Television viewing, fast-food consumption, and children's obesity

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I. INTRODUCTION

Childhood obesity is becoming widespread and growing problem in the world with significant medical, psychological, and economic consequences. Much like the United States and other countries, Taiwan has experienced a substantial increase in the prevalence of child obesity over the past few decades. To date, one in every four children in Taiwan is now considered overweight (Taiwan Medical Association for the Study of Obesity, 2007). Consequently, the prevention of childhood obesity is now one of the primary policy objectives in Taiwan (Chu, 2005; Hsieh and FitzGerald, 2005).

Child obesity is a major public health problem with both individual and environmental causes. Among all the factors that may be related to changes in a child's body weight, nutrition, and public health studies have highlighted the importance of hours spent on television viewing and fast-food consumption (e.g., Gortmaker et al., 1996; Hager, 2006; Hsieh and FitzGerald, 2005; Hui et al., 2003). It has been reported that children spend more time watching TV than any other activity. This is important since television has a powerful influence on the life of children (Strasburger, 1992). Time spent watching TV displaces more active pursuits such as outdoor physical activities. Moreover, fast-food consumption among children appears to be negatively associated with the quality of diet in ways that plausibly could increase body weight. Therefore, the primary purpose of this article was to assess the effects of children's hours spent on TV viewing and the amount of fast-food consumption on their body weight. We are first interested in the extent to which the factors, such as child's characteristics and household features, determine children's TV viewing hours and fast-food consumption. Given a better understanding of the determinants of these two activities, we then investigate the effects of these two activities on children's body weight and the risk of being overweight and obese. While weight status cutoff points tend to be clear for adults, the cutoff points for defining children's weight status vary significantly by gender and age. In other words, children's weight status is not monotonically increasing with their body weight. Therefore, a distinction between the effects of these two activities on children's Body Mass Indix (BODY MASS INDIX) and the risk of being obese or overweight is emphasized in this study.

A number of studies have examined the association between children's hours of TV viewing or the fast-food consumption and child obesity, but most of them are nutrition or public health studies and not much attention has been paid by economists on this subject. Exceptions are found in You and Nayga (2005) and Chou, Rashad, and Grossman (2006). You and Nayga (2005) estimated the effects of household fast-food expenditures and children's television viewing on children's dietary quality in the United States. Using the 1979 Child-Youth Adult National Longitudinal Survey of Youth and the 1997 National Longitude Survey of Youth, Chou, Rashad, and Grossman (2006) investigated the effects of fast-food restaurant advertising on childhood obesity. In contrast to previous studies, our study is unique in several ways. While evidence from the fields of public health and nutrition has shown that hours of TV viewing and fast-food consumption are two crucial factors that determine child obesity (e.g., Bowman et al., 2004; Hager, 2006; Hsieh and FitzGerald, 2005), there has been no attempt to investigate the extent to which these two activities are interrelated. It is reasonable to hypothesize that there should be certain correlation between these two activities since watching television decreases the time available for exercise and activity and also encourages the consumption of snacks and energy foods. With this working hypothesis, we then go on to address another issue: the censoring problem of hours of TV viewing and fast-food consumption. That is, for children who do not watch TV (or consume fast food), the numbers of hours (or consumption level) are observed to be zero values. Previous evidence has shown that failing to control for these zero observations will yield inconsistent estimates and misleading policy inferences (Tobin, 1958). In this study, we systematically account for this censoring problem both for hours of TV viewing and the consumption of fast food.

To reach the objectives of this study, a relatively innovative econometric model is proposed and estimated based on data drawn from the National Health Interview Survey at Taiwan (National Health Interview Survey At Taiwan). Our estimation method is an extension of the two-stage framework. In the first stage, a bivariate tobit model is estimated to capture the correlations between children's hours on TV viewing and fast-food consumption. The unconditional expectations of these two dependent variables are then calculated and included in the second-stage analysis. The second-stage analysis is on the examination of factors that are associated with child body weight and the risk of being overweight and obese. Two sets of regression models are estimated in the second stage: a discrete category of various weight status (normal weight, overweight, and obese) and the continuous measure of children's body weight (i.e., BODY MASS INDIX). These two models are estimated using a generalized ordered probit model and the ordinary least square (Ordinary Least Squares) method, respectively.

The remainder of this article is organized as follows. The data used in this study are introduced in the following section. We then discuss the econometric strategy, the empirical results, and finally conclude this article with a brief summary and a discussion of policy implications.

II. DATA SOURCE

We conduct the empirical analysis using data drawn from the National Health Interview Survey At Taiwan in 2001. National Health Interview Survey At Taiwan is an enumerative national survey conducted by the National Health Research Institute of Taiwan (National Health Research Institute Of Taiwan) and is one of National Health Research Institute Of Taiwan's primary vehicles for collecting and disseminating data on a wide range of health-related measures for children. Approximately 5,000 households were successfully selected for face-to-face interviews conducted between August 2001 and January 2002. The National Health Research Institute Of Taiwan also captured survey data on a total of 3,977 children younger than 12 years old. These two sets of data can be linked to each other based on the identification of each household. By including data on the Taiwanese family, the National Health Interview Survey At Taiwan database provides the basis for assessing the factors that are related to child obesity.

