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Fast-food consumption and child body mass index in China

Application of an endogenous switching regression model

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Abstract: The rapid economic growth experienced within the past two decades in China highly correlates with childhood overweightness. The epidemic has become an issue of grave concern. A principal factor considered to be responsible for the epidemic in the literature is unhealthy food intake, such as fast-food consumption. This paper has found a positive impact of fast-food consumption on children's body mass index. In addition to our finding of different characteristics between children who eat fast food and those who do not, we also found that the impact of fast-food consumption on body mass index is different among the children in each of the two groups.

Keywords: child body mass index, fast-food consumption, endogenous switching regression model
JEL classification: C01, C21, I15

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1 Introduction

The childhood obesity rate is on the rise in most countries in the developed and developing world. According to the World Health Organization (2012), childhood obesity is one of the most serious public health challenges of the twenty-first century. Available data from China's national surveys on the constitution and health of schoolchildren reveals a serious problem of childhood obesity and overweightness (Wu 2006). While the rate of obesity increased four times between 1985 and 2000 within the entire population, child overweightness increased by 28 times within the same period (Ji et al. 2004). By 2008, more than one in every three children and adolescents in the country was overweight or obese (Ogden et al. 2010). This problem constitutes a global epidemic, since China has about 15 per cent of the global population of children.

The troubling phenomenon of child obesity has attracted the attention of several public health experts and researchers, who want to unearth the possible causes (see e.g. Agency for Healthcare Research and Quality 2006; Bell et al. 2002; Lee et al. 2007; Levine 2008). As the issue remains complex with no simple solution, it requires further research. For example, while the consumption of high-calorie foods, such as hamburgers and sugary drinks, is positively correlated with weight, lack of physical activities also plays a critical role.

China's economic prosperity since the 1980s, its one-child policy, and the 2–4–8 extended family structure (two parents, four grandparents, and eight great-grandparents), has led to the 'little emperor syndrome'.[1] Thus, children are frequently overfed, and usually on high calorie and sugary beverages (Jing 2000; Ong et al. 2010; Shi et al. 2005). From a physiological point of view, weight gain could simply result from an imbalance between calorie intake and energy expenditure (Abdel-Hamid 2002), and fast-food consumption has been identified as a leading cause for the alarming rise of childhood obesity.

A number of studies in China have found that children from homes with a high socio-economic status (measured by the income, occupation, and education level of parents) or those who reside in urban areas are more likely to consume high-calorie foods such as soft drinks and hamburgers (Ma 2012; Shi et al. 2005), whereas their counterparts from low socio-economic status households or those who reside in rural areas are more likely to consume traditional staples and high-calcium drinks such as milk (Ma 2012; Ong et al. 2010). Similar results have been found for western countries (see e.g. Northstone and Emmett 2005; Vereecken et al. 2005). For example, in a recent study in the United States, Currie et al. (2010) found that obesity rates increase by 52.2 per cent among ninth graders if a fast-food restaurant is located within 0.1 mile of a school. Also, Ma (2012) found that, all else being equal, girls in China are less likely to be obese than boys in China. With regard to energy expenditure, most children are increasingly engaging in physically docile activities such as watching television and playing computer games. As evidenced in the study by Andersen et al. (1998), children who engage in the most television viewing tend to be the most overweight.

Although a number of studies exist on the determinants of child overweightness or obesity and several related factors, such as the socio-economic status of a child's household and the physiological characteristics of a child (see e.g. Andreyeva et al. 2011; Chang and Nayga 2009;

[1] This signifies the excessive amount of attention children receive from their parents and grandparents due to the one child policy.

