children, households and schools using detailed questionnaires. Children's ethnicity, childcare arrangements, time (in min) spent watching television, numbers of siblings and household members, and physical exercise patterns were investigated. Parents' education, occupation, and physical and emotional health were investigated. Annual household incomes were assessed (in US\$1000) and thirteen income categories were created (<5, 5–10, 10–15, 15–20, 20–25, 25–30, 30–35, 35–40, 40–50, 50–75, 75–100, 100–200, >200).

The responses to various questions were processed to form continuous variables or indices that reflected exposure. For example, time (in min) spent watching television per d were computed from responses in 1st, 3rd and 5th grades. Quantitative measures of physical exercise such as the number of d per week children exercised more than 20 min were used. Moreover, variables such as if respondent's health limited their functions and emotional wellbeing were investigated. For example, eleven emotional items enquired if the respondent had poor appetite, could not shake the blues, had trouble focusing, felt depressed, everything felt an effort, felt fearful, slept restlessly, talked less than usual, felt lonely, felt sad, and could not go out. Affirmative responses were scored as 1 and the average scores were used in the analyses.

Anthropometric measures and households' food insecurity scores

Children's heights and weights were measured in all survey rounds. A Shorr Board was used to measure height; duplicate measurements were taken and mean values were analysed. Children's weight was measured using digital scales. Households' food insecurity levels in the previous 12 months were investigated using an eighteen-item scale⁽²³⁾. The affirmative responses were scored as 1 and aggregate scores were used as continuous variables, with higher scores reflecting greater food insecurity. A categorical variable (1–4) for food insecurity status was also analysed⁽²⁴⁾; the four categories were 'food secure', 'food insecure without hunger', 'food insecure with moderate hunger' and 'food insecure with severe hunger'. Respondents were asked whether the household received food stamps in the previous 12 months and if children received reduced price or free lunches in school. Due to missing observations, complete data were analysed on 7635 children at 2-year intervals in the 1st, 3rd and 5th grades; demographic characteristics of the sample in our analyses were similar to the full dataset covering 11 479 children from kindergarten to the 5th grade.

The model

The model postulated for children's body weights is given in equation (1):

$$\begin{aligned} \ln(\text{Weight})_{it} = & a_0 + a_1(\text{Black})_i + a_2(\text{Hispanic})_i + a_3(\ln(\text{Age}))_i \\ & + a_4(\ln(\text{Age}))_i^2 + a_5 \ln(\text{Parental education})_i \\ & + a_6(\text{Number siblings})_i \\ & + a_7(\text{Respondent health limiting})_i \\ & + a_8 \ln(\text{Watch television})_{it} \\ & + a_9(\text{Non - parental care})_{it} \\ & + a_{10}(\text{Physical exercise})_{it} \\ & + a_{11}(\text{Household income})_{it} + a_{12} \ln(\text{Height})_{it} \\ & + a_{13}(\text{Food insecurity score})_{it} \\ & + a_{14} \ln(\text{Weight})_{it-1} + u_{it}. \end{aligned} \quad (1)$$

Here, \ln represent natural logarithms. Children's weights, age in months, time (in min) spent watching television, and

heights, and parental education category were transformed into natural logarithms, partly to reduce heteroscedasticity⁽²⁵⁾. Coefficients of variables expressed in logarithms were the ‘elasticities’ (% change in dependent variable resulting from 1% change in independent variables). Non-linearities with respect to children’s ages were incorporated in the model. A model for children’s BMI, derived by imposing the restriction $a_{12} = 2$ in equation (1), was also estimated. Moreover, a model for Z-scores of BMI utilising medians, CV and skewness⁽²⁶⁾ in height and weight data was estimated to assess the robustness of the results.

The dynamic model in equation (1) contained previous measurement of weight as an explanatory variable, enabling a distinction between short- and long-run effects of explanatory variables. For example, the short-run elasticity of body weight with respect to watching television was a_8 , while the long-run elasticity was $(a_8/(1 - a_{14}))$. The u_{it} were random error terms that were also decomposed in a simple random effects fashion as:

$$u_{it} = \delta_i + v_{it}, \quad (2)$$

where δ_i were children-specific random effects that were normally distributed with zero mean and constant variance, and v_{it} were normally distributed errors with zero mean and constant variance⁽²⁷⁾. The estimation techniques treated previous observations on body weights as ‘endogenous’ variables, i.e. correlated with the errors u_{it} . Realisations of time-varying explanatory variables such as household incomes in the three grades were assumed uncorrelated with the errors (‘exogenous’) and used as ‘instrumental variables’ in the estimation⁽²⁸⁾.

