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Estimating the effect of screen time on children's obesity using a structural model in South Korea

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1 Introduction

Obesity in children and youth is one of the biggest health concerns that pose threats to public health in the United States, South Korea, and in other developed countries. Growing evidence suggests that the obesity or overweight in childhood results in severe long-term health consequences on mortality and morbidity(Hales et al. (2002)). Others found that there exists a substantial linkage between children obesity and adulthood obesity such that 55% of total obese children remain obese when they are over age 30 (Dietz (1998)). Identifying the leading causes of childhood obesity and best intervention policy is essential, given the large amounts of social/health cost associated with obesity.

Substantial amount of studies have investigated the correlation between screen time and children's obesity, and in most cases, a positive and significant correlation has been found. However, theoretically, screen time can either increase or decrease children's obesity rates. The most widely discussed channel so far is that screen time can make children's lifestyles sedentary, and reduce the time they spend in physical activity, which can lead to obesity by reducing energy expenditure. However, there may be other directional influences because the home environments related to children's screen time are very complex and diversely connected. For example, one of the well-established results on children's obesity is that children of parents with higher income and educational background are less likely to be obese. However, in the case of working moms, they may show their children more screen time. This is because they may have less time and energy than stay-at-home moms who juggle work and parenting. However, they are more likely to earn more income and have more educational attainment than stay-at-home moms, which shows that there is not a

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simple causal relationship between mom's income, working hours, and child's screen time and obesity.

Most prior studies have used linear regression to reduce bias by including as many control variables as possible in the model. However, if we try to estimate the magnitude and even the direction of the correlation by using a simple reduced-form approach to such a diverse and complex causal relationship, there is a possibility that we will estimate the effect incorrectly. Additionally, it is impossible to be free from the problem of reverse causality. Too much screen time can lead to sedentary behavior in children, which can make them obese. However, on the other hand, obese children may also avoid vigorous physical activities and pursue sedentary behavior. This reverse causality also prevents us from accurately estimating the impact of screen time on children's obesity.

To address these issues, Oh (2022) adopts a structural approach to model the underlying dynamics and capture the accurate causal relationship. In her work, she tries to isolate and estimate the impact of screen time on children's obesity by modeling the mother's labor supply, time spent at home, and the children's decisions on screen time. In this paper, the children's screen time is implicitly considered as the mother's leisure time, and the mother gains utility from her child's health. Therefore, this paper sees the children's screen time as the optimization result of the mother's classical labor-leisure choice model. The advantage of this structural model is that it can appropriately incorporate meaningful cofactors into the model because it has an underlying theoretical background.

On the other hand, it is important to note that the meaning of showing screen devices to children varies by country, culture, and era. In some cultures, there is a more positive attitude towards showing videos to children, and they are more actively used in children's education. Additionally, in some countries or regions, the low coverage of the internet can lead to less use of screen devices in child rearing. In general, the amount of time spent enjoying these contents can vary depending on the development of technology and the amount of accumulated content (games, apps, videos). Therefore, if we compare how screen time differs between countries and its impact on children's obesity, we can obtain significant political implications.

This paper adopts the concept of modeling in Oh(2022) and assumes that children's screen time is derived from the mother's optimization problem. In addition, while Oh(2022) used American data, this study uses Korean data to estimate the impact of screen time on obesity in Korean children and compare it to the estimates in the United States. South Korea is one of the countries with the most developed internet technology and fast internet speed in the world, but it is also one of the countries with the lowest obesity rates among children. Therefore, comparing the impact of screen time on obesity between the two countries will

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provide meaningful insights.

Although not completely identical, this study is designed in parallel with Oh(2022)'s model set-up and survey question to make it easier to compare the two results. The differences between the two studies due to computational burden and data collection limitations are described in the model and data sections.

This study, through a simulation experiment, found that if children watch TV, smartphones, or tablets for an additional hour a day, their obesity rate will increase by 1.7 percentage points, from 20.4% to 22.1%. This result is slightly lower than the research results of Oh(2022), which was conducted on children in the United States. This difference may be due to the difference between the present study, which uses cross-section data, and the study of Oh(2022), which uses panel data to estimate a dynamic model. Additionally, differences can be found in the target countries of the studies. Based on similar age groups, American children already have more screen time than Korean children and have higher obesity rates. Therefore, if the relationship between screen time and children's obesity is increasing and concave-up, the marginal effect of an additional one hour of screen time may be smaller for American children than for Korean children.

