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Abstract: Development and subsequent changes in lifestyle have caused a dramatic increase in the prevalence of overweight and obesity in China (WHO 2000; Wu 2006). This is likely to lead to a higher incidence of non-communicable diseases (NCDs), given that obesity is one of the main risk factors, as well as an overall reduction in health human capital. We use the China Health and Nutrition Survey (CHNS) to carry out structural estimation of the health production function for children's obesity in China. The inputs of the production function are calorie intake and time on sedentary activities, and the output is the Body Mass Index (BMI). We use the Limited-Information Maximum Likelihood (LIML) estimator to get consistent and unbiased values for the structural parameters. Statistical tests show that the instruments are relevant (not weak) and exogenous. Results suggest that calorie intake is the most important input in the production of excessive weight with an impact on weight three times larger than sedentary activities. These results suggest that public health policies targeting obesity in children must focus on reducing excessive calorie intake.

***Covering Letter (WITH Author Details)**

Sample cover letter for World Development

Dear Editor:

We are pleased to submit an original research article entitled "Production of Health: Children's obesity in China", by Norman Maldonado and Joyce Chen. The problem addressed by this paper is the obesity epidemic in children in China, specifically, the relative importance of calorie intake and time spent on sedentary activities on the production of Body Mass Index (BMI) and deviations from normal ranges for BMI. The approach we follow uses the China Health and Nutrition Survey to estimate structural parameters of the BMI health production function for children and use instrumental variables and the Limited Information Maximum Likelihood estimator to correct for endogeneity bias, getting consistent and unbiased estimators. We also use a generalized functional form and different proxies for health endowments to show that estimates are robust.

Our work contributes to the literature on obesity in several respects. First, we provide consistent estimates of structural parameters for the health production function in children regarding obesity issues. Structural parameters quantify the effect of calorie intake and sedentary activities on children's BMI, providing a rich source of information to prioritize public health policies. Second, most studies on this issue have been done for developed countries, and little is known about the relevant policy parameters for developing countries like China, where access to health inputs is quite different, especially when it comes to children's health, and where there is a significant increase in the prevalence of obesity in children, making it a priority for public health authorities.

We submit this paper to World Development because of the relevance of its results to improvement of standards of living in issues related to malnutrition. In particular, policies tackling obesity in children have a huge potential to improve their living conditions in the short and the long-run because children have less information about the health and economic consequences of being obese and are less likely to fully internalize the expected future losses. Intervention have the potential to stop the increasing private and public costs of obesity, and is expected to be more effective than intervention in adults because children's bodies adapt easier to changes in lifestyle.

Look forward to your favorable consideration. Regards,

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Abstract

Development and subsequent changes in lifestyle have caused a dramatic increase in the prevalence of overweight and obesity in China (WHO 2000; Wu 2006). This is likely to lead to a higher incidence of non-communicable diseases (NCDs), given that obesity is one of the main risk factors, as well as an overall reduction in health human capital. We use the China Health and Nutrition Survey (CHNS) to carry out structural estimation of the health production function for children's obesity in China. The inputs of the production function are calorie intake and time on sedentary activities, and the output is the Body Mass Index (BMI). We use the Limited-Information Maximum Likelihood (LIML) estimator to get consistent and unbiased values for the structural parameters. Statistical tests show that the instruments are relevant (not weak) and exogenous. Results suggest that calorie intake is the most important input in the production of excessive weight with an impact on weight three times larger than sedentary activities. These results suggest that public health policies targeting obesity in children must focus on reducing excessive calorie intake.

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Highlights

- Estimation of structural parameters of the obesity health production function for children in China is carried out.
- Limited-Information Maximum Likelihood estimates control for endogeneity bias, which makes them consistent and unbiased.
- Calorie intake is the most important input in the production of excessive weight with an impact on Body Mass Index three times larger than sedentary activities.
- Public health policies targeting obesity in children will be more effective if they focus on reducing excessive calorie intake.

1 Introduction

Overweight and obesity, two major risk factors for non-communicable diseases (NCDs), have become epidemic, even in many developing countries (FAO 2013). NCDs such as diabetes, cardiovascular disorders, musculoskeletal disorders and cancer represent a significant financial burden for health systems because of the permanent stream of relatively high amount resources they demand. They also harm economic growth by reducing a country's health human capital. For the U.S., the prevalence of obesity for individuals between 20-74 years old climbed from 15.1% in 1976-1980 to 35.3% in 2007-2010[1], and the estimated costs associated with obesity represent 5.7% of the national expenditure on health (Wolf and Colditz 1998). The obesity epidemic has also affected developing countries like China. The World Health Organization (WHO) identified significant prevalence of obesity in the early 90s (WHO 2000), and more recent data shows increases of prevalence in adults from 3.6% in 1992 to 7.1% in 2002 (Shen, Goyal, and Sperling 2012). Since then, many studies have identified the same trend, and obesity has gradually become a public health issue in the country (Chen 2008; Wu 2006; Yan et al. 2012), especially because of the increase in prevalence of obesity in children (Luo and Hu 2002) that has skyrocketed from 1.5% in 1989 to 12.6% in 1997 (Cheng 2004) and 23% for boys and 14% for girls in 2014 (Ng et al. 2014).