To understand the prevalence of child obesity and overweight, we define the appropriate measurement of body weight and weight status. Following the conventional approach used in the analysis of obesity, the Body Mass Indix, a ratio of weight (in kilogram) to height squared (in meters), is used as the measure for body weight. In contrast to the definition of obesity for adults, the cutoff points on adults' Body Mass Indix cannot be applied directly for children since childhood mortality is not associated with weight, and weight-related morbidity is too low to define meaningful cutoffs (Barlow and Dietz, 1998; Boumtje et al., 2005). Consequently, child obesity thresholds or weight status has been defined by age and gender based on the distribution of the population in the same age. For instance, a child above 2-yr old with a Body Mass Index above the 85th percentile and less than the 95th percentile of the population is classified as at risk of being overweight. The same child with a Body Mass Index above 95th percentile is considered at risk of being obese. In this study, the cutoff points are made by age and gender and are determined by the Health Department at Taiwan. (1)

In the National Health Interview Survey At Taiwan, 3,977 children are included in the survey. Since the cutoff points are only available for children above 2 yr old, we first limit our analysis to a subsample of 3,344 children between 2 and 12 yr old. Since children's behavior may be influenced by parental factors, we then link the adult data to the child data set, which results in 2,932 children in our sample. (2) After further deleting the missing values of some key variables (such as Body Mass Index and fast-food consumption), 2,649 children are left. To further avoid the clustering effects as a result of multiple children from the same family, we follow the method used in McIntosh et al. (2006) to randomly select only one child from each household. This is because including more than one child per family can disproportionately give more weight on families with multiple children in the analysis. The final sample of Taiwanese children used in the analysis is 2,377.

In our sample, average TV viewing hours per day ranges from 0 to 11 h. About 19% of the children in our sample report watching 0 h of TV. With respect to fast-food consumption, respondents of National Health Interview Survey at Taiwan are asked the following questions: "How often does this child consume the following food item?" There are five categories that each respondent's answer may fall into: never, seldom, sometimes, often, and always. We assign a value between 0 and 4 to the above answers for each food item, respectively, and sum up the scores for fast-food items including French fries, pizza, hamburger, and soda as our measurement of fast-food consumption. Hence, our measure of fast-food consumption is based on an index of the frequency of children's consumption of items considered fast food in Taiwan. In our sample, the reported scores range from 0 to 12, and the proportion of zero fast-food consumption in the data is 13%.

To have a better understanding of the effect of television viewing hours and fast-food consumption on children's body weight and the risk of being overweight and obese, the sample statistics of body weight and weight status by different levels of TV viewing hours and by fast-food consumption are displayed in Table 1. As exhibited in Table 1, it appears that children's

Body Mass Index is positively associated with TV viewing hours and fast-food consumption. In addition, these two activities seem to increase the risk of being overweight and obese.

TABLE 1
Distributions of TV Hours, Fast-Food Consumption, and Body Weight

	Hours on TV Viewing			
Scores	0	1-4	5-8	9-11
Body Mass Index	16.95	17.06	17.17	18.51
Rate of being overweight	0.13	0.13	0.11	0.17
Rate of being obese	0.13	0.12	0.12	0.16
Proportions of censoring	0.19			
	Fast-Food Consumption			
Scores	0	1-4	5-8	9-12
Body Mass Index	17.21	17.04	16.96	17.12
Rate of being overweight	0.13	0.13	0.12	0.16
Rate of being obese	0.10	0.12	0.12	0.15
Proportions of censoring	0.13			

Note: Total selected sample is 2,377 children.

The dependent variables specified in this study are the scores of fast-food consumption, hours spent on TV viewing, and children's Body Mass Index and weight status. Among the 2,377 children, the average score for fast-food consumption is 2.85, and the average time watching TV is 1.79 h/d. With respect to children's body weight, the average Body Mass Index is 17.05, and 13% and 12% of children are classified as overweight and obese, respectively. The prevalence of child overweight and obesity in our data set is consistent with the findings from the previous studies (e.g., Taiwan Medical Association for the Study of Obesity, 2007).

Other variables that are included in our analysis are built on the empirical specification from some of the previous studies (e.g., Bowman et al., 2004; Crespo et al., 2001; Dietz and Gortmaker, 1985; Hager, 2006; Hui et al., 2003). For the hours spent on TV viewing and fast-food consumption, several children's and parental characteristics, household features, and geographical conditions are hypothesized to be associated with these two activities (e.g., Hager, 2006; Yalcin et al., 2002). The variables that capture children's characteristics are age and gender (AGE and MALE). In addition to children's characteristics, mother's characteristics are also included following Variyam et al. (1999). Two types of variables are specified. Four dummy variables EDU1, EDU2, EDU3, and EDU4 reflect mother's education level (i.e., junior high school, finished junior high, finished senior high school, and had college degree or higher education, respectively). To highlight the extent to which higher education can affect children's activity, mothers who did not go to junior high school are the reference group (EDU1) in the empirical analysis. Since mother's time use on family care may also be correlated with children's activity, the variable (WORKING) is also included in the model to indicate mother's working status.

Several household characteristics are included as well. Family size (HHSIZE) is measured as the number of persons living in the family. In general, three major ethnic groups in Taiwan are Mainlander, Taiwanese, and Hakka. Mainlander accounts for over half of the population. As a result, two variables reflecting ethnicity are specified for Taiwanese and Hakka.

To reflect the effects of other members' lifestyles on children's behavior, the variable DISABLE_HH is specified to indicate if any of the household members is a disabled. Following the conventional geographic categorization, regional dummies (NORTH, SOUTH, EAST, and CENTER) are specified to indicate if the household is located in the north, south, east, and center parts of Taiwan, respectively. Since northern Taiwan is the most populated, the variable NORTH is selected as the reference group. In addition, urbanization may be associated with children's obesity in that it may reflect access to restaurants, convenience stores, and so forth. Therefore, we specify three dummy variables (CITY, COUNTY, and TOWN) to indicate if the household is located in the central city, county area, or small township, respectively. For convenience, households in small towns are selected as the reference group. The descriptive statistics of the variables are displayed in Table 2.