Last, dynamic models were estimated for households’ food insecurity scores and food insecurity status that were similar to the model in equation (1). In addition, respondent’s emotional score, and children’s height and weight were included as explanatory variables, with emotional scores and children’s weights treated as endogenous variables.

Econometric methods

Because only three repeated observations were available on the children, the estimation theory assumed that the number of children (n) was large but number of time periods was fixed. Thus, initial observations on the dependent variables ($Weight_{i1}$ in equation (1)) were treated as correlated with the errors⁽²⁸⁾. The errors (u_{it}) were assumed independent across children, but correlated over time with a positive definite variance-covariance matrix. A numerical optimisation routine (E04 JBF)⁽²⁹⁾ was used to compute maximum-likelihood estimates under alternative assumptions on the variance-covariance matrix of the errors. The ‘exogeneity’ of households’ food insecurity scores was tested, i.e. if the time means of households’ food insecurity scores were correlated with children-specific random effects (δ_i in equation (2)). The likelihood ratio statistic was based on twice the difference between maximised values of log-likelihood functions and was distributed as a χ^2 variable with three degrees of freedom.

While sampling weights based on children’s age, sex and ethnicity were available in the ECLS-K data, they were not utilised in the modelling partly because of the

children-specific random effects (δ_i in equation (2)). The sampling weights, that are the inverse of probability of inclusion in the sample, would add another component into the error terms (u_{it}). Further, because ECLS-K covered 1277 schools, it was not feasible to include indicator variables (‘fixed effects’) for schools due to the ‘incidental parameters’ that increase with sample size⁽³⁰⁾. While the random effects (δ_i) captured unobserved between-children differences, ECLS-K data may exhibit certain group effects due to the multi-stage design. In many statistical models, however, ignoring such aspects mainly affects the estimate of the constant term⁽³¹⁾. Thus, third- and fourth-order moments of the residuals from the model for body weight were examined for assessing departures from the multivariate normal distribution due to possible violation of underlying statistical assumptions⁽³²⁾.

Results

Descriptive statistics

The sample means of the variables are in Table 1. Approximately 9% of the households were black, 16% Hispanic (of all races), 65% white and 4% Asian. The mean age of children in the 1st grade was 73 months and the mean number of siblings was 1.5. Approximately, 6% of respondents reported that poor health limited their ability to function.

For the time-varying variables, mean amount of time (min) spent watching television significantly ($P < 0.05$) increased with age. In contrast, time (h per week) of non-parental care received by children declined with age. The reported numbers of times per week that children physically exercised more than 20 min were approximately 3.9. Moreover, percentages of children reporting daily physical exercise in the three grades (1st, 3rd and 5th) were 23.0, 16.7 and 11.9, respectively, showing a significant decline over time. Sample means of household incomes were between categories 8 and 9, i.e. US\$ 35 000–45 000. Approximately, 9% of households received food stamps in the past 12 months, and 21% of children received free lunches in school. Households’ food insecurity scores in the three grades were 0.48, 0.39 and 0.53, respectively; 7% of households were ‘food insecure’ using the sum of percentages of the last three categories of food insecurity status. Using the cut-off points for BMI that incorporated medians, CV and skewness⁽³³⁾, percentages of overweight and obese children increased significantly from the 1st to the 5th grade.

Results for children’s body weights, BMI and Z-scores of BMI

Table 2 presents the results from models for children’s body weights, BMI and Z-scores of BMI. Likelihood ratio statistics for testing exogeneity null hypotheses for households’ food insecurity score in the models for weight, BMI and Z-scores of BMI were 0.318, 0.030 and 0.892, respectively, accepting the null hypotheses. Moreover, the likelihood ratio test for testing the restrictions implied by the BMI transformation showed a statistical preference for the model for body weight.