Murasko 2009), to the best of our knowledge, no research has been done to critically evaluate the impact of fast-food consumption on the weight of children by comparing the actual and counterfactual weights of children who patronize fast-food restaurants. Our research attempts to fill this gap by using data on fast-food consumption among children in China. The study uses an endogenous switching regression model to investigate two groups of children in China: (i) those who patronize fast food and (ii) those who do not. While we recognize that, as noted in earlier studies (see e.g. Jing 2000), it is the parents who indulge their children with fast food, we surmise that the decision to eat the fast food or not rests with the children. We do not delve into the intricacies of these complex decision-making processes, but rather take into consideration whether or not the child eats fast food. Our emphasis is therefore on the results of those choices but not the choice itself.

Our empirical results support the hypothesis that fast-food consumption has a positive impact on body mass index (BMI) of children in China. We found that children who eat fast food are from wealthier households, live in urban areas, and/or have parents who have relatively higher formal education. They also tend to have older fathers or mothers who have relatively lower BMIs. Among those who eat the fast food, boys and children whose mothers are not engaged in primary production activities such as fishing, farming, and hunting tend to have a higher risk of being overweight and obese.

The remainder of this paper is organized as follows: the econometric model is introduced in Section 2 and Section 3 describes the data; the empirical models and results are presented in Section 4; and Section 5 concludes the paper.

2 The econometric model

In order to determine the counterfactual BMI of children who eat fast food (i.e. fast-food eaters (FFE) and non-fast-food eaters (NFFE)), we use an endogenous switching regression model of fast-food-eating decision. The model uses a probit model in a first stage to determine the relationship between the decision to eat fast food and possible determinants of BMI. The second-stage regression estimates the determinants of BMI for FFE and NFFE conditional on specific criterion function. To clarify the method, consider a situation where a parent may consider whether or not to buy their child fast food. Let $\mathrm{A}_i^* > 0$ be a latent variable representing a composite index of the satisfaction from eating fast food. We specify the probit model of the decision to eat the fast food as:

$$A_i^* = \mathrm{Z}_i\alpha + \eta_i \text{ with } A_i = \begin{cases} 1 & \textit{if} \quad \mathrm{A}_i^* > 0 \\ 0 & \textit{otherwise,} \end{cases} \tag{1}$$

where Z_i is a vector of factors influencing the decision to eat fast food; α is a vector of unknown parameters; and η is an error term with a mean of zero and a variance of σ_η^2. Probit maximum likelihood estimation is used to estimate the parameters of Equation (1). The decision of whether or not to eat fast food impacts the BMI of the child. Let the child's BMI function be y=f(X), where y is BMI and X is a vector of possible factors that determines a child's BMI. To estimate a separate regression function for each of the two situations, we specify the following BMI functions:

$$\text{Regime 1 } (FFE): \mathrm{y}_{1i} = \mathrm{X}_{1i}\beta_1 + \varepsilon_{1i} \quad if \;\; A_i = 1 \tag{2a}$$

$$\text{Regime 2 } (NFFE): \mathrm{y}_{2i} = \mathrm{X}_{2i}\beta_2 + \varepsilon_{2i} \quad if \;\; A_i = 0 \, , \tag{2b}$$

where y_{1i} and y_{2i} are the BMI of *FFE* and *NFFE*, respectively, and β is the vector of parameters to be estimated. The error terms in Equations (1), (2a), and (2b) are assumed to have a trivariate normal distribution with zero mean and covariant matrix Σ (i.e. (η, ε_1, ε_2) : $N(0, \Sigma)$), with:

$$\Sigma = \begin{bmatrix} \sigma_\eta^2 & \sigma_{\eta 1} & \sigma_{\eta 2} \\ \sigma_{1\eta} & \sigma_1^2 & . \\ \sigma_{2\eta} & . & \sigma_2^2 \end{bmatrix},$$