When obesity affects children, the negative effects are magnified. An obese child has a higher risk of being obese in adulthood, which leads to increased likelihood of disability and NCDs (Daniels 2006) and a greater financial burden on health systems, threatening public and private finances. In the short-run, taking care of a child who has been diagnosed with a NCD might reduce household labor supply and income. In the long-run, the disabilities imposed by NCDs translate into lower productivity and lower permanent income. In addition, compared to adults, children have less information about the health and economic consequences of being obese and are less likely to fully internalize the expected future losses (Grossman

[1] Data provided by the Center for Disease and Control Prevention - CDC.

and Mocan 2011), which presents a clear role for intervention. Policies to tackle obesity in children have become a priority for policymakers (WHO 2012a), not only because private and public costs of obesity are higher for children than for adults, but also because children's bodies adapt easier to changes in lifestyle, making intervention in early ages more effective (Block JP 2013; Kroon MLA 2010).

Obesity is caused by a permanent imbalance between calorie intake and calorie expenditure. These two factors are determined by the demand for health inputs which, in turn, represents individual behavior and response to surrounding conditions. Thus, obesity has two components: the relationship between health outcomes and health inputs, also called the health production function, and the behavioral rules determining the demand for health inputs. This paper estimates the structural parameters of the health production function of obesity in children in China. Structural parameters of the health production function are key policy parameters because their relative magnitudes shed light on the most effective ways to tackle the obesity epidemic in children, helping policy makers to define and prioritize areas of action (WHO 2012b).

China is an important case for the study of overweight and obesity for several reasons. During the last three decades, China has experienced a significant increase in the prevalence of obesity, making it a priority for public health authorities (Wang, Marquez, and Langenbrunner 2011). Second, most studies on this issue have been done for developed countries, and little is known about the relevant policy parameters for developing countries like China (Mwabu 2007), where access to health inputs is quite different, especially when it comes to children's health. Also, China has unique data to carry out estimation of policy parameters, in particular, the China Health and Nutrition Survey (CHNS)[2], which is a longitudinal

[2]We thank the National Institute of Nutrition and Food Safety, China Center for Disease Control and Prevention, Carolina Population Center (5 R24 HD050924), the University of North Carolina at Chapel Hill, the NIH (R01-HD30880, DK056350, R24 HD050924, and R01-HD38700) and the Fogarty International Center, NIH for financial support for the CHNS data collection and analysis files from 1989 to 2011 and future surveys, and the China-Japan Friendship Hospital, Ministry of Health for support for CHNS 2009.

household survey with information at the individual, household and community level. Most of the collected data has to do with objective and subjective measures of health status and health inputs such as health care, time allocation, nutritional intake and physical activities. In addition, the CHNS collects information on basic socioeconomic variables[3].

The paper is organized as follows. Section 2 provides a theoretical framework for the empirical model presented in Section 3. Section 4 presents estimates of the structural parameters of the production function. Section 5 concludes.

2 Background

2.1 Theoretical framework

At the micro level, health human capital is determined by choices regarding a variety of goods and behaviors. Specifically, the literature in health economics suggests that the health status of an individual in the short-run is the result of a production process. In this process, inputs such as medical care or dietary habits are combined to produce health. The standard health production function, as proposed by Rosenzweig and Schultz 1983, uses three inputs: goods that affect both health and utility directly (e.g. alcohol, food), goods that only affect health (e.g. medication), and unobservable health endowments. By solving the utility maximization problem subject to the health production function and budget constraints, it is possible to derive reduced-form demand functions for health inputs and health outcomes, which will depend on prices, money income, health endowments, and technology.

Consider a simple model in which households' preferences U are defined over four goods: health H, a composite good that does not affect health X, n goods that affect health Y_n

[3] A detailed explanation of the survey is presented by Popkin et al. 2010.

($n = 1, \ldots, N$), and total time spent in energy-intensive activities (i.e., work) L as follows:

$$U = U(H, X, Y, L). \tag{1}$$

Given the physiological relationship between nutritional intake and energy expenditure, production of health is represented by

$$H = \Gamma(Y, L, \mu) \tag{2}$$

where μ represents the individual-specific health endowment. To close the model, the household faces a budget constraint:

$$\sum_j L_j w_j \quad = X p_x + \sum_n Y_n p_n, \quad j = 1, \ldots, m, \quad n = 1, \ldots, N. \tag{3}$$

where w represents the hourly wage for various activities and p represents the prices of consumption goods. Note that the wage w_i need not be strictly positive for all activities. For example, exercise does not generate labor income but does affect both health and utility. The solution is characterized by reduced-form demand functions:

$$[Y, X, L] = F(p, w, \mu) \tag{4}$$

with the subsequent reduced-form for health outcomes, also known as health demand function:

$$H = \psi(p, F, \mu) \tag{5}$$

Clearly, we have made several simplifying assumptions here in order to highlight the key features of the model that are addressed in our empirical work. Since we do not consider substitution between health inputs and other goods, we have not included any goods that affect health but not utility. Nor do we specify a household production function, since we do not study substitution among either home and market production, labor and leisure, or among non-health-related consumption goods. However, household chores could be viewed as an element of the L vector, with the associated w_i reflecting the value of that production. We assume that markets are complete such that households are price-takers in both the labor and goods markets. We have also implicitly omitted any link between health and productivity, as wages are dependent only on time and not efficiency. This assumption, however, is not central to our analysis, as our identification strategy allows for links between health on productivity in the input demand functions.