The main findings from the model for body weights were, first, black and Hispanic children were significantly ($P < 0.05$) heavier. The model accounted for age of the

Table 1. Sample means of selected variables for children in the Early Childhood Longitudinal Study-Kindergarten observed at 2-year intervals in the period 1999–2003

(Mean values and standard deviations for 7635 subjects)

Grade...	First grade		Third grade		Fifth grade	
	Mean	SD	Mean	SD	Mean	SD
Siblings (<i>n</i>)	1.49	1.08	–	–	–	–
Parental education (1–9)	4.56	1.73	–	–	–	–
Respondent health limiting (1 = yes, 0 = no) (%)	5.9	23.5	–	–	–	–
Respondent emotional score (1–11)	1.38	0.37	–	–	–	–
Boys (%)				50.5		
Age (months)	73.09	4.29	–	–	–	–
Black household (%)				8.9		
Hispanic (of all races) household (%)				16.2		
Household income category (1–13)	8.41	3.06	8.65	3.03	8.80	3.04
Food stamps in last 12 month (1 = yes, 0 = no) (%)	9.0	28.6	8.3	27.5	8.8	28.3
Food insecurity score (<i>n</i>)	0.48	1.60	0.39	1.48	0.52	1.78
Food insecurity status (1–4)*	1.09	0.33	1.07	0.31	1.09	0.35
Food secure (%)		93.0		94.3		92.5
Food insecure without hunger (%)		5.7		4.3		5.7
Food insecure with moderate hunger (%)		1.1		1.2		1.8
Food insecure with severe hunger (%)		0.2		0.1		0.0
Receive free lunch in school (1 = yes, 0 = no) (%)		23.2		21.0		18.1
Non-parental care (h/week)	5.09	8.61	3.83	7.12	3.43	7.18
Watch television (min/d)	100.95	64.82	105.48	65.36	113.68	67.72
Physical exercise > 20 min (d/week)	3.91	2.26	3.97	1.95	3.76	1.84
Height (m)	1.23	0.06	1.35	0.07	1.47	0.08
Weight (kg)	26.66	5.80	34.19	9.08	44.29	12.70
BMI (kg/m ²)	16.86	2.83	18.60	3.81	20.42	4.65
Overweight (%)†		27.6		39.1		43.1
Obese (%)†		11.9		17.5		18.6

* 1 = Food secure, 2 = food insecure without hunger, 3 = food insecure with moderate hunger, 4 = food insecure with severe hunger.

† Using cut-off points from Cole *et al.* (33).

child, and non-linearities with respect to age were evident. Second, children whose parents were more educated and had higher incomes were significantly lighter. Also, greater numbers of siblings in the households were associated with lower body weights. In contrast, children watching television for longer periods and spending more time in non-parental care were significantly heavier. Third, greater physical exercise was significantly associated with lower body weights. By contrast, children in households where respondents reported health limiting their activities were significantly heavier.

Fourth, children's height was a significant predictor of their weight in accordance with the anthropometric assessment literature. The estimated coefficient 1.67 of logarithm of height did not support employing children's BMI as the dependent variable, though the estimated parameters from the models for BMI and Z-scores of BMI were qualitatively similar. Further, households' food insecurity score was estimated with a small negative sign but was not a significant predictor of weight; coefficients of food insecurity scores were also not significant in the models for BMI and Z-scores of BMI. Coefficients of explanatory variables in the models for weights, BMI and Z-scores of BMI had generally the same signs and were similar in terms of attaining statistical significance.

Fifth, the estimated coefficient of the lagged dependent variable in the model for weight was 0.44 so that long-run impacts of explanatory variables were about twice the respective short-run effects reported in Table 2. Last, the third- and fourth-order moments of the residuals in the three time periods were 0.720, 0.392 and -0.002 and 5.570, 4.127 and 5.947,

respectively. These estimates reflected slight skewness and kurtosis in the distribution of the errors though were not far from the third- and fourth-order moments (0 and 3, respectively) of the multivariate normal distribution.

Results for households' food insecurity scores and status

Table 3 presents the results for households' food insecurity scores and status; exogeneity hypotheses for children's body weights and respondent's emotional scores were accepted. While the results for the two models were qualitatively similar, parameters were more precisely estimated in the model for food insecurity scores. The main findings were, first, that Hispanic households reported significantly higher food insecurity levels, whereas black households reported lower food insecurity. Second, households where parents were more educated and incomes were higher reported significantly lower food insecurity levels. By contrast, greater number of siblings was associated with higher food insecurity.