where σ_η^2 is the variance of the error term in the selection equation (1), which can be assumed to be equal to one, since the coefficients can be estimated only up to a scale factor (Lee 1978; Maddala 1983). σ_1^2 and σ_2^2 are the variances of the error terms in the BMI functions (2a) and (2b); $\sigma_{1\eta}$ represents the covariance of η_i and ε_{1i} and $\sigma_{2\eta}$ is the covariance of η_i and ε_{2i}. Note that y_{1i} and y_{2i} are not observed simultaneously, which implies that the covariance between ε_{1i} and ε_{2i} is not defined, and they are therefore indicated as dots in the covariance matrix. Since the error term of the selection equation (1) is correlated with the error terms of the BMI functions (2a) and (2b), the expected values of ε_{1i} and ε_{2i} conditional on the sample selection are non-zero and are defined as:

$$E\left[\varepsilon_{1i} \middle| A_i = 1\right] = \sigma_{1\eta} \frac{\phi(Z_i\alpha)}{\Phi(Z_i\alpha)} = \sigma_{1\eta}\lambda_{1i}, \tag{3a}$$

$$E\left[\varepsilon_{2i} \middle| A_i = 0\right] = \sigma_{2\eta} \frac{\phi(Z_i\alpha)}{1-\Phi(Z_i\alpha)} = \sigma_{2\eta}\lambda_{2i}, \tag{3b}$$

where $\phi(.)$ and $\Phi(.)$ are the standard normal probability density function and normal cumulative density function, respectively; $\lambda_{1i}=\phi(Z_i\alpha)/\Phi(Z_i\alpha)$ and $\lambda_{2i}=\phi(Z_i\alpha)/1-\Phi(Z_i\alpha)$. It is noteworthy that if the estimated covariances $\hat{\sigma}_{1\eta}$ and $\hat{\sigma}_{2\eta}$ are statistically significant, then the decision to eat and the BMI are correlated. This implies evidence of endogenous switching, and the null hypothesis of the absence of sample selectivity bias is rejected.

A more efficient method of estimating endogenous switching regression models is the full-information maximum-likelihood (FIML) method (Greene 2000; Lokshin and Sajaia 2004). Given the previous assumptions regarding the distribution of the error terms, the logarithmic likelihood function is:

$$\mathrm{In}L_i = \sum_{i=1}^{N} \left\{ A_i \left[\mathrm{In}\phi\left(\frac{\varepsilon_{1i}}{\sigma_1}\right) - \mathrm{In}\sigma_1 + \mathrm{In}\Phi\left(\theta_{1i}\right) \right] + (1-A_i) \left[\mathrm{In}\phi\left(\frac{\varepsilon_{2i}}{\sigma_2}\right) - \mathrm{In}\sigma_2 + \mathrm{In}(1-\Phi(\theta_{2i})) \right] \right\} \tag{4}$$

where $\theta_{ji}=Z_i\alpha+\rho_j\varepsilon_{ji}/\sqrt{1-\rho_j^2}\times ½$, with j=1,2; and ρ_j denotes the correlation coefficient between the error term η_i of the selection equation (1) and the error term ε_{ji} of the BMI functions (2a) and (2b), respectively.

2.1 Conditional expectations, treatment, and heterogeneity effects

The endogenous switching regression model can be used to compare observed and counterfactual BMIs. Thus, we can compare the expected BMI of a child who eats fast food (i.e. Case (a)) with the BMI of a child who does not eat fast food (i.e. Case (b)). Then, to investigate the expected BMI in the counterfactual hypothetical cases, we can compare the expected BMI of the child who usually eats fast food but does not eat it in the hypothetical case (i.e. Case (c)) with that of the child who usually does not eat fast food but eats it in the hypothetical case (Case (d)). The conditional expectations of the BMI in the four cases are presented in Table 1 and defined as follows:

$$E(y_{1i}|A_i=1)=X_{1i}\beta_1+\sigma_{1\eta}\lambda_{1i} \tag{5a}$$

$$E(y_{2i}|A_i=0)=X_{2i}\beta_2+\sigma_{2\eta}\lambda_{2i} \tag{5b}$$

$$E(y_{2i}|A_i=1)=X_{1i}\beta_2+\sigma_{2\eta}\lambda_{1i} \tag{5c}$$

$$E(y_{1i}|A_i=0)=X_{2i}\beta_1+\sigma_{1\eta}\lambda_{2i} \tag{5d}$$

Cases (a) and (b) in Table 1 represent the actual expectations observed in the sample, and cases (c) and (d) represent the counterfactual expected outcomes.

