Impact of Food Away From Home on Children's Diet

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Short Abstract

Poor diet and inactivity are key factors for the high incidence of obesity among children in US. Using household production theory, we derive the demand for children's health and apply cross-section and pseudo-panel techniques. FAFH has negative impact on children's HEI in both analysis and significant in cross-section analysis.

Key words: Food-Away-From-Home, Instrumental Variables, Pseudo Panel, Household Production Theory, Demand, Health Eating Index

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1. Introduction

U.S. Department of Health and Human Service (HHS) (News Release, Dec. 13, 2001) reported that overweight and obesity are among the most pressing new health challenges we face today and they may soon cause as much preventable disease and death as cigarette smoking. The total direct and indirect costs attributed to being overweight and obesity amounted to $117 billion in 2000. During the two decades between 1980 and 1999, obesity among adolescents has tripled. According to Heath Journal (Apr.9, 2002), about 25% of kids are overweight, twice as much as that of 30 years ago; and 14% of children are obese, 11% higher than it was five years ago. All these will bring severe social health crisis to the coming generation.

Can diet drugs do their work? According to the Health Journal, the side effects from diet drugs can be significant: some carry potential long-term health risks; and others have effects that are merely uncomfortable or embarrassing. The Journal also emphasized that in order to keep youngsters from reaching a danger level, parents should watch their kids' eating habits. From a long-term view, it is also a better way to prevent children's obesity from ever happening. However, not enough studies have showed quantitatively this type of relationship to call for the society's attention. On the other hand, children's diets are under parental control so it is obvious that there exist strong intra-family effects generated by the eating habits of individual members of the household. This is reason why this paper focuses on the household expenditure impact on children's diet quality.

A lot of studies have focused on the relationship between health knowledge and nutrition labeling usage on nutrition consumption and person's diet (e.g., Park and Davis, Capps and Schmitz; Carlson and Gould; Kim, Nayga, and Capps; Variyam et al.). The main focuses of these studies are on the two tradeoffs, which are between nutrition and taste, nutrition and costs. Recently, there has been a new trend of eating out or food away from home. The reasons are well-known: increasing percentage of women working in the workforce; higher income; increasing opportunity cost of time and demand for convenience. And the main driving force is convenience demanded by time constraints. The frequency of dining out increased by more than two-thirds over the past two decades rising from 16 percent of all eating occasions in 1977 to 27 percent in 1995 (Lin, Frazao, and Guthrie, forthcoming). Consequently, away-from-home food is becoming an increasingly important part of nutrient intakes. For example, food away from home provided 34 percent of total caloric intake in 1995, which nearly doubles the 19 percent in 1977. Similarly, it provided 38 percent of total fat intake and 29 percent of total calcium intake, and 27 percent of total iron intake in 1995 (Agricultural Outlook Forum 1999). Also, the demographic factors have different impacts on nutrient intakes from away-from-home versus at-home markets (Nayga and Capps, 1994). All these call for attention to another tradeoff: diet quality and convenience. This paper intends to address this issue and contribute to the literature by exploring the effect of household food-away-from-home expenditure on children's diets.

Because rising expenditures on food away from home may make it more difficult for consumers to make informed choices regarding the nutritional contents of meals, it is harder for parents to tell how to control children's obesity trend. Meanwhile, according to research results, food away from home contains more fat and cholesterol and less fiber (Agricultural Outlook Forum 1999) and the increasing frequency of food away from home is driven by increasing opportunity cost of time. For these sakes, this paper intends to examine the effect of household food away from home expenditure on children's health and to estimate and quantify the effect of selected socioeconomic factors on children's diet issue. So this paper's quantitative results expect to help to call for society's attention and may provide government the policy implication and provide education program for parents about this intra-family effect transmission. Finally, the paper also hopes to provide food away from home industry insights on how to develop more healthy foods targeting these particular time-constrained households.

2. Theoretical Background and Framework

This paper mainly focuses on the effect of food away from home on children's health issue. Children's health is one of the household outputs and it surely will bring utility to the whole household. Therefore, this paper put children's health issue into the context of Becker's household production theory and adapts the approaches suggested by Grossman, Becker and Lancaster. The basic idea of household production theory is that households are producers as well as consumers. The household utility function is maximized by consuming commodities the households produce by combining purchased market goods, income, time and human capital. For example, a household may get satisfaction from a meal, but this meal may be prepared at home with a variety of ingredients bought from markets and combined with preparation time, cooking skills, nutrition knowledge; or it can be prepared outside and eaten inside or outside the home which will save more time for work or for leisure. But because of the former arguments, the nutrient intakes from food-at-home and food-away-from-home will be different so the resulting utilities will not be the same also. Part of it will be children's diet issue.