Third, the indicator variable for respondent's health-limiting activities, and the scores on eleven items assessing emotional status were significant and positive predictors of food insecurity scores. Because higher (worse) scores on emotional health can arise from household food insecurity, this variable was treated as endogenous, though the likelihood ratio test accepted the exogeneity null hypothesis. Fourth, the models controlled for children's ages and included heights and weights as explanatory variables. The estimated coefficients of heights and weights were positive and significant, indicating that

Table 2. Maximum-likelihood estimates from dynamic random effects models for children's body weights, BMI and Z-scores of BMI in the Early Childhood Longitudinal Study-Kindergarten explained by background, environmental and socio-economic variables, 1999–2003 (Slope coefficients and standard errors for 7635 subjects)

Dependent variable...	ln (Weight) (kg)		ln (BMI) (kg/m ²)		Z-score of BMI	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Constant	4.787*	0.055	0.695*	0.012	0.886*	0.068
Black household (0–1)†	0.018*	0.005	0.010*	0.003	0.110*	0.034
Hispanic household (0–1)†	0.017*	0.004	0.002	0.002	0.088*	0.026
ln (Age) (months)	–1.429*	0.002	–0.260*	0.003	–	–
(ln (Age)) ² (n)	0.162*	0.003	0.032*	0.001	–	–
ln (Parental education) (1–9)	–0.030*	0.004	–0.012*	0.002	–0.159*	0.017
Number of siblings (n)	–0.004*	0.001	–0.001	0.001	–0.022*	0.007
Respondent health limiting (0–1)	0.008	0.006	0.002	0.003	0.050	0.035
ln (Watch television) (min/d)	0.004*	0.001	0.004*	0.001	0.032*	0.006
Non-parental care (h/week)	–0.0003*	0.0001	0.0002*	0.0001	0.002*	0.001
Physical exercise (d/week)	–0.002*	0.0004	–0.002*	0.0003	–0.009*	0.003
Household income (1–13)	–0.003*	0.0005	–0.002*	0.0004	–0.013*	0.002
ln (Height) (m)	1.671*	0.036	–	–	–	–
Food insecurity score (n)	–0.0003	0.0006	–0.0003	0.0005	0.003	0.004
Lagged dependent variable (kg or n)	0.439*	0.012	0.978*	0.013	0.239*	0.042
2 × (Maximised log-likelihood function)		103 039.8		101 532.5		425.2
χ ² Test for exogeneity of food insecurity score (3 df)		0.318		0.030		0.892
χ ² Test for BMI restrictions (1 df)		1507.3*		–		–

df, Degrees of freedom.

*P<0.05.

†Reference group: all other ethnicities.

households with children taller and/or heavier for their ages faced significantly higher food insecurity levels. This issue is addressed in the Discussion. Last, the coefficient of the lagged dependent variable was 0.16 and was statistically significant.

Discussion

The analyses of ECLS-K data provided several insights into the dynamics of children's weights and on the inter-relationships between children's anthropometric measurements and

households' food insecurity scores. First, higher parental education and household incomes, physical exercise and numbers of siblings were significantly negatively associated with body weights. By contrast, poor health status of respondents, time spent watching television and that in non-parental care were positively and significantly associated with weights. Moreover, black and Hispanic children were significantly heavier by 1.8% (i.e. 0.62 kg) than other children in the sample.

Second, household food insecurity score was not a significant predictor of children's weights, BMI and Z-scores of BMI. Jyoti *et al.*⁽¹⁰⁾ used the ECLS-K data from kindergarten

Table 3. Maximum-likelihood estimates from dynamic random effects models for households' food insecurity scores and status in the Early Childhood Longitudinal Study-Kindergarten explained by background, environmental, socio-economic and anthropometric variables, 1999–2003 (Slope coefficients and standard errors for 7635 subjects)

Dependent variable...	Food insecurity score (n)		Food insecurity status (1–4)	
	Coefficient	SE	Coefficient	SE
Constant	3.114*	0.024	1.551*	0.035
Black household (0–1)	–0.110*	0.046	–0.029*	0.010
Hispanic household (0–1)	0.129*	0.032	0.021*	0.008
ln (Age) (months)	–0.781*	0.006	–0.173*	0.008
ln (Parental education) (1–9)	–0.045*	0.009	–0.007	0.008
Siblings (n)	0.091*	0.010	0.018*	0.003
Respondent health limiting (0–1)	0.259*	0.057	0.046*	0.012
Respondent emotional score (n)	0.658*	0.013	0.121*	0.015
Household income (1–13)	–0.118*	0.006	–0.022*	0.001
ln (Height) (m)	1.187*	0.050	0.226*	0.035
ln (Weight) (kg)	0.067*	0.005	0.004	0.003
Lagged dependent variable (1–4 for food insecurity status) (n)	0.159*	0.036	0.175*	0.074
2 × (Maximised log-likelihood function)		–18 697.8		59 982.3
χ ² Test for exogeneity of body weight and respondent emotional scores (6 df)		7.00		–

Df, degrees of freedom.