To see how equations (2)-(5) can be used to characterize the changing incidence of obesity, consider the proximate causes. By definition, obesity is caused by an imbalance between calorie intake and calorie expenditure. Finkelstein, Ruhm, and Kosa 2005 review the economic causes and consequences of obesity identified in the literature. The imbalance has been mostly related to technological change (Cutler, Glaeser, and Shapiro 2003; Grossman and Mocan 2011; Lakdawalla, Philipson, and Bhattacharya 2005; Philipson and Posner 2003), which has reduced the relative price of mass-produced calorie-dense foods, increased the value of time, and reduced energy expenditure. This change in relative prices, reflected in the price vector p, has caused an increase in consumption of carbohydrates (including soft drinks), and changes in eating patterns characterized by higher frequency of consumption of snacks and increased portion sizes. The increase in real wages has led to an increase in the opportunity cost of time, which induces substitution of fresh foods in favor of processed foods, which generally have a higher calorie density. At the same time, higher wages make leisure and exercise relatively more expensive, while technological change has led to the proliferation of labor-saving devices, reducing energy expenditure in both the workplace and at home, all of which are reflected in the w vector.

2.2 Previous findings

There is a large literature on the structural estimation of the health production function. We highlight here only a few key works. Rosenzweig and Schultz 1983 examine the weight of children at birth, including as inputs the number of months the mother worked while pregnant, months of elapsed pregnancy before visiting a doctor, consumption of cigarettes, order of the live births and age. They dealt with the problem of endogeneity of inputs by using instrumental variables (IV), including prices at the community-level, husband's income and parents' education. The absence of panel data did not allow them to control for unobserved heterogeneity. Even though Rosenzweig and Schultz 1983 do not deal with obesity issues, they developed the standard methodology for estimation of health production functions. Contoyannis and Jones 2004 use data from the Health and Lifestyle Survey (HALS) in the UK and exploit the panel structure of the data to use lags of inputs and outcomes as regressors in a cross-sectional multivariate probit model. One important limitation is that the dataset only measures lifestyle variables (health inputs)[4] as binary variables[5]. Also, the dependent variable is a subjective health indicator that takes the value of 1 if the individual rates his health as excellent or good and zero otherwise, making it difficult to generalize the findings to other populations and contexts (Strauss and Thomas 2007). Rashad 2006 uses three waves of the National Health and Nutrition Examination Survey (NHANES) to estimate BMI in US adults as a function of activity-adjusted calorie intake and smoking, using prices, cigarette tax, temperatures and indoor air laws at the state-level as instruments. However, characteristics such as education, income, marital status, and state of residence, which are known to the demand for health inputs (e.g., via health knowledge, improved access, etc.) are not included in the first stage, introducing significant bias in the estimates (Rosenzweig and Schultz 1983). As

[4] Specifically, they include diet, smoking, exercise, alcohol consumption, sleep and absence of obesity.

[5] Additionally, one of the lifestyle variables is whether or not the individual is obese, based on measurements of BMI. Since BMI is by itself a measurement of health, the introduction of this variable adds simultaneity bias in the model.

better data has become available, more recent studies have been able to control for additional factors and to study the influence of more specific variables. One example is Brad and Jane 2011, which estimates participation and duration of physical activity for adults in the U.S., and the effect that income and opportunity cost of time have on those decisions.

Childhood obesity has received less attention in the literature estimating health production functions. MacInnis and Rausser 2005 study the effect of high-energy density in food on childhood obesity in the U.S. The study includes children aged two to ten years and uses household-level fixed-effects to get rid of unobservable determinants of health. As pointed out by the authors, they do not intend to establish causality, which is the main reason for not accounting for the endogeneity of energy intake. Chou, Rashad, and Grossman 2008 analyze the effect of television fast-food restaurant advertising on children (ages 3-11) and adolescents' (ages 12-18) overweight in the US, and Fertig, Glomm, and Tchernis 2009 examine the effect of maternal employment, but neither study provides structural estimates of the health production function. The WHO has identified the expansion of this epidemic (WHO 2000), which has motivated research on obesity in developing countries as well (Arroyo, Loria, and Méndez 2004; Loureiro and Nayga 2005; Philipson and Posner 2008). China has caught up quickly with the industrialization process of the Western countries, and the causes and consequences of obesity identified in the literature follow very closely the ones already explained for the U.S. and developed countries. Chen 2008 describes the recent trends of obesity in China and analyzes how this has affected the prevalence of chronic diseases, and Wu 2006 identifies reductions in physical activity and labour intensity associated with lower energy expenditure on traditional forms of transportation (e.g. walking, cycling) and the increasing popularity of cars, buses and motorcycles. However, to our knowledge, there have not yet been structural estimates of the health production function pertaining to children obesity in developing countries.