Let us just look at one of the outputs produced by household --- children's health. Using the household production model to study the determinants of health, health behaviors, and health inputs was pioneered by Grossman (1977). It is not because consumers gain utility from the choices of diet quality directly but rather because these choices influence health. So in this paper we are going to derive the reduced form (children) health demand function using information on one important health indicator, health eating index (HEI). Weekly expenditure amount on household food away from home (FAFH) can be considered as a household eating tendency or habit which is quasi-fixed in the short run. So we are dealing with conditional optimization process, assuming interior solutions. Through this way, we allow FAFH to be an argument of HEI demand function (Basmann).

Following Park and Davis' discussion flow (2001), we assume a quasi-concave direct utility function: U = U (H, Z, x, t), where H is children's health and Z are other household outputs, x are other market goods which may bring some direct utility, t is time which may also add direct utility, subjects to the following constraints:

(1) Income constraint: Y = p'q, where p and q are the vectors of prices and quantities of the market-good inputs used in producing H and Z. And our data do not have separated unearned income.

(2) Children's Health production constraint: H = H (N, x_H, t_H; FAFH, μ), where N is nutrients, x_H is the market goods inputs for producing children's health, t_H is time allocated to produce health including time for parents' to prepare foods. μ is a vector of demographic or

environmental variables, such as age, gender, children's obesity status (using Body Mass Index – BMI as indicator), etc.

(3) Time constraint: $T = t_H + t_Z + t_W + t_O$, where t_Z is the time spending on producing outputs Z including shopping time; t_W is the time to work; t_O is the time allocated to produce other outputs and purchasing other goods.

(4) Z outputs production constraint: a function of x_Z inputs variables (such as household nutrient production function).

We define FAFH as a household expenditure on fast food brought to home and eaten at home or away from home. So we will have a conditional demand function, derived form the above optimization process, for children's health using children's HEI as the indicator: HEI = f (p, T, Y; FAFH, μ). According to the theory, at the optimum point, the unconditional demand for HEI is equal to the conditional demand function evaluated at the optimal level of FAFH inputs. And because we are considering short-term optimization, we can assume that prices are held constant so that the notion of weak seperability is not problematic. Indeed, in our model specification, we assume that the demand for health is weakly separable from other household output demands, such as accommodation, etc. under this assumption, we can explore only those factors affecting the health eating without considering all the other factors affecting the household output demand. Due to the data limitation we do not have main food preparer's opportunity cost of time (such as hourly wage rate), we use household head's hours of work last week as an indicator for T, or, the opportunity cost of time. Y is annual household income. But just as the point made by Variyam, the response of conditional demand function with respect to μ variables is not the same as that of unconditional demand function, it brings some limitation to the application of our estimation results. After adjusting according to our data availability, the reduced form conditional demand for children's HEI is: HEI = f (t_w, Y; FAFH, μ).

3. Data Description and Econometric Model Specification

The data sets we used are: the 1994-96 Continuing Survey of Food Intakes by Individuals (CSFII 94-96) and HEI scores data provided by USDA. The CSFII 1994-96 provides information at the household level, including usual food expenditures, participation in the Food Stamp program and other food assistance programs, and the level of food sufficiency within the household, for approximately 8,000 households with CSFII participants. This survey is a nationally representative survey which is responsive to the National Nutrition Monitoring and Related Research Act (Public Law 101-445) for continuous national data on the dietary status of the U.S. population. It provides multiple days of dietary data, the most currently available, together with socio-demographic and health-related data for over 15,000 Americans of all ages. So in general, the sample sizes for each sex-age group can provide sufficient level of precision to ensure statistical reliability of the estimates.

The HEI scores data are the HEI scores calculated for CSFII participants by USDA and they were downloaded from http://www.usda.gov/cnpp/hei9496data.htm.

We merged two data sets: household level and individual (children) data in terms of household ID. The children age range is from 0 to 18 according to the youth age range.