This study contributes to studies that studies the effects of screen time in children in Korea on their obesity. Especially, this is the first study that model the screen time of the children as the optimized behavior derived from the mother's labor-leisure choice model amount those studies.

This study is organized as follows. Chapter 2 introduces the mathematical model used in this study. Chapter 3 describes the data and estimation method used to estimate the model, and Chapter 4 discusses the results. Finally, Chapter 5 discusses the conclusion, limitations, and future possibilities of this study.

2 Model

To assess the impact of children's screen time on their weight and obesity, I follow the model set-up in Oh(2022) and model the problem as follows: The decision maker is the mother, and she uses her given financial and temporal resources to work(ℓ), prepare food for the children(n), or show them screens(x). Here, the mother's leisure time is assumed to be proportional to children's screen time. The children's health (obesity) can be viewed as a household production, which is determined by inputs such as how healthy food the mother prepares for them and how much screen time she allows. The mother derives utility from this. This is a similar set up as the household production theory model by Becker(1996).

This model represents the trade-off that mothers face between supplying labor to the market and taking care of children. Mothers can earn income that can be used to purchase healthy food and other health-related resources for their children by working. On the other hand, working means that they have less time to take care of their children and to relax, so they may not have enough time to prepare healthy meals and supervise their children's physical activities, which could lead to a deterioration in the children's health.

Formally, the mother i maximize her utility constrained by a budget constraint, and a time constraint and given as:

$$\begin{aligned} \max_j U_{ij} = U(x_i, n_i, \ell_i | R_i) + \epsilon_{ij} = \overline{U} + \epsilon_{ij} \quad j = 0, 1, \ldots, J \\ \text{s.t} \quad f^m(x_i, n_i, \ell_i) = W_i \ell_i + Y_i \\ f^t(x_i, n_i, \ell_i) + \ell_i = \overline{T} \end{aligned} \tag{1}$$

Based on this maximization, she makes a discretized, collective choices on labor supply, screen time, and quality of diet she prepares for her children. Here, U_{ij} is the utility of the mother i, by choosing a choice $j = x, n, \ell$ from her choice set.

R is a vector of observable characteristics of the mother-child pair. ϵ_{ij} is an independent and identically distributed error that follows type 1 Extreme value distribution of the mother i choosing the alternative j. $f^m(\cdot)$ and $f^t(\cdot)$ are functions for total budget and time cost associated with choosing the decision $j = x, n, \ell$. W is the mother's hourly wage rate, Y is the exogenous income of the mother, and $\overline{T}$ is the total disposable time of her. I followed the notation of Oh (2023). Solving the optimization problem, we get the solution as an indirect utility function of choosing j,

$$V_{ij}(B_i, R_i, W_i, Y_i, \overline{T}; x_i = x, n_i = n, \ell_i = \ell) \tag{2}$$

The indirect utility function is a function that consists of the children's obesity, the mother's income and wage rate, exogenous income, the mother's decisions, and other observable characteristics of the mother and child. We can fully solve this structural model by assuming a functional form for utility, budget constraint, and time constraint, but this would face problems such as inaccurate parameterization, additional assumption on the behavior of the mother and her family, and heavy computational burden due to huge choice set and data point grid. Therefore, rather than fully solving the structural model, I approximated this indirect function using the 2nd-order Taylor Expansion, following the argument of Yang et al. (2009) and Bernal and Keane (2010). Because the error term is independent of the decisions of labor supply, quality of nutrition, and level of screen time, it is possible to estimate a single joint decision rule as three equations. Therefore, the approximated indirect

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utility function consists of three maternal demand functions that have a linear form for all arguments included in equation (2).