This paper contributes to the literature on obesity in several respects. First, we provide consistent estimates of structural parameters for the health production function in children regarding obesity issues. This allows us to quantify the effect of various inputs on children's health, providing a rich source of information to prioritize public health policies. A second contribution is to exploit a uniquely rich data source, the China Health and Nutrition Survey (CHNS). The CHNS has many advantages for estimation of production functions, including the panel-data structure, objective measures of health outcomes and inputs, detailed individual, household and community-level information that provide instrumental variables for endogenous inputs. We also contribute to the nascent literature on the determinants of the obesity epidemic in developing and emerging economies such as China.

3 Econometric Model

3.1 Data

Data are drawn from the China Health and Nutrition Survey, a longitudinal survey covering approximately 4,400 households and 26,000 individuals across nine provinces in China. The survey collects information at the individual, household and community levels. Currently, data are available for eight waves: 1989, 1991, 1993, 1997, 2000, 2004, 2006, and 2009[6]. We focus only on the last three waves, given that obesity was quite rare in the early 1990s, and significant changes in the questionnaire were introduced after 2000. Moreover, the dramatic changes in the Chinese economy at the turn of the century likely caused structural shifts in health as well, raising questions about the validity of combining earlier and later survey waves.

The sample of interest is children, defined by the survey as individuals between 6 and 17 years old. We focus on Body Mass Index (BMI), which is the ratio of weight in kilograms to height in meters squared, both of which are measured in detailed physical examinations

[6] Information was already collected for 2011 but not all datasets are available.

by trained clinicians. The World Health Organization and the Center for Disease Control and Prevention (CDC) use a standard classification for BMI: underweight, normal, overweight and obese. These categories are defined based on the 85^{th}, 90^{th} and 95^{th} percentiles of the distribution of BMI in a representative sample of individuals from a specific population. Thus, the critical values defining the categories change according to the population represented in the distribution. Standard values are usually based on samples of individuals in developed countries. For example, Cole et al. 2007 define categories of BMI based on a sample of children and adolescents from Brazil, Great Britain, Hong Kong, the Netherlands, Singapore, and the United States.

In spite of the popularity of these standard measures, the significant variation in anthropometric characteristics across regions in the world has undermined their relevance, and new studies suggest using cut-off values based on distributions representing people from the same region (Deurenberg-Yap and Deurenberg 2003). We use the cut-off values for children in Shanghai proposed by Jiang et al. 2006 to define normal weight, overweight and obesity by age and gender. The outcome of interest is the BMI and the difference between the child's BMI and the lower bound of the range for normal BMI for his/her age and gender[7]. We exclude all children whose BMI is below normal (thinness)[8] because the focus of the study is obesity and the structural parameters for the health production function for undernutrition are expected to differ from the ones for obesity.

In general, the inputs of the production function for obesity are calorie intake (calories

[7] An alternative is to classify individuals as obese based on reference ranges, and then use the binary variable derived from this classification to estimate the probability of becoming obese. This approach is not efficient, as it does not use all the information provided by the BMI. The standard in the literature is to take anthropometric measures from a representative sample and use them to infer the probability distribution of BMI in the population; then the deviation from the mean of this distribution, called the z-score, is calculated for each individual (Cole et al. 2007). Unfortunately, the CHNS is not a nationally representative survey, which means it cannot be used to infer the distribution of BMI in the country. The approach followed here also measures deviations, but the mean to calculate the deviation is not derived from the survey but taken from medical studies for children in Shanghai.

[8] These children represent around 20% of the sample, and this proportion is approximately constant across waves of the survey. Overweight and obese children represented 8% in 2000, and the proportion has been steadily increasing across waves, reaching 14.4% in 2009.

per day) and calorie expenditure. Calorie intake is measured in the CHNS by examining food consumption over three consecutive, randomly allocated days balanced across the days of the week. Enumerators, all of whom are trained nutritionists, examine changes in the household food inventory between the beginning and end of each day, as well as weighing all foods brought into the home, including purchases, home production, and processed foods, as well as any preparation waste, spoilage or food given out. Foods are then translated into calorie intake using the 2002 and 2004 Food Composition Tables for China, generated by the survey team and the National Institute of Nutrition and Food Safety (Popkin et al. 2010).

Calorie expenditure can be measured either by hours spent doing physical activity or by hours spent in leisure or sedentary activities, with the last one being interpreted as lack of calorie expenditure. Since both are measured as time allocation, they are mutually exclusive. Physical activity is measured as the number of hours per day spent doing exercise, working and doing chores[9]. Exercise includes the time spent in school and outside school doing physical exercise as well as the time spent in transportation by walking or biking in round trip from home to school. Working includes the time the child spent in a job as well as the time in other occupations such as home gardening, collective and household farming and fishing, raising livestock, handicraft and household business. Regarding chores, we include the number of hours per day the child spent in buying food for the household, preparing and cooking food, washing and ironing clothes and cleaning the house. Sedentary activities are measured by the number of hours per day the child spends in watching tv, playing video games, using the computer, reading books and playing with toys[10]. A notable advantage of these data is that children are asked to report their "usual" time spent in each of these activities, which provides a better measure of typical energy expenditure (or lack of) and is

[9]An alternative method to measure physical activity in the CHNS is measuring motion in a 24-hour period using the Caltrac Actometer. We do not use it because data collection from this device was discontinued in 2004.