Then except including FAFH[1] , our model has demographic variables such as urbanization, region, race, sex, household size, age, number of children aged 1 to 5 and household income. Some other variables indicating detail household condition are also included, such as children's body mass index (BMI), children's hours spent watching TV/Video per day, indicators about any household member is on diet or not, participating supplementary program or not such as food stamp program and WIC (woman, infant and children). Also, we have some household heads' data to indicate household time constraints, such as household heads' average time in front of TV/Video per day, usual working hours per week. Because of survey data limitation, we have some missing individual data concerning household income, BMI, HEI, and hours of watching TV. These missing data points are due to individuals who failed to provide the information or technique limitation, which prevent the collectors from determining the scores. Also, HEI scores are only available for age 2 and above. So after we merged the data sets, our sample size is totally 1,948 for three years total.

4. Empirical results

4.1 Cross-Sectional Analysis

In the summary statistics table (See Table 1), we see that standard deviation of the health-eating index is very high, with a minimum of 26.78 and a maximum of 94.47. This big variation indicates great heterogeneity among the households regarding children's healthy eating attitudes. However, the mean of the health eating index is 65.41, meaning that the sample children's health level is still below the healthy criterion that is 80 but higher than American average level that is 60. Our work will give some explanation as to

[1] FAFH here is the household fast food expenditure;

what are the factors driving the different attitudes towards children's health eating. The mean household weekly dollar amounts spent on fast food (FAFH) is $13.55, also with a large standard deviation, in levels range from $0 to $130. This kind of heterogeneity may help us explaining how FAFH would affect health. Mean of usual working hours of the household heads is 42.36 hours per week, but has a standard deviation 10.75, ranging from 3 to 140 hours. This variable would help us in telling the time constraint in the demand for health and give us a hint on each household's value of time. Also, from the variables plots we can see that there are no specific outliers in the data set. So we may not need to worry about the influential observation problems. For example, although the household annual income has huge deviation, all the observations scatter randomly within the range from $1200 to $100,000.

We employed simple OLS to each year first, correcting for heteroskedasticity in the residual (See Table 2). Also, we tried to pool these three cross-section together into one model to gain more data advantages. First, we performed Chow-test to test the poolability of our data across three years. We get RRSS from pooled model (restricted model) and URSS from each cross-section regressions (unrestricted models). Then form the following statistics: $F = \dfrac{(RRSS - URSS)/K'(T-1)}{URSS/T(N-K')}$, where K' is the number of RHS variables including constant term. We got 4.16 statistics which is bigger than F (44,5778) at even 90% significance level. It turned out that we reject the stability of our three-year results. However, as Baltagi (1981) showed, if the true specification of the disturbances is an error components structure than the Chow-test tend to reject poolability too often when in fact it is true. Also from table 2, we can see that across three years and the pooled model FAFH has the same negative sign and similar magnitudes, ranging from -

0.06809 to -0.05490, and it is significant in all four models. Age, Black, NE and Central have the same consistency too. Income has three models' consistency except in 1995 model in which it is not significant. HHSIZE, SEX, Avdtv, Pavdtv, diet and WIC have the same reasonable signs across years. The puzzling ones are BMI and Pworkhr which can not keep same expected signs across years.

As we know that FAFH may also be affected by other factors such as the prices of other goods, other opportunity cost of time effect, etc, which we do not included in our estimation (although we assume that the price is fixed in the short-run). Also, it is possible that BMI may be affected by influences we didn't put into our regressors such as unobservable individual effect, so we suspect that there might be something in the error term that affects FAFH and BMI which may cause regressor-error correlation problem. In our model, because of the data limitation and the undeveloped nature of household production theory, we propose household heads' HEI (phei) and BMI (pbmi) as instrumental variables for the FAFH and BMI. So, in order to test our model's poolability, we should refer to a generalization of Chow-test which takes care of the general variance-covariance matrix (Baltagi, Econometric Analysis of Panel Data, 2nd edition). This means we should do IV estimation to transform our model so that we can have homoskedastic variances, then apply the Chow-test form.