TABLE 2
Sample Statistics

Variable	Definitions	Mean	SD
Dependent variables			
FASTFOOD	Scores of fast-food consumption	2.85	1.88
TVHOUR	Average hours spent on TV viewing per day	1.79	1.44
Information related to children's body weight			
Body Mass Index	Body mass index (kg/[m.sup.2])	17.05	3.30
NORMAL	If the child is normal weight (= 1)	0.75	0.43
OVER	If the child is overweight (= 1)	0.13	0.33
OBESE	If the child is obese (= 1)	0.12	0.33
Other explanatory variables Children's characteristics			
AGE	Age of the child in years	7.13	2.86
MALE	If the child is male (= 1)	0.51	0.50
TAIWANESE	If live in Taiwanese	0.41	0.49

	household (= 1)		
HAKKA	If live in Hakka household (= 1)	0.01	0.07
OTHERRACE	If live in other race households (= 1)	0.58	0.63
Mother's characteristics			
EDU 1	If her education is less than junior high school (= 1)	0.06	0.24
EDU 2	If she finished junior high school (= 1)	0.22	0.41
EDU 3	If she finished senior high school (= 1)	0.51	0.50
EDU 4	If she had college degree or higher (= 1)	0.21	0.41
WORKING	If she is currently working (= 1)	0.60	0.49
Household characteristics			
DISABLE_HH	If one of the family members is disabled (= 1)	0.12	0.33
HHSIZE	Number of persons living in the household	5.68	2.31
CITY	If the household is located in central city (= 1)	0.56	0.50
COUNTY	If the household is located in county area (= 1)	0.23	0.42
TOWN	If the households is located in small town (= 1)	0.21	0.41
NORTH	If located in northern Taiwan (= 1)	0.31	0.46
CENTER	If located in central Taiwan (= 1)	0.39	0.49
SOUTH	If located in southern Taiwan (= 1)	0.26	0.44
EAST	If located in eastern Taiwan (= 1)	0.04	0.20

Note: The selected sample is 2,377 children.

III. ECONOMETRIC MODEL

To investigate the effects of TV watching and the frequency of fast-food consumption on child's Body Mass Index and the risk of being overweight or obese, a two-stage estimation process is used to obtain consistent estimates. In the first stage, a bivariate tobit model is estimated for TV viewing hours and fast-food consumption. In the second stage, the focus of the analysis is on the examination of factors associated with children's Body Mass Index and their weight status. The details of the estimation procedure in each stage are discussed below.

A. TV Viewing and Fast-Food Consumption

To address two econometric issues, a bivariate tobit model is estimated for child's TV viewing and fast-food consumption. The first issue is related to the zero-observation (censoring) problem. Since not every child watches TV and consumes fast-food items in our data, we need to account for the censoring problem to avoid yielding inconsistent estimates (Tobit, 1958). The second issue is to accommodate the potential correlation between TV viewing hours and fast-food consumption. In contrast to previous literature that conventionally applied a single equation tobit model to analyze TV viewing or fast-food consumption (e.g., McCracken and Brant, 1987) (3), a seemingly unrelated regression version of a two-equation tobit model is estimated to capture the potential interrelationship between these two activities. (4) In a bivariate tobit model, the equations of hours spent on TV watching and fast-food consumption can be specified as:

[y*.sub.TV] = [X'.sub.TV][[beta].sub.TV] [[epsilon].sub.TV]; [y*.sub.FF] = [X'.sub.FF][[beta].sub.FF] [[epsilon].sub.FF]; [y.sub.TV] = max([y*.sub.TV], 0); = [y.sub.FF] = max([y*.sub.FF], 0), (1)

where [y*.sub.TV] and [y*.sub.FF] are the latent variables of TV viewing hours and fast-food consumption, respectively. Both the latent variables and their observed counterparts ([y.sub.TV] and [y.sub.FF]) occur simultaneously. The vectors [X.sub.TV] and [X.sub.FF] are covariates that are associated with these two activities, respectively, and the vectors ([[beta].sub.TV] and [[beta].sub.FF]) are parameters of interests. The joint distribution of the error terms ([[epsilon].sub.TV] and [[epsilon].sub.FF]) are assumed to follow a bivariate normal distribution [PHI](0, 0, [[sigma].sub.TV], [[sigma].sub.FF], [zeta]), where [[sigma].sub.TV] and [[sigma].sub.FF] are standard errors and [zeta] captures the correlation of these two error terms.

There are four regimes that can be realized in the data. To estimate Equation (1), we need to specify the joint density of each regime. Extended from the binary tobit model, these four probability densities can be derived as (5):

(2) [MATHEMATICAL EXPRESSION NOT REPRODUCIBLE IN ASCII]

where [[PHI].sub.2](*) and [[PHI](*) are the cumulative density function of the bivariate standard normal distribution and of the univariate standard normal distribution, respectively. Given the probability density of each regime, consistent estimators can be obtained by a maximum likelihood method with the following likelihood function:

(3) [MATHEMATICAL EXPRESSION NOT REPRODUCIBLE IN ASCII]

B. Marginal Effects

Although the estimated coefficients of the bivariate tobit model reveal the association between exogenous variables and children's TV viewing and fast-food consumption, the magnitude of the associations can be better understood through the marginal effects. The marginal effects evaluate the changes of the exogenous variables on the expected mean of children's fast-food consumption and TV viewing. To calculate the marginal effects, it is necessary to derive the unconditional mean of children's fast-food consumption and TV viewing. Following other censored demand system studies (e.g., Dong et al., 2004; Shonkwiler and Yen, 1999; Vermeulen, 2001), the unconditional expected values of TV viewing hours and fast-food consumption:

[MATHEMATICAL EXPRESSION NOT REPRODUCIBLE IN ASCII] (4)

where [phi](*) is the probability of the standard normal distribution.

Differentiating the unconditional mean functions, the marginal effects can be shown as (Su and Yen, 2000):

(5) [MATHEMATICAL EXPRESSION NOT REPRODUCIBLE IN ASCII]

where [[^.[beta]].sub.jTV] and [[^.[beta]].sub.jFF] are the estimated coefficient of the jth exogenous variables in the TV viewing and fast-food consumption equations, respectively. The standard errors of the marginal effects can be calculated based on the delta method.