[10]Sleeping might also be considered as a sedentary activity. However, all the aforementioned sedentary activities are choices, but sleeping is not. For this reason, we exclude sleeping time from the analysis.

less likely to reflect idiosyncratic shocks.

Whether to use physical or sedentary activity to represent calorie expenditure is a matter of identification. Both cannot be included in the structural equation because they represent the same variable. Physical activity is the first candidate, because it is commonly associated with lower weight through higher calorie expenditure. However, the effect might be ambiguous because more exercise leads to higher demand for energy or calories and higher BMI, although these calories contribute to muscle mass and not to accumulation of adipose tissue. Since BMI does not discriminate excess weight due to muscle mass or adipose tissue[11], identification of the structural parameter for physical activity becomes problematic. In contrast, the effect of sedentary activities on BMI is positive, even when considering the correlation with calorie intake, which facilitates the identification of the structural parameter. For this reason we choose sedentary activities and the variable represents lack of calorie expenditure.

The third variable in the structural equation is health endowments (μ). In principle, μ is unobservable and constant over time. Thus, one way to control for this is to exploit the panel structure of the data and use a fixed-effects estimator, although this requires to have most observations reporting data on consecutive waves. An alternative is to use parents' health, specifically whether the head of the household is either the father or the mother of the child[12] and has ever been told by a doctor that he/she suffers from a NCD. Even though this causes missing values for children whose none of his parents is the head of the household, the number of missing values is lower than the missing values caused by children not having two data on two consecutive waves. For this reason we use parents' health to represent health endowments. Summary statistics are presented in Table 1.

Looking only at children who are at least normal weight, it can be seen that, on average, children in the sample have BMI of 18.43 kilograms per meter squared, and deviate 2.85 kilograms per meters squared from their ideal BMI. The average calorie intake is around

[11] Underwater weighing, not available in the CHNS, can measure adipose tissue.
[12] Kinship is defined in the CHNS relative to the head of the household.

Table 1: Descriptive statistics

Variable	Mean	Standard Deviation		
		Overall	Between	Within
BMI	18.43	2.97	2.88	1.07
Deviation ideal BMI	2.85	2.57	2.47	0.87
Calorie intake	1,830.76	687.47	633.41	338.22
Sedentary activity	3.64	2.24	2.08	1.16

Source: CHNS for 2004, 2006 and 2009. 1857 individual-year observations. Body Mass Index (BMI) is the ratio of weight in kilograms to height in meters squared, while deviation from ideal BMI is the difference between BMI and cutoff values defining overweight proposed by Jiang et al. 2006. Calorie intake is the three-day average consumption of kilocalories, and sedentary activity is the daily time spent in watching tv, playing video games, using the computer, reading books and playing with toys.

1,830 kilocalories per day, and children, on average, spend 3.64 hours per day in sedentary activities. Table 1 also shows that most of the standard deviation comes from between variation, which doubles the within variation in most cases. Thus, the estimator to be used has to identify the parameters by taking advantage of this characteristic. The next section discusses identification of the parameters.

3.2 Model

The structural equation to be estimated is the health production function (equation 2). For child i in year (wave) t the structural equation for obesity is:

$$BMI_{i,t} = \Omega\,(\,C_{i,t}\,, L_{i,t} \mid \mu_i\,, X_{i,t}\,) + \varepsilon_{i,t} \tag{6}$$

where $BMI_{i,t}$ is the child's Body Mass Index, $Y_{i,t} \equiv [C_{i,t}, L_{i,t}]$ is the vector of health inputs, including $C_{i,t}$ calorie intake per day and $L_{i,t}$ hours per day spent in leisure activities. Production of BMI is conditioned on the health endowment μ_i, and a vector $X_{i,t}$ representing variation in BMI caused by demographic characteristics such as gender and age.

Ω is the functional form for the health production function. It represents a technical-biological relationship between behavioral inputs and health outcome. Besides the results obtained in previous work, there is no economic rationale to specify a functional form a priori[13]. For this reason we use a translog function, which can be interpreted as a second-order Taylor series approximation to a general but unknown production function (Christensen, Jorgenson, and Lau 1973)[14]. Thus, the production function we estimate is:

$$
\begin{aligned}
\ln BMI_{i,t} \; &= \alpha_1 \ln C_{i,t} + \alpha_2 \ln L_{i,t} + \frac{1}{2}\gamma_1 \left(\ln C_{i,t} \cdot \ln C_{i,t}\right) \\
&\quad + \frac{1}{2}\gamma_2 \left(\ln L_{i,t} \cdot \ln L_{i,t}\right) + \beta \left(\ln C_{i,t} \cdot \ln L_{i,t}\right) \\
&\quad + \phi X_{i,t} + \theta \mu_i + \varepsilon_{i,t}
\end{aligned}
\tag{7}
$$