Following Park and Davis (2001), we perform the two-part test procedure proposed by Godfrey and Hutton (1994). First step, using Phei and Pbmi as the IV instruments for FAFH and BMI, we conduct Godfrey/Hutton J test. This test gives a hint as to whether the IV model is misspecified or not. If the statistic is significantly large, then the specification of the model and/or the validity of the instruments must be reconsidered, and IV estimation based upon those instruments are of little value. If the observed value of J is insignificant, then the second stage should be implemented. The statistic is distributed as a Chi-squared distribution with the degrees of freedom equal to the number of instruments less the number of RHS endogenous variables in the equation. In our problem its degree of freedom is 21 for both BMI and FAFH as endogenous variables (case1) and 22 for either one of them are endogenous. So we conducted J test for the pooled model and got the statistic value 0 for case1, 143.76 for treating BMI as endogenous, 0 for treating FAFH as endogenous (case2). Thus our test fails to reject that the model and/or the instruments are free of misspecification at 5% significance level for case 1 and case 2. Based on the test results, we are good to go for the second step.

If we get small value of J statistics, the second stage is to conduct Hausman test to see whether our model has endogenous problem or not. However we have low auxiliary R^2: for FAFH it is 0.10 and for BMI it is 0.18. This may affect the power of the Hausman test. As Godfrey and Hutton (1994), Park and Davis (2001) mentioned, in this case the nominal size of the Hausman test should be increased. The overall significance level should be: $\pi = 1-(1-\pi_J)(1-\pi_H)$, where π_J and π_H are the significance levels for J test and Hausman test. So as recommended by Lehmann, let π_H = 0.2 and π_J = 0.05, we get 0.24 as the significance level for Hausman test. We get the statistics value 16.73 which is smaller than the critical values ranging from 0.10 significance level to 0.50 significance level. But it is significant at 0.70 significance level. So we fail to reject the null which means the OLS estimator may efficient and consistent. For case 2, it is almost the same. However there's a caveat to these results. The low auxiliary R^2 is still problematic for the conventional (first order) asymptotic inference techniques (Hahn J. and J. Hausman, 2002). Recognizing this, we still performed a robust IV estimation using the instruments for later comparison, which corrects for heteroskedasticity automatically.

We have a total of 1948 observations, and the number of parameters need to be estimated is 22. Our OLS and IV estimates are listed in Table 2. The OLS gives 13 significant parameters out of 22 parameters while two IV estimations each gives 9 significant parameters. The Fastw (FAFH) variable has the same negative signs and significant, however the magnitudes of the IV estimations are obviously different than OLS estimation. Also, there are so many changes in signs and magnitudes across OLS and IV estimations.

4.2 Pseudo-Panel Estimation

The above section, we went through cross-section analysis and tried IV estimations to overcome possible endogeneity problem. However, we can also refer to panel data methods to control the individual effects in our model. Although our data set is a series of independent cross-sections which means it is not a genuine panel that track the same individual over the time. But as Deaton (1985) suggested, it is possible to track 'cohorts' through such data and estimate economic relationships based on cohort means rather than individual observations and it is called pseudo panel data. Deaton (1985) defined a 'cohort' as a group with fixed membership and it is a group of individuals sharing some common characteristics such as sex or age. These groups are defined in such a manner that each individual is a member of exactly one cohort, and remains a member of this cohort for all periods. If there are additive individual fixed effects, there will be corresponding additive cohort fixed effects for the cohort population. Also, Deaton (1985) argued that these pseudo panels do not suffer the attrition problem that plagues genuine panels, and may be available over longer time periods compared to genuine panels.

From 4.1 section results, we can see that age has significant and consistent effects in our models and it shows that as child's age increase its HEI score goes down. This shows that age cohort may work to form pseudo panel in our case. However, we only have three cross-sections and total 1,948 individuals. We will suffer significant observation loss when we form pseudo panel from such small data set. Note that there is a trade-off between the number of observations in the pseudo panel and the accuracy of these observations which is the trade off between the bias and variance of the estimator. We may have not large enough sample size to get sample means closer to population means for each cohort and may have not enough total observations for the pseudo panel. Due to the data limitation, we just performed pseudo panel technique to give us a hint about how it will do to our model in terms of coefficient signs, cohort effects validation and it may be more useful once we have larger size data available.