C. Children's Body Weight and the Risk of Being Overweight or Obese

To examine the factors that determine children's Body Mass Index and the risk of being overweight or being obese, several econometric concerns have to be taken into account. First, TV viewing hours and fast-food consumption may be endogenous to children's body weight due to unobserved heterogeneity (Taveras et al., 2006). If endogeneity exists, failing to control for it will yield inconsistent estimates. The second issue is related to the extent to which TV viewing hours and fast-food consumption may differentially affect child Body Mass Index and the risk of being overweight or obese. To address this issue, we analyze two sets of econometric models to study child Body Mass Index and the risk of being overweight or obese based on an Ordinary Least Squares and an ordered discrete choice regression methods, respectively.

D. Child Body Mass Index Equation

Since TV viewing hours and fast-food consumption may be endogenous to child's Body Mass Index due to some unobservable factors, we account for endogeneity using instrumental variables (IV) to obtain consistent estimates. (6) Similar to the endogenous treatment effect model (Maddala, 1983), the predicted values of the unconditional expected values of children's fast-food consumption and hours spent on TV viewing estimated from the first stage are used as regressors in the second-stage analysis (7). When the unconditional values are used, each child's body weight equation can be written as:

Body Mass Index = Z' r [d.sub.1] x E([y.sub.TV]) [d.sub.2] x E([y.sub.FF]) e, (6)

where Body Mass Index is the body mass index and Z is a vector of predetermined factors. The scalar e is the random error. Estimating Equation (6) by Ordinary Least Squares can thus generate consistent estimates for the coefficients r, [d.sub.1], [d.sub.2].

E. The Risk of Being Overweight or Obese

To examine the factors that are related to the risk of being overweight or obese, an ordered discrete choice model is estimated. Two kinds of ordered response econometric models are estimated: the conventional ordered discrete choice and the generalized ordered discrete choice model. If W* represents the unobservable latent variable of a child's weight status, this equation can be shown under the ordered discrete choice model as:

W* = Z'r [k.sub.1] x E([y.sub.TV]) [k.sub.2] x E([y.sub.FF]) u = X'[beta] u. (7)

Since W* is unobservable, what can be observed from the data is the variable w that indicates the ordered category of child's weight status. Assuming there are J categories of child's weight status, the observed rule is (Greene, 2003):

w = 0 if w * [??]0 w = 1 if 0 < w* [??] [U.sub.1] ... w = J if [U.sub.[J-1]] < w *, (8)

where [U.sub.s] (s = 1 ... j - 1) are unknown parameters of threshold points to be estimated. If the random error follows a standard normal distribution across individuals with zero mean and unit variance, this forms the ordered probit model. The probability of child's weight status in each category is:

Pr(w = 0|[X.sub.i]) = [PHI](- [X'.sub.i][beta])

Pr(w = 1|[X.sub.i]) = [PHI]([U.sub.1] - [X'.sub.i][beta]) - [PHI](-[X'.sub.i][beta]) ... Pr(w = J|[X.sub.i]) = 1 - [PHI]([U.sub.[J-1]] - [X'.sub.i][beta]). (9)

Given the probability of each category, the consistent estimators of the ordered probit model can be obtained by implementing the maximum likelihood method with the following likelihood function:

(10) [MATHEMATICAL EXPRESSION NOT REPRODUCIBLE IN ASCII]

where [d.sub.J] is an indicator specifying the Jth category that each individual falls into.

Although applying an ordered probit model provides the consistent estimates of factors that are associated with child's weight status, it cannot be used to investigate if the effects of exogenous variables differ across different categories of child's weight status. In other words, the estimated coefficients of the exogenous variables on the child's weight status are assumed to be the same across different weight status in the ordered probit model (Boes and Winkelmann, 2006). (8) To relax this restriction imposed on the conventional ordered probit model, a generalized ordered probit model is also estimated. If the coefficients of explanatory variables are allowed to be varied across different categories of child's weight status, the consistent estimates of the generalized ordered probit model can be obtained by using the maximum likelihood estimation method on the following likelihood function (Boes and Winkelmann, 2006):

(11) [MATHEMATICAL EXPRESSION NOT REPRODUCIBLE IN ASCII]

Since the generalized ordered probit model is an extension of the ordered probit model, it is possible to conduct a formal statistical test to compare one model against the other. The imposed restriction (the parallel coefficients) of the constraints can be tested based on the likelihood ratio test on the null hypothesis that all the coefficients across categories are the same ([H.sub.0]: [[beta].sub.1] = [[beta].sub.2] ... = [[beta].sub.j]).

IV. EMPIRICAL RESULTS

Several sets of results are presented in this section. Table 3 presents the estimations and the marginal effects of the bivariate tobit model for children's TV viewing hours and fast-food consumption. (9) The results of the statistical tests for model validations are presented in Table 4. Table 5 presents the estimation of the marginal effects of the generalized ordered probit model for the factors that determine the weight status of children. Additionally, the estimates for child Body Mass Index equation are also presented.

TABLE 3
Estimation and Marginal Effects of Fast-Food Consumption and TV Hours

	Fast-Food Consumption		
Variable	Coefficient	SE	Marginal
Constant	1.658 ***	0.317	--
EDU2	0.310	0.283	0.152
EDU3	0.425	0.284	0.208
EDU4	0.141	0.213	0.069
WORKING	0.190 **	0.091	0.093 ***
DISABLE_HH	-0.151	0.138	-0.074
HHSIZE	-0.026	0.024	-0.013
AGE	0.088 ***	0.016	0.043 ***
MALE	0.036 **	0.019	0.018 **
CITY	0.449 ***	0.122	0.220 ***

COUNTY	0.084	0.133	0.041
CENTER	-0.112	0.113	-0.055
SOUTH	-0.359 ***	0.129	-0.176 ***
EAST	-0.348 *	0.183	-0.171 **
TAIWANESE	0.113	0.095	0.055
HAKKA	0.189	0.650	0.093
			Correlation Coefficient and SE
[sigma]Fastfood	2.076 ***	0.268	
[sigma]TVHOUR	1.659 ***	0.180	[H.sub.0]: [rho] = [0.sup.a] 9.46
[rho]	0.268 **	0.132	Log likedlihood: -8,973