Table 1: Conditional expectations, treatment, and heterogeneity

Subsamples	Decision stage		Treatment effects
	To eat	Not to eat	
Fast-food eaters	(a) $E(y_{1i} \mid A_i=1)$	(c) $E(y_{2i} \mid A_i=1)$	TT
Non-fast-food eaters	(d) $E(y_{1i} \mid A_i=0)$	(b) $E(y_{2i} \mid A_i=0)$	TU
Heterogeneity effects	BH_1	BH_2	TH

Note: (a) and (b) represent observed expected body mass index (BMI); (c) and (d) represent counterfactual BMI.

A_i = 1 if the child eats fast food; A_i = 0 if the child does not eat fast food.

y_{1i} = BMI of the child, if the child eats fast food; y_{2i} = BMI of the child, if the child does not eat fast food.

TT represents the effect of the treatment (eating fast food) on the treated group (children who eat fast food); TU represents the effect of the treatment (eating fast food) on the untreated group (children who do not eat fast food); BH_1 and BH_2 are the effect of base heterogeneity for children who eat fast food (i=1) and those who do not eat fast food (i=2), respectively; TH = (TT–TU), which represents transitional heterogeneity.

Source: Authors' illustration.

In addition, following Heckman et al. (2001) and Di Falco et al. (2011) among others, we calculate the following effects:

$$TT=E(y_{1i}|A_i=1)-E(y_{2i}|A_i=1)=X_{1i}(\beta_1-\beta_2)+(\sigma_{1\eta}-\sigma_{2\eta})\lambda_{1i} \tag{6a}$$

$$TU=E(y_{1i}|A_i=0)-E(y_{2i}|A_i=0)=X_{2i}(\beta_1-\beta_2)+(\sigma_{1\eta}-\sigma_{2\eta})\lambda_{2i.} \tag{6b}$$

$$BH_1 = E(y_{1i}|A_i = 1) - E(y_{1i}|A_i = 0) = (X_{1i} - X_{2i})\beta_{1i} + \sigma_{1\eta}(\lambda_{1i} - \lambda_{2i}) \quad (6c)$$

$$BH_2 = E(y_{2i}|A_i = 1) - E(y_{2i}|A_i = 0) = (X_{1i} - X_{2i})\beta_{2i} + \sigma_{2\eta}(\lambda_{1i} - \lambda_{2i}) \quad (6d)$$

Conditions in Equations (6a)–(6d) can be described as follows:

(1) The treatment 'eating fast food' on violation (*TT*) is the difference between (a) and (c), which is given by Equation (6a).

(2) The effect of the treatment on non-eaters of fast food (*TU*) (i.e. children who do not eat fast food) is the difference between (d) and (b), which is given by Equation (6b).

(3) The effect of heterogeneity of fast-food eaters is the difference between (a) and (d).

(4) The effect of base heterogeneity (*BH*) of children who do not eat fast food is the difference between (a) and (d).

(5) The transitional heterogeneity (*TH*) is obtained by the difference between *TT* and *TU*.

Thus, we seek to determine whether the effect of eating fast food is smaller or larger for children who actually eat fast food and those who do not eat fast food relative to their counterfactual cases.

3 Data description

The data for the paper is extracted from the China Health and Nutrition Survey (CHNS) conducted in 2006. The CHNS is a nationally represented survey conducted by the Carolina Population Center and the National Institute of Nutrition and Food Safety at the Chinese Center for Disease Control and Prevention. The issues considered include health, nutrition, and family planning. The data was collected through face-to-face interview. The sample used for this paper includes children up to the age of 18 years.