We tried two ways to construct our pseudo panel. First, we use each age year as cohort. In our data set, children's age ranges from 2 to 18. So it gives us 17 cohorts each year. And total three cross-sections end up with 51 observations. The average number of observations in each cohort in one year is 38.1. Let us call it Type1. Second, we put same sex same age individual in one year into one cohort, which means that one cohort may have male aged 10 while another one may have female aged 10. This way, we decrease our number of observations in each cohort but increase the total observations in our data. It gives us 34 cohort (which split the cohort from first method into two small cohorts) and total 102 observations. Let us call it Type 2. These two ways have trade-off between them. However they are all limited by the cross-sections available now. As Deaton (1985) argued, the sample cohort means from the surveys are consistent but error-ridden estimates of the unobservable cohort populations means. But in order to conduct errors-in-variable estimation, we need to know details of measurement errors of this particular survey which is not available in such small data set. Also as Verbeek and Nijman (1993) argued, Deaton's estimator is inconsistent if the number of time periods is small (which is exactly our case), even if the number of cohorts tends to infinity. So let us assume we have reasonable representative sample cohort means which may be supported by the large enough heterogeneity of our sample statistics and the design of the CSFII survey.

We conducted fixed effect and random effect, along with maximum likelihood estimation for the above two types of pseudo panel data sets. The results are in Table 3. We can not get random effect estimation from "xtreg.., re" command for the first type pseudo panel. It reduced to OLS estimation. But we can get random effects Maximum Likelihood Estimation results. This may because the first command is a generalized method of moments (GMM) estimator that is just a matrix weighted average of the between and within estimators. The ML random-effects regression estimator, "xtreg ..., re mle", is an MLE that fully maximizes the likelihood of the random-effects model.

From Table 3, we can see that Type 1 panel data gives us more significant coefficient estimators. Type 1 data has more observations in one cohort which will for sure bring more accurate sample means for the cohorts and so the more accurate observations for the pseudo panel. MLE estimation gives both types relatively more reasonable signs and magnitudes, such they show FAFH have negative. We also conducted instrumental variable panel estimations treating FAFH as endogenous variable. Panel estimations can control cohort effect which may get rid of the possibility of BMI endogeneity. But these IV panel estimators do not have good turnouts and the Hausman tests comparing them with FE estimators are failed to reject. Also, both models have significant cohort effects according to the fixed effect F statistics. And from the Breusch-Pagan random effect Lagrange Multiplier test, we can see both types have significant random effects. These show that for Type 1, the age cohort does have impact; for Type 2, the age-sex cohort impact does exist. So by controlling these effects, the model is supposed to perform better if our sample cohort mean is close to population mean.

Baltagi, Bresson and Pirotte (2003) argued that RE model assumes exogeneity of all the regressors and the random individual effects, the FE model allows for endogeneity of all the regressors and the individual effects but Hausman and Taylor (1981) proposed a world where some of the regressors are correlated with the individual effects. So, for Type 2 data, we follow their proposed pretest procedure: First, we conduct Hausman Test based on the difference between the FE and RE estimators; Then if the test reject the null, we conduct another Hausman test based on the difference between FE and HT estimators. We failed to reject the first test at 5% significance level which means the pretest estimator reverts to the RE estimator.

4.3 Results Compare (Cross-section vs. Pseudo Panel)

Compare OLS results with pseudo panel results, we can see that demographic variables are commonly significant and almost all have positive signs. FAFH and children's average hours spent in front of TV have more negative sign appearance that confirms to our expectation. WIC is significant in Pseudo Panel estimation but not in OLS on pooled model but it has all positive signs and means that the participants in WIC have higher HEI which is one of the goal of WIC program because they paid more attention on the nutrient intake education to their participants. Household's working hours have mostly positive signs across estimations which is confusing because we expect that the more household head's working hours the tighter the time constraints to the household and they are more likely to purchase fast food which will decrease the HEI of the household child.

5. Conclusion

Now let us get some interesting overall results analysis. First, Income has been showed that it has significant positive impact to children's HEI. Although it has small magnitude, it is because of the huge magnitude of the income in our data. So we calculate the elasticities for HEI with respect to income which is 0.027 for OLS estimation and 0.15 for Type 1 pseudo estimation. This is intuitively true since higher income household can afford more healthy food[2] for children. But we also need to take into account that more expensive food doesn't mean more nutritionally healthy. That might be part of the reasons why the elasticity is not that big.

Second, our estimators show that the larger the household size, the lower the children's health eating index score. Usually the larger the household, the more difficult to care each child's health eating and help them to form a good eating pattern, also more work is needed to select healthy food fitting each child's need.

[2] The more healthy food often has more value-added. Even if the household has tight time constraint, they can afford go out for decent restaurant meal often instead of choosing fast food.