TV Hours

Variable	Coefficient	SE	Marginal
Constant	1.289 ***	0.255	--
EDU2	-0.336 **	0.161	-0.173
EDU3	-0.163 *	0.091	-0.084 **
EDU4	-0.931 ***	0.168	-0.480 ***
WORKING	0.065 *	0.033	0.034 **
DISABLE_HH	0.182 *	0.106	0.094 **
HHSIZE	0.020	0.066	0.010
AGE	0.078 ***	0.013	0.040 ***
MALE	-0.047	0.072	-0.024
CITY	-0.101	0.102	-0.052
COUNTY	-0.011	0.121	-0.006
CENTER	-0.042	0.091	-0.022
SOUTH	-0.054	0.094	-0.028
EAST	0.196	0.218	0.101
TAIWANESE	0.140 *	0.079	0.072 **

HAKKA	0.999	0.938	0.514
	Correlation Coefficient and SE		
[sigma]Fastfood			
[sigma]TVHOUR			
[rho]			

(a) Critical value is [x.sup.2](0.95,1) = 7.81.
*** Significant at 1%; ** significant at 5%; * significant at 10%.

A. Factors Associated with Children's TV Hours and Fast-Food Consumption

We begin our discussion of the results in Table 3 by looking at the correlation between TV viewing hours and fast-food consumption. A significant correlation (.268) is found, which points to the evidence that these two activities are interrelated. The formal test result further confirms this finding. The test value of the likelihood ratio test under the null hypothesis that these two activities are uncorrelated ([H.sub.0]: [rho] = 0) is 9.46, which is higher than the conventional significant level of the chi-square distribution, [x.sup.2] (0.95, 1) = 7.81. Therefore, we may conclude that ignoring this correlation will lead to misleading policy inferences since a significant correlation is found. The finding of a positive correlation between these two activities is consistent with the evidence from the nutrition or public health studies (e.g., Taveras et al., 2006).

Other factors that significantly affect children's TV viewing hours and fast-food consumption are children's and parental characteristics, household characteristics, and geographic or regional conditions. Specifically, our results indicate that age is positively related to TV viewing hours and fast-food consumption. The estimates of the marginal effects show that an additional year in child's age increases fast-food consumption by 0.043 unit and TV viewing by 0.04 h. On average, boys consume more fast food (0.018 units) than girls. Consistent with previous studies (e.g., Variyam et al., 1999), our results point to the importance of the mother's characteristics in determining the child's activities. The mother's working status is positively associated with children's fast-food consumption and TV viewing hours. For instance, compared to mothers who do not work, the result of the marginal effect shows that the children of working mothers have additional 0.093 units of fast-food consumption and 0.034 h/d of TV viewing. Also, the mother's education affects the child's TV viewing. For instance, compared to mothers with less than junior high school education, the result of the marginal effect shows that the children of mothers with a college degree spend 0.48 h less on TV viewing.

Household characteristics also play an important role on TV viewing. For instance, a physical disability of a household member is positively associated with the child's TV viewing. Compared to households without disabled members, children living in a family with disabled individuals spend 0.094 h more on TV viewing. The reason for this finding is not clear. However, it is possible that the disability condition of some household members may decrease the advice or control on children's activities, such as hours of TV viewing.

Finally, geographical and location conditions also significantly influence children's fast-food consumption. Results show that children who live in city areas consume 0.22 units more on fast foods than children who live in small towns. This finding may reflect the fact that children who live in city areas are more likely to access convenience stores and other places that provide fast foods and therefore show increased frequency of fast-food consumption. This argument may be reinforced by the finding that fast-food consumption is 0.176 and 0.171 units lower for children living in households located in southern and eastern Taiwan. Compared to the north part of Taiwan (reference group), these two areas have lower amounts of business and commercial activity. Therefore, fast-food consumption of children may be lower due to the limited availability of fast-food restaurants in these areas.

B. Validation of Empirical Models

Before discussing the empirical results of the factors that are associated with children's Body Mass Index and weight status, we report the results of some statistical tests to support our empirical specification. (10) We conduct three tests related to selected instruments and these statistical tests are displayed in Table 4 and the results of the test are encouraging. We start our discussion by justifying if there is a need to correct for the endogeneity between children's fast-food consumption, hours spent on TV viewing, and their weight status. The p value under the null hypothesis that fast-food consumption and TV viewing hours are exogenous to children's Body Mass Index is .002. In addition, we also reject the null hypothesis that these two activities are exogenously correlated to children's likelihood of being overweight and obese due to the low p values under the null hypothesis (.018). Therefore, we may conclude that fast-food consumption and TV viewing hours are endogenous to children's body weight.

TABLE 4
Statistical Tests of Model Validations

	Endogeneity Test (a) (p Value)	
Children's weight status	0.018	
Children's Body Mass Index	0.002	
	Overidentification Test (b)	
	Test Value	p Value
Children's weight status (c)	2.38	0.67
Children's Body Mass Index (d)	1.93	0.75
	Weak Instrument Test (e)	
	Test Value	Critical Value
Children's body weight and Body Mass Index (f)	11.56	10.00

(a) [H.sub.0]: the observed variables are exogenous to children's weight status/Body Mass Index.
(b) [H.sub.0]: the restricted constraints are appropriate.

(c) Likelihood ratio test: [H.sub.0], the coefficients of the instruments are equal to zero.
(d) The test procedure follows Wooldridge (2002).
(e) [H.sub.0]: the coefficients of additional instruments are jointly equal to zero.
(f) The critical value is 10 suggested by Staiger and Stock (1997).