Specifically, the demand for screen time for children is

$$\begin{aligned} x_i =&\alpha_0 + \alpha_1 B_i + \alpha_2 n_i + \alpha_3 p_i + \alpha_4 f_i + \alpha_5 age + \alpha_6 age^2 + \alpha_7 age^C + \alpha_8 male + \alpha_9 father \\ &+\alpha_{10} Nsib + \alpha_{11} Nyounger + \alpha_{12} educ + \alpha_{13} condition + \alpha_{14} famincome + \alpha_{15} sleep \\ &+\alpha_{16} stress + \alpha_{17} depression + \alpha_{18} Z_i^X + \varepsilon_i^x \end{aligned} \tag{3}$$

The amount of screen time that a child engages in may be correlated with their obesity level. For example, overweight or obese children may be more likely to avoid vigorous activities and prefer sedentary activities, such as watching videos or playing games. Other factors that can affect children's screen time include the mother's opportunity cost of time(wage rate), the child's age and gender, family income, and the child's mental health. The mother's opportunity cost of time is the value of the activities that she could be doing instead of supervising her child's screen time. This is likely to be higher for mothers who are older, have more children, or have children with chronic health conditions. The child's age and gender are also likely to affect screen time. Younger children and boys are typically more likely to spend more time on screens than older children and girls. Family income is another factor that can affect screen time. Children from families with higher incomes are more likely to have access to electronic devices and may be more likely to use them for entertainment. Finally, children's mental health can also affect screen time. Children who are sleep-deprived, stressed, or depressed may be more likely to spend time on screens as a coping mechanism. The error term ε_t^x follows iid standard Normal distribution.

Next, the demand for the quality of nutrition the mother prepares for her children is specified as:

$$\begin{aligned} n_i =&\beta_0 + \beta_1 B_i + \beta_2 x_i + \beta_3 p_i + \beta_4 f_i + \beta_5 age + \beta_6 age^2 + \beta_7 age^C + \beta_8 male \\ &+\beta_9 father + \beta_{10} Nsib + \beta_{11} Nyounger + \beta_{12} educ + \beta_{13} condition \\ &+\beta_{14} famincome + \beta_{15} Z_i^N + \epsilon_i^n \end{aligned} \tag{4}$$

where Z_i^n is the vector of exogenous, identifying variables. The quality of a meal depends on the amount of time that a mother spends cooking and grocery shopping. The more time that a mother spends on these tasks, the higher the quality of the meal is likely to be. However, the mother's opportunity cost of time also plays a role. This is the value of the activities that the mother could be doing instead of cooking and grocery shopping. Mothers with higher opportunity costs of time are less likely to spend a lot of time on these tasks,

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which could lead to lower quality meals. The number of children and the number of younger siblings can also affect the quality of meals. Mothers with more children may have less time to cook and grocery shop, which could lead to lower quality meals. However, mothers with more children may also be more motivated to provide them with nutritious meals, which could lead to higher quality meals. Similarly, mothers with more younger siblings may have to spend more time cooking and grocery shopping, which could lead to lower quality meals. However, they may also be more motivated to provide their younger children with nutritious meals, which could lead to higher quality meals. The error term is assumed to be *iid* and follows standard Normal distribution.

The last decision is the mother's labor supply. She could work full-time, part-time, or not working. The multinomial-logit probability of working full-time and part-time compared, to not working is that:

$$\begin{aligned}\ln\left[\frac{Pr(\ell_i=\ell)}{Pr(\ell_i=0)}\right] =&\delta_0^\ell+\delta_1^\ell B_i+\delta_2^\ell x_i+\delta_3^\ell n_i+\delta_4^\ell E_i+\delta_5^\ell age+\delta_6^\ell age^2+\delta_7^\ell age^C+\delta_8^\ell gender\\ &+\delta_9^\ell father+\delta_{10}^\ell Nsib+\delta_{11}^\ell Nyounger+\delta_{12}^\ell educ+\delta_{13}^\ell condition\\ &+\delta_{14}^\ell famincome \quad \ell=1,2\end{aligned} \tag{5}$$

A mother's decision about whether or not to work is influenced by a number of factors, including her opportunity costs of time, family income, cumulative work experience, screen time and nutrition of her child, and the presence of a father in the household. The opportunity costs of time are the value of the activities that a mother could be doing instead of working. Mothers with higher opportunity costs of time are less likely to work, because they would be giving up more valuable activities by doing so. Family income is another important factor. Mothers from families with higher incomes are more likely to be able to afford to stay home with their children, even if they have high opportunity costs of time. Cumulative work experience can also affect a mother's decision to work. Mothers with more work experience may be more likely to want to continue working, even if they have young children. This is because they may have developed a career that they enjoy and that they are good at. The screen time and nutrition of her child can also affect a mother's decision to work. Mothers who are concerned about their child's screen time or nutrition may be more likely to stay home with their children, in order to monitor their activities and ensure that they are getting the right amount of exercise and healthy food. The presence of a father in the household can also affect a mother's decision to work. Mothers with partners who are able to provide financial support and help with childcare are more likely to be able to work. However, mothers with partners who are not able to provide as much support may be more

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likely to stay home with their children. Finally, the obesity status and obese-related chronic health condition of her child can also affect a mother's decision to work. Mothers who are concerned about their child's health may be more likely to stay home with their children, in order to monitor their health and ensure that they are getting the care they need.