The sign of age shows that the higher the child's age, the lower the quality of healthy eating. This might due to the reason that as children grow up, they may have right to select food but they obviously will prefer taste than nutrition. The elasticity is -0.097 in OLS estimation. This cautions parents that children's own choices might not be that healthy and the eating pattern may continue to their adulthood. So parents should have a role in guiding children to form healthier eating habits in their early age. Also, the average hour children spent on watching TV/Video also has mostly negative impact on children's health across all estimations. This intuitively can be understood as the more time children spend on watching TV, the less time they spend on exercise, hence this will affect their health.

Time is an important variable pertaining to the household production theory. We chose the average household heads' usual working hours as the index for the opportunity cost of time for the household. We expected that the more working hours, the higher the opportunity cost of time. Our estimators show that this impact is not statistically significant, showing that working hours may not really have impact on the children's HEI. However, by including the opportunity cost of time in the estimation, we make the estimators for household income more reliable. And because we do not have the opportunity cost of time for main food preparer, this insignificance may not bring conclusion that this variable is not important and at least the sign is what we expected.

We are comparing race factors with "White", so all the magnitudes and signs of the race factor can give economic difference comparison. The estimation shows that Black people have lower health eating index than White people in OLS estimation, also in RE and MLE estimation we can see that the proportion of Black in one cohort have negative impact on the cohort children's HEI mean. For regions, all the regions are significant in OLS and almost all have positive signs across estimations. All signs of "region" dummies are positive which tells that South has the lowest health eating condition. Policy makers may consider why different regions have different children health eating patterns. City indicators all have positive signs and OLS and MLE estimations show that they all have statistically significant influence. All the positive signs show that central city and non central city residents consume more healthy diet than non-MSA residents do.

Our major interest is in the estimators for FAFH and BMI. Although only in cross-section estimation, FAFH are statistically significant. The magnitudes and signs in all estimations are close. The sign of FAFH reflects that FAFH has negative impact on children's health eating, this confirms what we previously stated that convenience might not go along with nutrition. This cautions people that although FAFH might have good taste and meet the needs for convenience, it might not be good, especially for children's health. The children's BMI also have a negative impact on the children's health eating across all estimations but it is not that significant. This reflects the obesity problem is related to the healthy diet issue. The insignificance of BMI impact may be because that our sample has maximum BMI score 49.39 which is not in obesity stage.

References

Baltagi. H.B.: *Econometric Analysis of Panel Data*, 2nd ed. New York: John Wiley & Sons, Ltd. 2001.

Baltagi, H.B., G. Bresson, A. Pirotte. "Fixed effects, Random effects or Hausman-Taylor? A pretest estimator." Econ. Letters. 79(2003): 361-369.

Blaylock, J., D. Smallwood, K. Kassel, J. N. Variyam, and L. Aldrich. "Economics, Food Choices, and Nutrition." Agr. Outlook Forum. Feb. 1999.

Deaton, A. "Panel data from time series of cross-sections." J. of Econometrics. 30(1985): 109-126.

Lewbel, A. "Constructing Instruments for Regressions with Measurement Error when No Additional Data are Available, with an Application to Patents and R&D." *Econometrica* 65(1997): 1201-14.

Nayga, R.M., and O.Jr. Capps. "Analysis of Away-From-Home and At-Home Intake of Saturated Fat and Cholesterol." Rev. Agr. Econ.16(1994): 387-98.

Park, J., and G.C. Davis. "The Theory and Econometrics of Health Information in Cross-Sectional Nutrient Demand Analysis." Amer. J. Agr. Econ. 83(2001): 840-51.

Park, J., and G.C. Davis. "The Theory and Econometrics of Health Information in Cross-Sectional Nutrient Demand Analysis." Faculty Paper Series FP 01-02, Dep. Agr. Econ., Texas A&M University, October 2000. Available at http://agecon.tamu.edu/publications/fp01-02.pdf.

Pollak, R.A. "Conditional Demand Functions and Consumption Theory." Quar. J. Econ. 83(1969) :60-78.

Rosenzweig, M.R., and T. P. Schultz. "Estimating a Household Production Functioin: Heterogeneity, the Demand for Health Inputs, and Their Effects on Birth Weight." J. Polit. Econ. 91(1983): 723-46.

Verbeek, M., T. Nijman. " Minimum MSE estimation of a regression model with fixed effects from a series of cross-sections." J. or Econometrics. 59(1993): 125-136.