Given the fact that there is a need for instruments, the next question of interest is to see if the overidentification restrictions are valid and if the instruments are statistically weak. Finding the appropriate excluded restrictions is not an easy task. In a similar strategy used by Variyam et al. (1999) who studied the influence of mother on children's dietary quality, four variables that reflect mother's education levels (EDU2, EDU3, and EDU4) and her working status (WORKING) are selected as instruments (or exclusion restrictions) of children's fast-food consumption and hours watching TV. It may not be unreasonable to argue that these exclusion variables we have chosen may influence children's behaviors related to fast-food consumption and TV viewing but are not directly related to body weight. The mother's education is highly associated with her knowledge and mother's working status may reflect time spent on her children and both these factors will directly influence children's activities, such as fast-food consumption and TV viewing. On the other hand, these factors are not directly related to body weight of children. (11) Undoubtedly, it is always difficult to know the appropriateness of our instruments, but some statistical tests may provide some guidance on this issue. For children's weight status and Body Mass Index, the test values of the overidentification restrictions are 2.376 and 1.925, respectively. Since the corresponding p values are .667 and .749, we fail to reject the null hypothesis that the overidentification restrictions are valid for children's weight status and Body Mass Index equations.

The results of the weak instruments test are also supportive of the selected instruments. The chi-square statistic of the likelihood ratio test is 92.5, which is asymptotically equivalent to an F statistic of 11.563. Since the F statistic value is larger than the critical value 10 suggested by Staiger and Stock (1997), we reject the null hypothesis that the selected instruments are statistically weak.

C. TV Viewing, Fast-Food Consumption, and Children's Body Mass Index and Obesity

Table 5 reports the marginal effects that measure the additional changes of explanatory variables on the probability of each weight status estimated by the generalized order probit model. (12) For the children's Body Mass Index equation, this is equivalent to the estimated coefficient under the linear model. We begin the discussion of Table 5 by comparing the performances between the ordered probit model and the generalized ordered probit model. Since the test value of the likelihood ratio test on the null hypothesis that the generalized ordered probit model is equivalent to the conventional ordered probit model is 37.8, which is higher than the 5% significance level, [x.sup.2] (0-95, 13) = 22.4, we may conclude that the generalized ordered probit model fits our data better. Therefore, we only present the estimation results of the generalized ordered probit model in Table 5.

TABLE 5
Marginal Effects for the Different Status of Body Weight

Generalized Order Probit Model
on Weight status

	Normal		Overweight	
	Coefficient	SE	Coefficient	SE
FASTHAT	-0.219 ***	0.035	0.147 ***	0.053
TVHAT	-0.058 **	0.028	0.056 *	0.030
AGE	0.000	0.006	0.007	0.005
MALE	0.002	0.018	0.003	0.014
HHSIZE	0.004	0.004	-0.009 ***	0.003
DISABLE_HH	0.001	0.030	-0.050 **	0.024
TAIWANESE	0.034 *	0.020	-0.021	0.016
HAKKA	-0.096	0.190	0.213	0.190
CITY	0.008	0.040	0.019	0.033
COUNTY	0.012	0.029	-0.045 **	0.022
CENTER	0.018	0.023	-0.042 **	0.018
SOUTH	-0.033	0.037	-0.067 **	0.029
EAST	0.112 ***	0.042	-0.098 **	0.039
Log likelihood	-1705			
Specification test				
[H.sub.0]: Ordered probit is equal to generalized ordered probit (a)			Likelihood ratio 8 test = 37.	

	Generalized Order Probit Model on Weight status		Linear Model	
	Obese		Body Mass Index	
	Coefficient	SE	Coefficient	SE
FASTHAT	0.072 *	0.039	0.286 *	0.169
TVHAT	0.001	0.026	0.286 *	0.173
AGE	-0.007	0.005	0.309 ***	0.044
MALE	-0.005	0.013	0.379 ***	0.115

HHSIZE	0.004	0.003	-0.011	0.036
DISABLE_HH	0.049 *	0.027	0.253	0.235
TAIWANESE	-0.013	0.015	-0.151	0.143
HAKKA	-0.117 *	0.067	0.343	0.993
CITY	-0.027	0.029	-0.133	0.281
COUNTY	0.033	0.024	-0.154	0.201
CENTER	0.024	0.019	-0.037	0.177
SOUTH	0.100 ***	0.034	0.354	0.230
EAST	-0.014 ***	0.004	-0.862 **	0.347
Log likelihood		Adjusted [R.sup.2]: .076		

Specification test

[H.sub.0]: Ordered probit is equal to generalized ordered probit (a)	Likelihood ratio 8 test = 37.

Notes: FASTHAT and TVHAT are predicted values of the fast-food consumption and TV hours, respectively. The standard errors are calculated on the bootstrap method with 1,000 replications.
(a) Critical value is [x.sup.2](0.95,13) = 22.4.
*** Significant at 1%; ** significant at 5%; * significant at 10%.

With respect to the effects of hours on TV viewing and fast-food consumption, our results show that these two activities positively contribute to children's body weight. (13) Specifically, each additional hour spent on TV viewing and each additional fast-food unit increases children's Body Mass Index by 0.286 units. Moreover, each hour increase in TV viewing increases the probability of being overweight by 5.6%, while each additional unit of fast-food score increases the probability of being overweight by 14.7%.

D. Other Factors Associated with Children's Body Mass Index and Weight Status

Other factors that are significantly associated with children's body weight and weight status include the characteristics of children, household, and geographical and regional conditions. These factors, however, affect children's body weight and weight status in different ways. For example, children's age is positively related to Body Mass Index. An additional year in age increases Body Mass Index by 0.309 units. Gender effects are also apparent. Compared to girls, boys weigh 0.379 units more in Body Mass Index. These two factors are statistically significant and are in agreement with the epidemiological evidence found in Taiwan (e.g., Chen et al., 2006). However, the age of children is not significantly associated with the probability of being obese and overweight.

Number of household members is also found to be associated with children's body weight status. One additional person living in the household decreases child's probability of being overweight by 0.9%. Also, children who live with the household with disabled members are 4.9% more likely to be obese. This result is consistent with our finding in the bivariate tobit model in that children living in a family with disabled members are more likely to watch TV and hence may have less control from other family members.