Simultaneously with these decisions, the obesity status, is determined such that the logit probability of the child getting overweight or obese in log odd is:

$$\begin{aligned}\ln\left[\frac{Pr(B_i=1)}{Pr(B_i=0)}\right] =& \beta_0+\beta_1 x_i+\beta_2 n_i+\beta_3 p_i+\beta_4 f_i+\beta_5 maler+\beta_6 age^C+\beta_7 famincome\\ &+\beta_8 father+\beta_9 Nsib+\beta_{10} educ+\beta_{11} condition+\beta_{12} stress\\ &+\beta_{13} depression+\beta_{14} sleep+\beta_{15} breastfeed+\beta_{16} Z_i^B\end{aligned} \tag{6}$$

Here, B_i is the binary variable where overweight or obesity equals 1, and 0 otherwise. Demographic factors of the child and family environment, such as age, gender, race, family income, presence of a biological father in the household, and whether the child has obesity-related chronic health conditions, are also controlled for in the analysis. As mentioned earlier, correlations between sleep deprivation, breastfeeding history, and the level of stress and depression can also be captured in this specification. Z_i^B is included for the exclusion restrictions.

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The final piece of the system is the wage equation. Wage is determined by those factors that were mentioned previously which captures the opportunity cost of time of the mother, and the maternal employment history. The observed log of wage W_i is given as:

$$\begin{aligned}\ln W_i =& \alpha_0+\alpha_1 f_i+\alpha_2 E_i+\alpha_3 age^C+\alpha_4 age+\alpha_5 age^2+\alpha_6 Nsib+\alpha_7 Nyounger\\ &+\alpha_8 condition+\alpha_9 educ+\alpha_{10} father+\alpha_{11} Z_t^W+\varepsilon_i^w\end{aligned} \tag{7}$$

where f_u is the binary indicators for working full-time and E_i is the work experience (p_i is left- out to avoid perfect multicollinearity problem since wage is only observed for either part-time or full-time working mother). Z_i^W is exogenous variables that shifts the demand side of the labor market are included for the exclusion restriction. ε_i is assumed to be i.i.d. and follows standard normal distribution.

This study follows the model used in Oh(2022), but there are some differences. First, Oh(2022) used panel data to model dynamic decisions, but this study uses a contemporaneous model due to data limitations. Therefore, addiction of screen time, accumulation effects of energy intake and expenditure, etc. are not considered in this model. Second, unobserved heterogeneity of each mother, child, and household is not specifically modeled. This study assumes that there is no systemic correlation between mothers' decisions and children's obesity, and all errors are idiosyncratic.

3 Data and Estimation

This model requires demographic and health data, as well as time use information, on Korean mothers, children, and their families. However, most of the data on the screen device usage of Korean children only collect information about the child, and there is almost no in-depth information about the child's family, especially the child's mother's age, education level, working hours, and wages. Therefore, I designed a survey specifically for this study and collected the data directly.

The survey consisted of a total of 30 or so questions and was conducted on mothers with elementary school students who were the subjects of this study. The survey items are divided into four parts: mother's demographic and work-related information (age, education level, occupation, working status, working hours, wages, etc.), child's healthy diet information, child's screen time information, and child's physical and mental health information. The full list of survey items is attached in the appendix.

The survey was conducted on mothers of children attending 12 different elementary schools in a city in Korea from March to May and September to November 2022, for a total of about 20 days. A booth was set up near the main entrance of the elementary schools, and a piece of paper printed with a QR code that leads to an online survey was distributed to children or their guardians who visited the booth. The reason why the survey was not conducted directly with the guardians who accompanied the children is to prevent systemic bias in the sample of mothers who participate in the survey. Additionally, elementary school students often walk to school on their own without the help of a guardian, so this method was used. During the survey period, a total of 416 flyers were distributed to elementary school students (the flyer requesting participation in the survey was distributed to 198 boys and 218 girls), and 172 mothers eventually participated in the survey.