From the data set, the variables of interest include: the BMI of a child and that of his/her mother; whether the child eats fast food; the gender of the child; years of education of the child (which is a proxy for the child's age); the child's current school attendance; location of the child's residence (urban or rural); the child's television viewing preference; the household income; the mother's years of formal education; whether the father has high blood pressure; the parents' ages; the father's residence (whether in the same household as the child); and whether the mother's occupation is in primary production. The descriptive statistics of the variables is presented in Table 2.

Table 2: Descriptive statistics of variables used for the regressions

Variable	Total sample		Fast-food eaters		Non-fast-food eaters	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Body mass index (BMI) of child (continuous)	18.09	4.88	19.25	4.922	17.72	4.204
Male child (1/0)	0.538	0.50	0.490	0.50	0.52	0.50
Years of education of child (continuous)	5.597	3.231	6.071	3.498	5.471	3.084
Currently in school (1/0)	0.916	0.278	0.948	0.223	0.916	0.277
Urban dweller (1/0)	0.280	0.449	0.671	0.471	0.223	0.416
Likes watching TV (1/0)	0.302	0.459	0.433	0.497	0.413	0.493
Mother's BMI (continuous)	23.086	5.848	22.762	3.800	23.507	7.439
Household income (continuous)	1643.26	6507.85	3721.24	12,795.33	1199.03	4194.74
Mother's years of formal education (continuous)	8.355	3.546	10.246	3.299	7.715	3.384
Father's years of formal education (continuous)	9.281	3.149	10.895	3.063	8.620	3.041
Father has high blood pressure (1/0)	0.017	0.130	0.029	0.167	0.018	0.135
Father's age (continuous)	37.340	6.085	40.267	6.314	39.091	5.717
Mother's age (continuous)	35.724	6.467	37.873	5.498	37.790	5.334
Father lives in same house (1/0)	0.878	0.327	0.929	0.258	0.895	0.307
Mother in primary production (i.e. fishing, farming, hunting) (1/0)	0.324	0.468	0.090	0.288	0.410	0.492

Source: China Health and Nutrition Survey (2006).

First, the mean BMI of both groups of children (i.e. those who eat the fast food and those who do not eat it) is 18.09. Comparing the two groups, the mean of those who eat it is slightly higher than that of their counterparts. Second, the proportion of boys in the total sample is 0.53. However, there are more girls among fast-food eaters and fewer girls among their counterparts who do not eat fast food. Third, only less than one per cent of the children are not currently in school and the mean years of education is about six. Furthermore, 30 per cent of all the children like watching television. However, among those who eat fast food, 43 per cent like watching television whereas only 41 per cent among their counterparts like doing so. Finally, a high proportion of the households (around 90 per cent) have both parents in the household, with the proportion being higher for children who patronize fast food than for those who do not. Although the number of observation for each variable exceeds 1,000, due to missing observations across variables, the number of complete observations used for the actual estimation is slightly below 700.

4 Empirical model and results

4.1 The empirical model

The empirical equations to be estimated are a probit regression of the decision to eat fast food or not and a regression equation of the determinants of the BMI of the children. The decision (selection) equation, which is equivalent to Equation (1), is specified as:

$$EFF = f\left(\mathbf{A}\right), \tag{7}$$

The dependent variable is binary, taking the value of one if the child eats fast food and zero otherwise. The vector of explanatory variables (**A**) includes the gender of the child, years of education of the child, whether the child is currently in school, whether the child lives in an urban or rural area, whether the child likes watching television, mother's BMI, household income, mother's years of formal education, whether the father has high blood pressure, father's age, mother's age, and whether the father lives in the same household.

The separate BMI function for eaters and non-eaters of fast food, similar to Equation (2), is as follows:

$$\ln(BMI) = g\left(\mathbf{A}_1, \mathbf{Z}\right), \tag{8}$$

where ln is a notation for natural logarithm; $\mathbf{A}_1$ includes all variables in vector **A** except father's years of formal education; and vector **Z** includes additional variables such as whether the father lives in the same household and whether the mother is engaged in primary production activities such as fishing, farming, and hunting.