OLS estimates of (7) are inconsistent because health inputs Y are endogenous. We use a limited-information approach to deal with endogeneity, specifically we use the number of locally available TV channels, the month of the survey, the number of sisters and whether the individual lives in a rural or in a urban area. None of these variables is expected to have a direct effect on the child's BMI. With regard to the number of TV channels, it is a community-level variable that includes channels on central, local, satellite and cable TV. This variable is expected to indirectly affect BMI only through the positive effect it has on sedentary activities, in particular on the time spent on watching TV. The month of the survey, by definition, is not determined by the same variables as the ones that determine decisions taken by the household. It is expected to work as an instrumental variable because it captures differences in children's behavior caused by changes over the last four months of the year,

[13]In contrast, production functions for firms only represent a technological process, the outcome is a tradable good and market competition leads to zero profits. These conditions allow to impose some structure to the function, such as homogeneity, diminishing marginal returns, etc. In the context of households, the function represents a technological and also a biological process of a nontradable good, which does not allow to impose structure in the functional form.

[14]Boisverf 1982 presents the properties of the translog function and possible interpretations. Kim 1992 analyzes methods of estimation.

for example, changes related to weather.

Another instrument is a dummy variable representing whether the child lives in an urban or rural area. Location is expected to have an indirect effect on the child's BMI only through local supply of food and goods and services that can change time allocation on sedentary activities (e.g. gyms, parks or internet). For exogeneity, households decisions on permanent migration are not as frequent as the daily or weekly decisions on food and time allocation. Indeed, permanent migration between rural and urban areas are long-term decisions and the number of episodes of permanent migration across the life course is low. The same argument of long-term horizon works for the number of sisters. The argument is reinforced by the fact that we estimate a short-term health production function. For these reasons both of these instruments can be considered as exogenous. With regard to the relevance of the number of sisters, it is expected to affect both time allocation on sedentary activities and calorie intake through intrahousehold allocation.

The second issue to deal with is the fact that health endowments are unobservable. There are two ways to deal with this issue. The first one is to assume that μ is constant over time, which makes the model (7) a Fixed-Effects model, and the parameters can be consistently estimated by a Fixed-Effects estimator. The assumption is justified in the fact that these endowments are genes, that are not expected to change during childhood. Unfortunately, within variation in the sample is small, specially for BMI, and this lack of variation casts doubt on the capacity of this estimator to identify the structural parameters.

Another way to deal with μ is to include good proxies for health endowments. By exploiting the panel nature of the dataset, the lagged BMI ($BMI_{i,t-1}$) might be considered a good proxy for health endowments because any unobservable genetic disorder that causes obesity in t should have also caused obesity in $T < t$. However, lagged BMI can be endogenous[15] and there is a significant loss of observations and statistical power when the sample only

[15] For example, preferences for some types of food, like sodas and candy, can be constant during childhood, affecting both current and lagged BMI.

includes children that were observed in two consecutive waves.

Physicians get information for health endowments by asking about health disorders in biological family. We use this approach and represent health endowments by obesity-related disorders of the head of the household when this member is the biological father/mother of the child[16]. Specifically we use a dummy variable that equals 1 if the parent has ever been told by a doctor that he/she suffers from diabetes, and 0 otherwise. Under this strategy both within and between variation can be used to precisely identify the parameters of the structural equation, and coefficients of time-invariant regressors can also be identified. Since the goal is to get consistent estimates of the structural parameters, we use the Limited-Information Maximum Likelihood (LIML) estimator, which is more robust to weak instruments.

4 Results

4.1 First-stage

The first result is that the interaction terms and squared terms in the translog production function are neither individually nor jointly significant in any specification. For this reason, from now on we only consider estimates under the Cobb-Douglas production function, that is, assuming $\beta = \gamma = 0$. Table 2 shows results of the first stage of the estimation, one column for each endogenous variable.

Results show that instruments for individual regressors are relevant. The month of the survey significantly affects both calorie intake and sedentary activity. This happens because during the last four months of the year there is a transition from autumn to winter, and the drop in the temperature is expected to increase calorie intake. Following the same argument, sedentary activities should increase with this variable. However, school year in China runs

[16] Other studies support the choice of this variables to control for health endowments. For example, Luo and Hu 2002 find that early childhood overweight and parental overweight are good predictors for overweight in children between 10-14 years old.