Of the 172 observations, 9 were interviewed by someone other than the biological mother of the child, so they were dropped from the sample. 8 mothers did not respond or did not know their child's weight and height, 13 observations did not respond or did not know their child's screen time, and 4 mothers did not respond or did not know their wages. All surveys with missing or unknown values were dropped from the sample, and 138 observations were finally used to estimate the model.

Table 1 summarizes the data for the endogenous and exogenous variables in the model. The endogenous variables are the child's obesity status, three maternal decisions, and the log of maternal wage rate. The child's obesity status is measured using Body Mass Index

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(BMI), which is a common measure of body fat. BMI is calculated by dividing weight in kilograms by height in meters squared. Children's BMI categories are different from those of adults, because children's body composition varies by age and gender. According to the CDC, overweight is defined as a BMI that is greater than the 85th percentile for age and gender, but less than the 95th percentile. Obesity is defined as a BMI that is greater than the 95th percentile for age and gender. In this study, a dichotomous variable B_i is used to indicate whether the child is overweight or obese. If the child's BMI is greater than the 85th percentile, then B_i equals 1. Otherwise, equals 0.

To measure the level of screen time, the mothers in the sample were asked to report their child's total daily screen time for typical weekdays and weekend, and then they are averaged. The quality of nutrition is measured by asking mothers a series of questions about their children's daily food intake. These questions are designed to assess whether children are eating a variety of healthy foods in the recommended amounts. The answers to these questions are converted into a nutritional index that ranges from 0 to 9, with a higher score indicating a better quality of nutrition.

The maternal labor decision is a categorical variable that measures whether the mother works for money, and if so, how many hours per week she works. Mothers who do not work for money are assigned a value of 0, mothers who work part-time are assigned a value of 1 for p_i, and mothers who work full-time are assigned a value of 1 for f_i. For part-time employees, the weekly working hours are 20 hours, and for full-time employees, the weekly working hours are 40 hours.

Many studies have shown that sleep, stress, and depression can contribute to obesity. To measure stress, researchers counted the number of negative life events that a child had experienced in the past year, such as the death of a family member, a parent's job loss, or a move to a new school. Depression was measured by a binary variable that indicated whether a child had been diagnosed with depression. Sleep was measured by a variable that equaled 1 if the child slept more than 7 hours per day. The average daily screen time for the entire sample was 5.84 hours, 5.76 hours for boys, and 5.91 hours for girls. On average, boys were more likely to be overweight or obese.

Finally, relevant exogenous variables were included in each equation for the identification purpose.

When estimating a system of equations, the endogeneity problem should be always considered. To get exogeneity of the model and estimation, theoretically relevant, exogenous variables are included in each equation. Table 2 illustrates the exclusion restriction in each equation, which are elements of $\{Z_t^B, Z_t^X, Z_t^N, Z_t^\ell\} \in Z_t$.

The child's weight at birth is a proxy for their initial health status, which can affect their

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likelihood of becoming obese later in life. The number of hours a child spends in physical activity during school also affects their risk of obesity. These two factors do not directly affect other maternal decisions or wage formation, but they do affect the child's health. Children with more social media accounts are more likely to spend more time using screen devices. However, this does not affect other maternal decisions, the child's health, or the mother's wage. From the demand side of the labor market, the national average wage is likely to be a reference point for firms when setting wages, except in extreme urban or rural markets. This is because unions and regulations can affect wages in these markets. On the supply side, even if there is a discrepancy between the local wage and the national average wage, individuals are less likely to move to a different location for a higher wage. This is because of the costs associated with relocation.

Finally, mothers who have a better understanding of nutrition and who maintain a healthy weight are more likely to provide their children with a healthy diet. Indicators that the mother or father of a child works in an occupation that is likely to be familiar with nutritional information (e.g., dietitian, nutritionist, health educator, food industry worker, or healthcare provider) were used as a proxy for this knowledge.

All the parameters in the model are estimated using Maximum Likelihood Estimator jointly. Estimation is done using software Matlab.