4.2 Results

Estimated results for the endogenous switching regressions are given in Table 3. The estimations were implemented in STATA using the *movestay* command (Lokshin and Sajaia 2004). The result of the likelihood ratio test reported in Table 3 rejects, at a significance level of one per cent, the hypothesis that the three equations are jointly independent. In addition, the correlation term ρ_i in one equation is negative and statistically significant at one per cent, indicating a failure to reject the hypothesis of sample selection bias. The parameter has a negative sign in the equation for fast-food eaters, implying that children who eat fast food have a significantly higher BMI than a child randomly selected from the sample. In contrast, the parameter was not significant in the equation for non-fast-food eaters, indicating that children who do not eat fast food do not have a higher or lower BMI than a child randomly selected from the sample.

Table 3: Full-information maximum-likelihood estimate of the switching regression

Model (dependent variable)	Logit (eat fast food) (1/0)	Endogenous switching regression	
		Fast-food eaters (Log(BMI))	Non-fast-food eaters (Log(BMI))
Male children	-0.018 (0.117)	0.078 (0.034)**	0.008 (0.019)
Years of education of child	-0.001 (0.026)	0.0178 (0.007) ***	0.202 (0.004)***
Currently in school	-0.017 (0.225)	-0.0226 (0.056)	-0.046 (0.026)*
Urban dweller	0.991 (0.134)***	0.008 (0.051)	-0.077 (0.030)***
Likes watching TV	0.0005 (0.163)	-0.005 (0.040)	0.0183 (0.025)
Mother's BMI	-0.0135 (0.007)*	0.005 (0.004)	0.0046 (0.0026)*
Household income in Chinese Yuan (1000.00)	0.197 (0.067)***	0.004 (0.0123)	-0.038 (0.020)*
Mother's years of formal education	0.055 (0.021)***	0.0004 (0.006)	0.0048 (0.0034)
Father's years of formal education	0.077 (0.230)***	—	—
Father has high blood pressure	-0.300 (0.416)	0.007 (0.0719)	-0.0046 (0.0710)
Father's age	0.034 (0.019)*	-0.007 (0.005)	0.006 (0.0036)*
Mother's age	-0.029 (0.023)	0.001 (0.006)	-0.0062 (0.0030)**
Father lives in same house	—		-0.069 (0.0266)***
Mother is in primary production	—	-0.107 (0.049)**	-0.010 (0.018)
Constant	-2.270 (0.687)***	2.936 (0.211)***	2.697 (0.113)***
σ_i	—	0.214*** (0.015)	0.208*** (0.020)
ρ_i	—	-0.782*** (0.082)	-0.041 (0.257)

Note: Likelihood ratio test of independent equations: $\chi^2(2) = 24.31$; probability > $\chi^2 = 0.0000$. ***, **, * depict significance at 1%, 5%, and 10%, respectively.

Source: Authors' estimates from sample observations.

In the selection (i.e. logit/probit) regression, the probability of eating fast food depends on whether a child lives in an urban or rural area, the mother's BMI, household income, the father's or mother's years of formal education, and the father's age. Except the father's age and the mother's BMI, both of which are significant at ten per cent, all these variables are highly significant at one per cent. First, the computed average partial effects indicate, in general, that the probability of a child eating fast food increases by 0.3 if the child lives in an urban area. Second, a child whose mother has a relatively high BMI is less likely (albeit weakly) to patronize fast-food restaurants. Indeed, one percentage increase in a child's mother's BMI lowers the probability of eating fast food by 0.003. Third, children from relatively well-off homes are more likely to eat fast food. A percentage increase in household income increases the probability of eating fast food by 0.05. Fourth, the years of formal education of both parents increases the probability of the child eating fast food.[2] The corresponding elasticity is approximately 0.02 for each of the parents. Finally, the