Regional conditions also significantly influence children's body weight. Compared to households in the north area, children who live in households located in the central, southern, and eastern parts of Taiwan have lower probability of being overweight by 4.2%, 6.7%, and 9.8%, respectively. These results may reflect the relative availability of fast-food restaurants and other convenience stores in the different regions.

V. CONCLUSIONS AND SELECTED POLICY IMPLICATIONS

Our objective of this article was to assess the effects of TV viewing hours and fast-food consumption on children's body weight and the risk of being overweight and obese. In contrast to previous studies, our analysis is unique in several ways. First, we capture the potential interrelation between these two activities and account for the censoring (zero observation) problem of TV viewing hours and fast-food consumption that may occur in the household survey data. In addition, we examine the extent to which these two activities may have different effects on children's body weight and the risk of being overweight and obese.

Using a nationwide survey data in Taiwan, our empirical findings reveal some interesting findings with policy implications. First, a statistically significant correlation (27%) between hours spent on TV viewing and fast-food consumption is found. This result points to the evidence that ignoring the potential interrelationship between these two activities may result in misleading policy inferences. Second, different effects of these two activities on children's body weight and the risk of being overweight or obese are found. Interestingly, TV viewing hours and fast-food consumption positively contributes to body weight and the risk of being overweight. While these results are not very surprising and consistent with prior expectations, they point to the importance of limiting children's TV viewing hours and fast-food consumption to control body weight and the risk of being overweight among children. As You and Nayga (2005) alluded to, the times used for television viewing and physical activity are generally substitutes and that it is possible that reductions in television viewing could also have a positive effect on physical activity, which could then possibly decrease children's obesity. Our results are also consistent with the findings of Chou, Rashad, and Grossman (2006) suggesting that TV advertising is positively associated with children's body weight.

Our findings have significant implications for public health policies/programs. First, they suggest that public health and childhood obesity programs should educate the parents of the critical influence of TV viewing and fast-food consumption on child obesity. These programs should provide concrete and understandable guidelines for parents that reflect the potential consequences of excessive TV viewing and fast-food consumption. Second, the government can encourage the fast-food industry to develop and sell healthier food selections for children and provide point of sale nutritional information of these products. While not directly related to our study, the government could also encourage the food industry to limit TV advertising of less healthy food items or junk foods targeted to children.

APPENDIX

STATISTICAL TESTS FOR MODEL VALIDATIONS

To account for endogeneity of fast-food consumption and TV viewing hours on children's Body Mass Index and weight status, the expected values of these two activities are used as instruments in children's body weight analysis (i.e., Equation (4)). For identification purposes, some of the exogenous variables specified in the fast-food consumption and TV hour equations (the vectors [X.sub.TV] and [X.sub.FF] in Equation (1)) have to be excluded from the children's body weight equation (the vector Z in Equation (6) and (7)) (see Wooldridge 2002). These exclusion variables are discussed in the Results section. To provide convincing evidence of our empirical specifications in the choice of the excluded instruments, three specification tests are conducted: the tests for endogeneity and the tests for over-identification restrictions and weak instruments. We briefly introduce the procedure in each test below.

Test for Endogeneity

When Instrumental Variable methods are used, it is essential to test for endogeneity as means of validating the approach. If the variables for which we are instrumenting (i.e., children's fast-food consumption and hours spent on TV viewing) are not endogenously associated with outcome variable of interest (i.e., children's Body Mass Index and weight status), there is no need for the Instrumental Variable method In this study, we test for the endogeneity of children's fast-food consumption and TV viewing hours on their Body Mass Index and weight status using the procedure outlined in Wooldridge (2002).

Suppose all the exogenous variables can be shown as ZX (i.e., (Z, [X.sub.FF]) or (Z, [X.sub.FF]) (Z, [X.sub.TV])). Following Wooldridge (2002), the test for exogeneity can be conducted in two steps. (14) First, we need to reestimate the bivariate tobit model by replacing the vector [X.sub.TV] or [X.sub.FF] with all the exogenous variables (ZX). That is:

[y*.sub.TV] = ZX'[[theta].sub.TV] [u.sub.TV];

[y*.sub.FF] = ZX'[[theta].sub.FF] [u.sub.FF];

(A1) [y.sub.TV] = max([y*.sub.TV], 0); [y.sub.FF] = max([y*.sub.FF], 0),

where [[theta].sub.TV] and [[theta].sub.FF] are vectors of parameters and [u.sub.TV] and [u.sub.FF] represent random errors. After estimating Equation (A1), the predicted residual of each activity can then be calculated as ([[^.u].sub.TV] and [[^.u].sub.ff])- in the second stage, we reestimate Equations (6) and (7) in the text by adding the predicted residuals ([[^.u].sub.TV] and [[^.u].sub.FF]) as new variables along with the observed variables for fast-food consumption and TV watching hours.

(A2) Body Mass Index = Z'r [d.sub.TV] x [y.sub.TV] [d.sub.FF] x [y.sub.FF] [[lambda].sub.TV][[^.u.]sub.TV]] [[lambda].sub.FF][[[^.u].sub.FF]] e

(A3) W* = Z' r [k.sub.TV] x [y.sub.TV] [k.sub.FF] x [y.sub.FF] [[PSI].sub.TV][[[^.[u].sub.RV]] [[PSI].sub.FF][[^.u].sub.FF] u.

Equations (A2) and (A3) form the basis for the exogeneity test. A test to see if the observed values of children's fast-food consumption ([y.sub.FF]) and TV viewing hours ([y.sub.TV]) are exogenous to their Body Mass Index or weight status is equivalent to testing the null hypotheses that ([[lambda].sub.TV] and [[lambda].sub.FF]) or ([[PSI].sub.TV] and [[PSI].sub.FF]) or ([PHI].sub.TV] and [PHI].sub.FF]) are statistically equal to zero.