4 Results and Discussion

In this section, I present the results of the model estimation. Because the three maternal decisions, health production function, and wage equations are jointly estimated, it is very complex and difficult to interpret the estimated coefficients in each equation. Therefore, the effect of children's screen time on obesity can be best viewed using simulation. The parameter estimates of each equations in the joint system are presented in Appendix section B.

This simulation begins by endowing each mother-child pair sample with a set of idiosyncratic errors. These errors can be obtained by randomly drawing from the distribution that each error term was assumed to follow, as discussed in the Model section. The number of draws used in the simulation is 500. The key idea of this simulation can be illustrated using this simple Ordinary Least Squares example: if the original model is $y = \alpha + \beta x + \varepsilon$, we can estimate $\hat{\alpha}$ and $\hat{\beta}$. Conversely, if we want to simulate y, we draw the error term ε 500 times from the standard normal distribution. We use $\hat{a}$, $\hat{b}$, and the drawn error terms to retrieve 500 $y's$. Point-simulated y can then be calculated by taking the average of these 500 $y's$.

The advantage of the structural model is that once we estimate and retrieve the structural

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parameters in the model, we can impose a policy or a scenario of our interest, and this can work as a counterfactual analysis. Here, I simulate the system without imposing any behavioral change (base scenario) and then compare it with the simulated result where I add one additional hour to the daily screen time in all of the data sample (counterfactual scenario). By comparing these two scenarios, I can get the marginal effect of an additional one hour of screen time.

The result, which can be found in Table 3, show that if children spend one additional hour in front of the screen per day, the percentage of children who are either overweight or obese will increase from 20.4% to 22.1%. This is 1.7 percent point increase. This finding is consistent with previous studies that have found a positive correlation between children's screen time and obesity. For example, Cleland (2018) found that one extra hour per day of television viewing is associated with a BMI increase of 0.41 kg/m^2 among a cohort of children between the ages of 7 and 15 in Australia. Similarly, Danner (2008) found that children who watched four hours per day have a 0.42 kg/m^2 higher BMI than those who watched only one hour per day.

This is a smaller effect than the results found in Oh (2022). Considering the similarities between the models and data used in the two studies, this difference can be attributed to two main factors. First, Oh (2022) used panel data to estimate a dynamic model, while my study used cross-sectional data. Although it is a two-time period, her model also considers the contemporaneous effect of screen time. Since many studies have shown that screen usage is addictive, the effect of screen time on children's obesity may be larger than what was estimated in this study.

Second, there could be differences in the characteristics of the populations between countries. Oh (2022)'s study used data on American children aged 9 to 12 and their mothers, while this study was conducted on Korean elementary school students (6-12 years old) and their mothers. One possible explanation for the higher increase in obesity rate for US children with an additional hour of screen time is that they have higher daily screen time than Korean children. The marginal effect of one additional hour of screen time on children's obesity may not be constant for all children. It could be increasing and concave up, meaning that children who already use screen devices heavily are more likely to be obese or overweight with an additional hour of screen time. According to Korea Creative Content Agency, "2022 Game User Survey" and US Near Media Research, "2022 US Game User Trend Report", American elementary school students play games for an average of 6.5 hours per day, while Korean elementary school students play for an average of 5.5 hours per day. There are several factors that can explain this difference. In the United States, games are more commonly encountered in everyday life due to cultural background. Additionally, American elementary schools have fewer extracurricular activities than Korean elementary schools, so children often spend their free time playing games.

The amount of screen time that children have can also affect other decisions that mothers make, such as their food choices and whether they work full-time. For example, if a child is allowed to have one additional hour of screen time per day, the percentage of mothers who work full-time increases from 46.0% to 47.8%. Additionally, the quality of the child's diet decreases, as measured by the nutrition index score, which falls from 5.87 to 5.487. This suggests that mothers who allow their children to have more screen time may be more likely to work full-time, which leaves them with less time to prepare healthy meals for their children. This finding is consistent with the research of Cawley (2012), who found that an increase in maternal labor supply is associated with less time for preparing home-cooked meals and less time spent with children.

5 Conclusion

Obesity in children is a major public health concern. There is a strong correlation between screen time and obesity in children, but the causal relationship is complex and not fully understood. Most studies have used linear regression to estimate the impact of screen time on obesity, but this approach can be biased. Additionally, it is difficult to control for all of the factors that may influence the relationship between screen time and obesity.