Appendix

< TABLE 1> Data Description and Summary Statistics for Three-Year Pooled Model				
	Description	**Means**	**Min**	**Max**
HEI	Children's Health Eating Index Scores	65.42	26.78	94.46
Region	(Compare with South)			
NE	1 if individual resides in the Northeast; 0 otherwise	0.15	0	1
Midwest	1 if individual resides in the Midwest; 0 otherwise	0.27	0	1
West	1 if individual resides in the West; 0 otherwise	0.20	0	1
City	(Compare with Non MSA)			
Central	1 if individual resides in MSA, central city; 0 otherwise	0.28	0	1
Noncen	1 if individual resides in MSA, noncentral city; 0 otherwise	0.50	0	1
Race	(Compare with White)			
Black	1 if individual is Black; 0 otherwise	0.13	0	1
AP	1 if individual is Asian or Pacific Islander; 0 otherwise	0.02	0	1
Other	1 if individual is of some other race other than White; 0 otherwise	0.06	0	1
HHSIZE	Household size	4.38	1	16
Income	Annual Household Income (Actual Reported Amount)	44,890.88	1200	10,0000
Age	Age of the individual child in years	9.66	2	18
AVDTV	Children's average Hours spent on watching TV/Video	2.97	0	16
Sex	1 if individual is male; 0 if individual is female	0.50	0	1
Pavdtv	Parents' average Hours spent on watching TV/Video	2.29	0	12
WIC	1 if household is participating WIC program; 0 otherwise	0.07	0	1
Phei	Household heads' average HEI scores	61.26	31.85	89.83
Pbmi	Household heads' average BMI scores	26.48	17.72	49.92
Diet	1 if any household member is on diet; 0 otherwise	0.22	0	1
Fstamp	1 if household is receiving food stamps; 0 otherwise	0.10	0	1
Child1-5	Number of children aged within 1 to 5 range	0.59	0	3
Pworkhr	Household heads' average usually working weekly hours	42.36	3	140
Fastw	Household's weekly fast food expenditure amounts (FAFH)	13.55	0	130
BMI	Children's Body Mass Index scores	19.79	6.73	49.39

<Table 2>Cross-Sectional Analysis Results (Robust)

	1994	1995	1996	1994-96		
Variable Name	OLS	OLS	OLS	OLS	IV-Both	IV-FAFH
HHSIZE	-0.05050	**-1.06044**	-0.39250	**-0.53079**	-0.16992	**0.00029**
INCOME	**0.00005**	0.00002	**0.00006**	**0.00004**	**0.00030**	-0.31365
BMI	0.00627	0.03737	-0.06418	-0.00850	0.062596	-0.18932
AGE	**-0.67763**	**-0.88786**	**-0.48355**	**-0.65763**	-0.37067	1.831133
SEX	0.46040	1.09714	0.34159	0.61749	1.806778	**1.64000**
AVDTV	**-0.51420**	-0.06919	-0.31680	**-0.29607**	**1.66472**	**0.27879**
PWORKHR	-0.04004	0.00112	0.05467	0.00457	**0.28233**	0.130966
PAVDTV	-0.38134	-0.25158	-0.27855	**-0.29389**	0.14081	-2.00494
FSTAMP	0.31309	**-2.61405**	0.64752	-0.50080	-1.91887	***4.469317***
DIET	-0.48719	-0.59460	-1.02054	-0.53277	***4.461826***	***5.989854***
WIC	0.20137	0.61321	1.04375	0.55631	***6.234648***	-1.18698
CHILD1-5	-0.54298	-1.25732	**1.44528**	0.13545	-1.23881	0.511305
FASTW	**-0.05504**	**-0.06809**	**-0.06295**	**-0.05490**	**-2.32896**	**-2.28031**
BLACK	**-3.93348**	**-2.84542**	**-3.19883**	**-3.15542**	0.363188	9.720895
AP	0.34815	2.81664	0.03691	0.99526	10.0528	-4.19937
OTHER	-0.01317	2.57644	-1.95744	0.33424	-4.42552	1.518763
NE	**3.58222**	**2.97923**	**3.29317**	**3.36080**	1.517849	0.525403
MW	1.11296	**2.45675**	**1.44969**	**1.69143**	0.534258	***-4.20714***
WEST	1.61003	0.57263	1.53329	**1.32853**	**-4.27343**	2.088924
CENTRAL	**5.12560**	**2.17838**	**2.44645**	**3.32140**	2.062695	***3.641126***
NONCEN	**2.29225**	**2.81891**	0.44076	**1.96636**	***3.702887***	-0.12613
_CONS	**71.03185**	**76.26552**	**67.89445**	**71.31229**	**66.15663**	**69.46958**
R-square	**0.1983**	**0.2448**	**0.2297**	**0.1989**		