[2] A popular Chinese poem from the Song Dynasty stipulates that 'In the book, there is a lot of food, a house made of gold, and a pretty girl.' By implication, schooling could make it possible for the people of China to climb the social ladder. China is a patriarchal society; hence, we surmise that a father's education may influence the decision to eat fast food. This is consistent with the findings of Ong et al. (2010) that children who are cared for by their fathers consumed less healthy food more frequently than their counterparts who are cared for by their mothers or grandparents.

older the father, the more likely the child will eat fast food. Specifically, on average, the probability of a child eating fast food increases by 0.008 if the father's age increases by one per cent.

With regard to the determinants of BMI among children who eat fast food, we found that boys weigh more than girls; a child's years of education positively correlates with BMI; and mothers employed in primary production have children with lower BMIs. Specifically, on average, boys have 0.04 per cent higher BMI than girls; a percentage increase in a child's education increases the BMI, on average, by 0.11 per cent; and children whose mothers perform primary production activities such as fishing, farming, and hunting have 0.01 per cent lower BMI. This finding is interesting and underpins the fact that mothers are likely to engage their children in primary production activities and this is likely to reduce their BMI. This indicates that engagement in physical activities could reduce the BMI of children who eat fast food.

Among the children who do not eat fast food, years of education and fathers' age positively correlate with their BMI; BMI decreases if a child is currently in school, dwells in an urban area, comes from a well-off household, has a mother who is relatively older, and a father in the same household. The computed elasticities show BMI will increase by 1.11 and 0.24 per cent, respectively, if the child's years of education or father's age increases by 1 per cent. A child who is in school has a 0.04 per cent lower BMI than his/her counterparts who are not currently in school. Children in urban areas or who have their father living in the same house have 0.017 and 0.062 per cent lower BMI, respectively, than their counterparts. Furthermore, while increasing household income by 1 per cent decreases the child's BMI by 0.005 per cent, the BMI decreases by 0.23 per cent if the mother's age is 1 per cent higher.

Table 4 indicates that eating fast food increases BMI among eaters of fast food, and, if those who do not currently eat fast food were to eat it, their BMI would increase as well. Specifically, the average BMI of a typical child who eats fast food is 19.24, but would be lower (18.61) if the child did not eat the fast food. On the other hand, for a typical child who does not eat fast food, eating it would increase his/her BMI by 3.88 per cent. This implies that children who do not currently eat fast food would gain a higher percentage of weight if they were to eat it, compared to the weight gained by their counterparts who currently eat fast food.

Table 4: Conditional expectations, treatment, and heterogeneity

Sub-samples	Decision stage		Treatment effects
	Eating	Not eating	
Fast-food eaters	(a) 19.2448	(c) 18.6108	TT = 0.634
Non-fast-food eaters	(d) 17.7338	(b) 13.8545	TU = 3.8793
Heterogeneity effects	BH_1 = 1.511	BH_2 = 4.7563	TH = -3.2453

Source: Authors' estimates from sample observations.

5 Conclusion

This paper, which sought to investigate the impact of fast-food consumption on the BMI of children in China, has unearthed some interesting results with far-reaching policy implications. First, the results support the hypothesis that fast-food consumption has a positive impact on the BMI of children in China. Children who eat fast food are from wealthier households, live in urban areas, have parents who have relatively higher formal education or older fathers, or have mothers

who have relatively lower BMIs. In order to discourage these children from consuming such foods, public policies must target urban households with educated parents who are relatively better off. Policies must also be directed at boys who eat fast food, and at mothers who are not engaged in primary production activities such as fishing, farming, and hunting which engage children in physical activities that could reduce their weight. Finally, we found that children who self-select to eat fast food have higher BMIs than a child selected at random, and those who refrain from consuming such foods have BMIs that are no different from that of a child selected at random.

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