Test for Overidentification

Overidentification occurs when there are more instruments included than are needed to identify the equation of interest. In our case, if the number of variables specified in the vector [X.sub.TV] or [X.sub.FF] (Equation (1) in the text) is larger than the number of variables specified in X (Equation (6) in the text) then our empirical model is overidentified. To test if the overidentified restrictions are appropriate, we conduct our empirical tests based on two different ways. For children's Body Mass Index equation, a simple regression-based procedure suggested in Wooldridge (2002) is followed. (15) Under the homoskedasticity assumption, a test for validating the over-identification restrictions can be obtained by simply regressing the predicted residual of Equation (6) (say e) on all the exogenous variables (the vector ZX). If the estimated [r.sup.2] of this equation is denoted as [R.sup.2], and the sample size is denoted as N, the test statistics can then be shown as [NR.sup.2], which follows the chi-square distribution with degree of freedom equal to the overidentifying restrictions (i.e., the number of variable specified in [X.sub.FF] or [X.sub.TV] minus 2). (16)

For children's weight status, the test conducted in this study is based on the spirit of Kan (2007) and Rashad and Kaestner (2004). Following Kan (2007), testing the validity of the excluded restrictions is equivalent to testing if the instruments have statistically contributed to the first-stage analysis. That is, we can test the null hypothesis that the coefficients of the instruments (excluded variables) are jointly equal to zero in the bivariate tobit model. This can be easily done based on the likelihood ratio test. (17)

Test for Weak Instruments

The weak instruments test is to investigate if the excluded instruments in children's fast-food consumption and hours of spent on TV viewing have enough explanatory power to serve as valid instruments. This is important because if the excluded instruments are weak then the Instrumental Variable estimators are likely to be worse than the case without correcting for endogeneity (Staiger and Stock, 1997). Although most of the applications of the weak instrument tests proposed by Staiger and Stock are used in the linear model, Kan (2007) provided a modification to a nonlinear model. Using a similar strategy in Kan (2007), the weak instruments test involves estimating the bivariate tobit model (Equation (1)) and tests if the excluded instruments (the additional exogenous variables specified in Equation (1) but not appear in

Equation (5) or (6)) have enough explanatory power. A likelihood ratio test is implemented and the test statistic follows a chi-square distribution (say [x.sup.2]), with the degree of freedom M (the number of the excluded variables). To be consistent with Staiger and Stock (1997), the likelihood ratio test statistic can be covered to a F statistic as: [X.sup.2]/M ~ [F(M, [infinity]). (18)

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ABBREVIATIONS

BMI: Body Mass Index

IV: Instrumental Variable

NHRIT: National Health Interview Survey at Taiwan

NHRIT: National Health Research Institute of Taiwan

Ordinary Least Squares: Ordinary Least Squares

(1.) In this study, three categories of weight status are specified: normal, overweight, and obese. We do not, however, separate the underweight and normal weight children into two subgroups. This is due to the difficulty and unclear cutoff points for defining the underweight status of children. In addition, the focus of this article is on the overweight and obese children. The cutoff points for determining overweight and obese weight status in Taiwan can be found on the Web site http://www.vghtpe.gov.tw/~nutr/forum/forum02/Body Mass Index2.htm.

(2.) We thank an anonymous reviewer for pointing out the importance of mother's influence on children's behavior.

(3.) In food consumption study, Hsiao (1986) have shown that assuming no interdependence and applying the univariate Tobit model to each food item may produce biased parameter estimates.

(4.) The evidence from the field of public health and nutrition has shown that the TV viewing and fast-food consumption may be correlated. For instance, Taveras et al. (2006) have found that the odds ratio for consuming fast food at least once per week is 1.6 for each 1 h increases of TV/video watched per day of preschool age children in the United States.

(5.) The model used here is a bivariate version of the multivariate tobit model. A generalization to the multivariate distribution can be found in Amemiya (1974). The bivariate tobit model had been applied to the bank and credit problem (Roszbach, 2004) and the household bottled water expenditures (Yoo, 2005).

(6.) The other possibility may be due to the reverse causality. We thank a thoughtful reviewer for this observation.

(7.) The consistency of the two-stage framework is similar to the endogenous treatment effect model where the expected value of the first-stage choice is used as an instrument in the second-stage regression (Maddala, 1983). The model identification can be reached through the nonlinear function of the expected values. However, since the Body Mass Index is observed for every child regardless of his hours of TV viewing and fast-food consumption, the unconditional expectation is more appropriate, than the conditional means, to serve as instruments for their observed counterparts in this case.

(8.) This is referred to as the "parallel regression" (see Boes and Winkelmann, 2006; Terza, 1985).

(9.) For the continuous explanatory variables, the analytical derivatives of the probabilities with respect to each of the continuous variables are computed and evaluated at the sample means of all the explanatory variables. For the dummy explanatory variables, the differences between two computed probabilities, one conditional on the variable being equal to one and the second conditional on the variable being equal to zero is evaluated. The standard errors of the marginal effects are calculated using the delta method.

(10.) Details of the statistical tests are introduced in the Appendix.

(11.) We thank a reviewer for suggesting these instruments.

(12.) Since the instruments are used in the second-stage analysis, the reported standard errors in Table 5 are calculated using the bootstrap method with 1,000 replications.

(13.) This finding is consistent with Lin, Huang, and French (2004) who have also found a positive correlation between TV watching and children's Body Mass Index based on a national survey data in the United States. In their study, however, they do not account for the censoring and endogeneity issues.

(14.) The detailed discussion of the test procedure can be found in Wooldridge (2002, pp. 11-119).

(15.) The detailed discussion of the test procedure can be found in Wooldridge (2002, pp. 122-123).

(16.) Details of the discussion of the test procedure can be found in Wooldridge (2002, p. 123).

(17.) The discussion can be found in Kan (2007, p. 72).

(18.) A detailed discussion of the proposed test procedure can be found in Kan (2007, pp. 71-72).

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