Table 2: First-Stage LIML estimation

Coef.	Ln Calorie intake	Ln Sedentary activity
Month	0.0296***	-0.0812***
survey	(0.009)	(0.018)
TV	-0.0025***	0.0013
channels	(0.001)	(0.001)
Number	-0.0379**	-0.068
sisters	(0.018)	(0.049)
Urban?	0.0461**	0.1377***
	(0.019)	(0.031)
Age	0.0406***	0.0067
	(0.003)	(0.005)
Male?	0.149***	0.0298
	(0.016)	(0.03)
Diabetes	0.0509	0.0786
head (μ)	(0.097)	(0.142)
Constant	6.6638***	1.8382***
	(0.098)	(0.195)
F excluded		
F(4,1103) = 6.03	6.03	14.22
Prob > F = 0.0001	0.0001	0.0000
SW Chi-sq (Underid)		
F(3,1103) = 7.64	23.02	55.41
Prob > F = 0.0000	0.0000	0.0000
SW F (Weak id)		
F(3,1103) = 7.64	7.64	18.38
Prob > F = 0.0000	0.0000	0.0000

Source: CHNS. 1811 individual-year observations. Standard errors are shown in parenthesis below the estimates, and allow for intra cluster correlation. Clusters are defined by individual and household. (*) denotes significance at 10%, 5% (**) and 1% (***).

from September to July, which means that the effect of weather might be compensated by time dedicated to school activities. The effect of the number of TV channels is unexpected, because it reduces calorie intake and it has no effect on sedentary activity. With regard to household composition, specifically the number of sisters, it seems to decrease the number of calories, which might happen because of allocation of resources in the household, although it does not affect time allocation. Living in an urban area provides more access to food and technology, which explains increases in calorie intake and sedentary activities. Older and male children are expected to have higher calorie intake. In the last place, health endowments represented by whether the head of the household (parent) has ever been diagnosed with diabetes, do not have an indirect effect on BMI through effects of health inputs.

The bottom of the table shows underidentification and weak instruments tests for individual endogenous regressors. The Sanderson-Windmeijer (SW) first-stage chi-squared rejects the null hypothesis that the corresponding endogenous regressor is unidentified. In addition, the SW first-stage F statistic shows that in both cases the null hypothesis of weak instruments is rejected. These results seem to suggest that instruments are not weak. However, given that there are two endogenous regressors in the structural equation, the first-stage results are indicative but not conclusive, and only the second-stage tests for multiple regressors allow to conclude for relevance.

4.2 Structural estimates and assumptions

Estimates for the structural parameters of the health production function are shown in Table 3. Because of the functional form, coefficients for calorie intake and sedentary activities are interpreted as output elasticities, i.e. the percentage change of BMI due to a percent change in either calorie intake or sedentary activities. Both elasticities are statistically different from zero and have the expected sign. A 10% increase in calorie intake increases by 2.8% in average a child's Body Mass Index, and a 10% increase in time spent on sedentary activities, or lack of physical activity, increases a child's Body Mass Index by 0.8%. It can be seen that the effect of calorie intake on BMI is three times larger than the effect of lack of physical activity. This implies that policies targeting calorie intake are expected to have a higher impact on tackling the obesity epidemic than those related to promotion of exercise and discouragement of sedentary activities.

Table 3: Structural estimation of the health production function

Coef.	Ln BMI	
	LIML	OLS
Ln Calorie intake	0.2878**	0.0213**
	(0.12)	(0.01)
Ln Sedentary activity	0.0864**	0.0076
	(0.041)	(0.005)
Age	0.0129**	0.0248***
	(0.005)	(0.001)
Male?	-0.0354*	0.004
	(0.019)	(0.007)
Diabetes head (μ)	0.0869*	0.1187***
	(0.045)	(0.044)
Constant	0.5228	2.4462***
	(0.836)	(0.07)

Source: CHNS. 1811 individual-year observations. Standard errors are shown in parenthesis below the estimates and allow for intra cluster correlation. Clusters are defined by individual and household. (*) denotes significance at 10%, 5% (**) and 1% (***).

Coefficients for the conditioning variables X and μ are statistically significant and have the expected sign. BMI curves show that the values defining normal BMI for children increase with age and stabilize after the age of 20. The positive and significant coefficient for age confirms that fact. During childhood, boys are expected to have a slightly lower BMI than girls, and this explains the negative sign for the Male variable in the estimation. Health endowments, in particular whether the head of the household (parent) has ever been diagnosed with diabetes, have a direct effect on children's BMI. This means that behavioral response, that is, parents whose low health might induce healthy behavior in their children, does not seem to compensate genetic predisposition for obesity.

The comparison between columns in Table 3 shows the difference between the LIML estimator and the OLS estimator. It can be seen that not accounting for endogeneity leads to misleading conclusions. The OLS estimates suggest that calorie intake matters for BMI but the output elasticity is 0.21%, approximately 10 of the consistent and unbiased output elasticity obtained in LIML. Another misleading conclusion from the OLS estimates is time spent on sedentary activities play no role on BMI. The OLS effect of age on BMI is twice as large as the LIML effect, and the effect of health endowments is also higher.

Table 4 shows tests for the assumptions of the LIML estimation. The first block shows the results of the Kleibergen-Paap Lagrange Multiplier test, whose null hypothesis is that the equations are unidentified. The Chi-square p-value rejects the null hypothesis, which allows to conclude that equations are identified and instruments are correlated with the endogenous regressors.