*P<0.05.

and 3rd grade and reported that food insecurity (measured via a single affirmative response to eighteen items) was a significant positive predictor of weight changes for girls but not for boys. We estimated the dynamic models for weight separately for boys and girls. For both groups, coefficients of food insecurity scores were not statistically significant; the coefficient was -0.0003 ($P < 0.729$) for boys and -0.0001 ($P < 0.920$) for girls and these were close to the combined estimate (-0.0003 ; Table 2). The differences in our findings were presumably due to different model formulations, use of appropriate econometric techniques for longitudinal data at three time points and systematic treatment of households' food insecurity scores. For example, Jyoti *et al.*⁽¹⁰⁾ approximated food insecurity via a dichotomous variable that did not reflect intensity; statistical significance of its coefficient in the model for girls' weight changes may have been due to chance, given the low explanatory power of the model.

Further, using the ECLS-K data from kindergarten, Rose & Bodor⁽¹⁹⁾ reported that household food insecurity was a significant negative predictor of children's overweight status assessed using cut-off points for BMI. However, their findings were not robust to changes in model specification. Alternative measures of food insecurity were not significant predictors of children's overweight status and, in contrast with Jyoti *et al.*⁽¹⁰⁾, disaggregating the sample for girls and boys led to insignificance of the food insecurity variables. Thus, it seems reasonable to conclude that food insecurity levels in the ECLS-K were not significant predictors of children's body weights.

Third, the inter-relationships between children's growth and household food insecurity scores are likely to be complex in the USA because poor households receive food via the Food Stamp programme and children consume reduced price or free lunches in school. While such programmes can increase overall food intakes, it is difficult to assess their impacts in the ECLS-K because children's energy and nutrient intakes were not recorded. Even so, we re-estimated the model for children's body weights and found that coefficient of households' participation in the Food Stamp programme in the past 12 months was -0.013 ($P < 0.05$). Thus, children in such households were lighter by 0.45 kg and the programme was likely to have reduced food insecurity. By contrast, in the extended model, coefficient of the indicator variable for children receiving free school lunch was 0.007 ($P < 0.05$), i.e. such children were heavier by 0.24 kg. While free school meals may be essential for children from poor households, measuring food intakes at home and in school in the ECLS-K would enable investigation of the effects of entitlement programmes on food intakes.

Fourth, results from the model for food insecurity scores showed that households with children who were taller and/or heavier for their ages faced significantly higher food insecurity levels. The estimated coefficient of children's height was 1.19, which was 17 times larger than the coefficient (0.07) of weight. The WHO report⁽¹²⁾ emphasised the importance of energy expenditures for defining energy requirements. Energy requirements depend on individuals' BMR, heights and weights, and physical activity⁽¹²⁻¹⁶⁾. If all households in the ECLS-K data had scored zero on food insecurity score, then there would not be any relationship between children's anthropometric measures and food

insecurity scores. The fact that households with taller children faced higher food insecurity suggests that it is important to focus on overall nutritional status of children from poor households including their micronutrient status⁽⁶⁾. Because children consuming inadequate food at home can increase intakes via school meals, it is important that school meals supply vital micronutrients, while facilitating the energy balance. Increasing the intake of fresh fruits and vegetables and wholegrain products, and discouraging consumption of flavoured drinks can help achieve these objectives. Last, it would be useful to measure parental heights and weights in the ECLS-K for further analyses of the determinants of food insecurity.

Finally, it is common among chronically undernourished populations in developing countries to observe weight gain and weight loss in 'peak' and 'lean' seasons, respectively⁽³⁴⁾. While Dietz⁽⁷⁾ conjectured that weight gain in an African-American teenager from a poor household could be an 'adaptive' response to food shortages, this can strictly be true in the short run. In fact, weight gain increases individuals' long-term energy requirements, thereby compounding the problems of hunger. Further, less than 7% of households in ECLS-K reported food insecurity (Table 1). By contrast, 27.6% of children in 1st grade were overweight and this figure increased to 43% by the 5th grade. Moreover, decline in regular physical activity from kindergarten to the 5th grade was evident in the data. The fact that approximately two-thirds of adults in the USA are overweight suggests that unhealthy eating habits and low physical activity levels are the most important factors underlying the obesity epidemic⁽³⁵⁾.

Acknowledgements

The opinions expressed in this article do not reflect the views of the Economics Research Service or the United States Department of Agriculture and there is no conflict of interest. The authors would like to thank two reviewers and the editors for several helpful comments.

The study was supported by a Cooperative Agreement between the Economic Research Service (ERS) of the US Department of Agriculture and University of Houston, and by the Texas Learning and Computation Center.

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