*The **bold fonts** are the coefficients which are significant different from zero at 5% significance level.
*The ***Bold and Italic fonts*** are the coefficients which are significant at 10% significance level
*Note: column "1994" to "1996" are the results from each year's cross-section analysis;
column "1994 -1996" are the results from pooled-model analysis;
subcolumn "IV-Both" are the IV estimation results treating FAFH and BMI as endogenous variables;
subcolumn " IV-FAFH" are the IV estimation results treating FAFH as endogenous variable.

< Table 3 > Pseudo Panel Estimation Results

	Type 1			Type 2					
Variable	**FE**	**MLE**	**FE-2SLS**	**FE**	**RE**	**MLE**	**FE-2SLS**	**G2SLS**	**EC2SLS**
SEX	3.587	4.157	1.710	-	-	-	-	-	-
HHSIZE	-2.665	**-2.834**	-1.089	-0.411	-0.663	-0.654	-0.491	-1.088	-0.885
INCOME	**0.00022**	**0.00022**	***0.00022***	0.00001	0.00004	0.00004	0.00003	0.00006	0.00005
BMI	0.176	**-0.749**	0.228	0.455	-0.239	-0.255	0.544	0.082	-0.008
AVDTV	-1.107	-0.048	-1.535	-1.148	-0.131	-0.113	-0.059	1.149	0.281
Pworkhr	0.031	0.104	0.092	-0.006	0.072	0.074	0.020	0.103	0.074
Pavdtv	**4.744**	**4.619**	***6.593***	1.333	1.278	1.281	0.306	-0.132	0.675
Fstamp	-1.446	11.687	2.958	0.462	2.844	3.003	1.601	2.864	2.100
Diet	**10.124**	**11.499**	9.971	-0.538	1.319	1.363	0.156	1.954	1.323
WIC	***23.179***	**25.466**	18.533	**15.944**	**19.377**	**19.422**	***14.445***	**17.214**	**18.244**
Child1-5	1.054	1.082	-1.037	1.549	**2.617**	**2.572**	1.203	**2.883**	**2.944**
Fastw	0.044	-0.024	0.405	0.042	-0.023	-0.026	-0.240	-0.454	-0.187
Black	3.681	-5.961	6.117	-2.280	-7.061	***-7.274***	-3.535	-6.899	-5.983
AP	-13.031	**-27.180**	-6.074	-0.292	-6.658	-6.845	-5.611	-12.425	-8.030
Other	18.836	11.593	30.545	-1.386	-2.820	-2.880	-6.911	-10.236	-5.602
NE	-0.627	1.663	-0.635	2.283	2.522	2.475	2.941	3.380	3.038
MW	***13.128***	**14.910**	11.840	2.627	4.060	4.055	2.489	3.814	3.936
West	-0.533	-1.163	-2.125	0.844	0.577	0.508	3.214	4.104	2.307
Cenral	0.325	**9.110**	-0.225	2.212	**6.992**	**7.143**	2.442	***6.115***	**5.828**
Noncen	1.711	***7.111***	0.656	-0.464	1.359	1.419	-0.774	0.726	0.777
_Cons	***42.552***	**50.578**	26.422	**54.231**	**59.531**	**59.672**	**54.233**	**58.318**	**58.207**
sigma_u	3.811	1.787	4.962	3.534	1.968	1.736	3.543	3.180	3.180
sigma_e	1.376	1.001	1.688	2.327	2.327	2.155	2.470	2.470	2.470

*The **bold fonts** are the coefficients which are significant different from zero at 5% significance level.
*The ***Bold and Italic fonts*** are the coefficients which are significant at 10% significance level
* Note: "FE" are the results from fixed-effect estimation;
"MLE" are the results from random-effect maximum likelihood estimation;
"FE-2SLS" are the results from fixed-effect two-stage least square estimation treating FAFH as endogenous variable;
"G2SLS" are the results from general two-stage least square estimation treating FAFH as endogenous variable;
"EC2SLS" are the results from error components two-stage least square treating FAFH as endogenous variable.