In order to test for weak instruments, Table 4 shows the Cragg-Donald Wald F and the Kleibergen-Paap Wald rk F statistics, the first one assuming i.i.d. errors and the second one extending the test for non i.i.d. errors. The value for both tests are higher than the Stock-Yogo weak identification test critical values, and so the null hypothesis of weak instruments is rejected. The third set of tests is related to inference, and test the significance of the endogenous regressors in the structural equation, with the null hypothesis of endogenous regressors in the structural equation being equal to zero. The tests show rejection of the null hypothesis, which means that even in the presence of weak instruments, both calorie intake and sedentary activities have a significant impact on BMI. Based on all these tests it is possible to conclude that instruments are relevant, that is, they are related to the endogenous regressors, and this relation is not weak.

The last block shows the Hansen J statistic, a test of overidentifying restrictions that tests

Table 4: Tests for underidentification and weak instruments

Underidentification	
Kleibergen-Paap rk LM	18.06
Chi-sq (3) P-value	0.0004
Weak identification	
Cragg-Donald Wald F statistic	8.376
Kleibergen-Paap Wald rk F statistic	5.127
Stock-Yogo weak ID test critical values for K1=2 and L1=4:	
10% maximal LIML size	4.72
15% maximal LIML size	3.39
20% maximal LIML size	2.99
Weak-instrument-robust inference	
Anderson-Rubin Wald test	4.69
F(4,1103) P-value	0.0009
Anderson-Rubin Wald test	18.87
Chi-sq(4) P-value	0.0008
Stock-Wright LM S statistic	15.97
Chi-sq(4) P-value	0.0031
Overidentification of all instruments	
Hansen J statistic	4.225
Chi-sq(2) P-value	0.121

Source: CHNS. 1811 individual-year observations. Tests applied to LIML estimates.

the assumption of exogeneity. The null hypothesis is that the instruments are uncorrelated with the error, that is, instruments are valid. The values confirm the validity of the instruments

4.3 Discussion

Estimates showed in Table 3 seem to be consistent and unbiased because their estimation relies on exogenous and relevant instruments. One alternative of estimation that does not rely on a proxy variable for health endowments is the use of panel models, in particular the Fixed-Effects (FE) estimator. However, FE estimates are not reliable for two reasons. First, they rely on within variation, that is relatively small in the sample. The second reason is that the need for having at least two observations for each child takes the number of observations down to 1,000, which represents a loss of 44% of observations compared to LIML estimation. This second issue is also present in any estimator that relies on lags of BMI as a proxy for health endowments, including the Random-Effects estimator.

To identify the parameters, we considered multiple candidates for instrumental variables. One of the candidates was the price of food, either at the free market (local stores) and supermarkets. The sample has missing values for supermarkets because they do not operate in small provinces. This represents an additional loss of observations, and for that reason we did not use these prices. Regarding prices at the free market, they were not relevant instruments in any specification of the model. Even though prices can explain the demand for different types of food, they do not seem to guide decisions regarding calorie intake. This happens because prices do not capture differences in calorie count. This also suggests that calorie-intensive food is not necessarily the cheapest food in many provinces. One way to go around this in future research is to estimate structural equations linking prices, demand for food, and calorie count. Even though there might be some aggregation issues, the CHNS seems to have the data for that kind of estimation.

Structural parameters shown in Table 3 are robust to the use of other proxies for health endowments related to parents' health, including household head's BMI and previous diagnosis of high blood pressure. We also checked for robustness regarding other measures of health, specifically the deviation from ideal BMI, that takes into account the cutoff values for children in Shanghai. Estimates of structural parameters are similar, and as expected, age and gender become not significant.

Our estimates have some limitations. By using a translog function, we assumed that the elasticity of transformation is constant. A way to go around that is to perform nonlinear estimation of generalized functional forms. However, adding that to the issue of endogeneity of health inputs made it impossible for us to get consistent estimates. Future waves of the CHNS will provide more observations that might provide more variation and statistical power to simultaneously estimate a nonlinear function and correct for endogeneity bias.

5 Conclusion

Overweight and obesity have become a public health issue in China. We estimate the structural parameters of the health production function for children's BMI in China. Estimation of these parameters provide valuable information for policymakers because they identify the inputs with higher impact in the production of children's health.

Estimations suggest that calorie intake is the most important input for unhealthy extra weight in children. The impact on BMI of reducing calorie intake is around three times higher than the one from reducing sedentary activities. These results imply that the most effective way to tackle children's obesity in China is through policies targeting calorie intake. Given the externality that NCDs impose on healthy people, policies should target food with high caloric density. Tests of assumptions show that the instruments we use are relevant and valid (exogenous). Comparison to OLS estimates show that not accounting for endogeneity of instruments leads to wrongly conclude that calorie intake do not matter that much for BMI and time on sedentary activities have no effect on BMI.

Further research can provide a better understanding of the effect of different policy instruments on reduction of calorie intake. Future studies should pursue structural estimation of the demand system and the relationship of the vector of foods with equivalents on caloric intake. Joint structural estimation of the health production function and the demand system allows to understand all the effects of policies such as soft drink taxes targeting calorie intake (Fletcher, Frisvold, and Tefft 2010). This is important because current literature only analyzes the effect on consumption decisions or on health, without providing a link between the economic and the health side of the problem.

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***Conflict of Interest Statement**

The authors certify that they do NOT have affiliations with or involvement in any organization with any financial or non-financial interest in the subject matter or materials discussed in this manuscript.