This research proposes a theoretical framework to investigate the relationship between children's screen time exposure and their obesity as a resource allocation problem for their mothers. The study jointly estimates a model of the mother's decision on the level of screen time for her child, the quality of nutrition, the level of labor supply for the mother, the health production function for the child's obesity, and the wage equation. A structural approach is used to model the underlying dynamics and capture the accurate causal relationship. In this approach, the mother's labor supply, time spent at home, and the children's decisions on screen time are all modeled together.

This study found that an additional hour of screen time per day is associated with a 1.7 percentage point increase in the obesity rate. This result is slightly lower than the results of a previous study that was conducted on American children.

This study contributes to the literature on the impact of screen time on obesity in children. It is the first study to model the screen time of children as the optimized behavior derived from the mother's labor-leisure choice model in South Korea.

This study illustrates the trade-off that mothers face in everyday life. A mother can participate in the labor market and earn an income, but this will reduce the amount of time

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she has to spend with her children and to supervise their screen time. On the other hand, if she chooses to stay at home, she will have more time to spend with her children and to supervise their screen time, but she will earn less income.

This study has several limitations. First, it ignores the unobserved heterogeneity that exists between each mother, child, and their family, which exists between the various decisions made by the mother and the child's health productions. Some families may be more interested in their children's obesity and education, while others may not be very concerned. This can systemically affect the mother's various decisions. Another limitation is that obesity is the result of the accumulation of energy intake and energy expenditure over a long period of time, but this study uses cross-sectional data, so such long-term effects may not have been properly captured. Finally, this study does not consider other forms of alternatives such as nanny employment or telecommuting. Future research should address these issues to improve the accuracy of the study.

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Table 1: Descriptive statistics by level of screen time of children

		Total N=138	Boy N=65	Girl N=73
Endogenous variables				
Bt	1(obese or overweight), period t	0.20	0.23	0.18
xt	daily screen time, period t	3.5	4.5	3.0
nt	nutrition quality index, period t	5.84	5.76	5.91
pt	1(work part-time), period t	0.10	0.11	0.09
ft	1(work full-time), period t	0.45	0.45	0.46
lnWt	log hourly wage(in $), period t	1.60	1.58	1.61
Exogenous variables				
age	age of mother (divided by 10)	4.15	4.01	4.22
age^2	age of mother, squared (divided by 10)	17.74	16.56	18.08
age_child	age of child	9.34	9.37	9.31
male	1(the child is male)	0.47	1.00	0.00
father	1(the child living with biological father)	0.92	0.92	0.93
Nsib	number of sibling	0.80	0.78	0.84
Nyounger	number of younger sibling	0.34	0.31	0.37
educ	years of education of mother	17.14	16.16	17.53
Et	cumulative work experience	5.2	4.97	5.34
condition	1(child have obesity-related chronic condition)	0.18	0.16	0.19
famincome	combined family total income (in $1000, yearly)	6.89	6.79	7.03
sleep	1(child sleeps more than 7 hours per day)	0.91	0.89	0.93
stress	number of bad life event happened in the past year	0.85	0.71	0.88
depression	1(child has sympton, or diagnosed to have depression)	0.11	0.09	0.15
Naccount	Number of social media account the child has	4.50	3.60	4.87
breastfeed	Duration of breastfeed (in months)	9.00	7.18	9.77
birthweight	Weight of child at the time of birth (in kg)	3.20	3.41	3.10
activity	Hours of physical activity in school	6.89	7.32	6.43
avewage	Occupation and industry specific average hourly wage (in $)	2.63	2.73	2.44
knowledge	1(parents have food or health related occupation)	0.15	0.16	0.15

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Table 2: Exclusion restrictions in the model

variable	x_t	n_t	ℓ_t	B_t	$\ln W_t$
B_t	X	X	X		
x_t		X	X	X	
n_t	X	X	X	X	
p_t	X			X	X
f_t	X			X	X
$\ln W_t$	X				
age^C	X	X	X	X	X
age	X	X	X		X
age^2	X	X	X		X
gender	X	X	X	X	
famincome	X	X	X	X	
father	X	X	X	X	X
school	X	X	X	X	
Nsib	X	X	X	X	X
Nyounger	X	X	X		X
educ	X	X	X	X	X
sleep	X			X	
condition	X	X	X	X	X
stress	X	X		X	
depression	X	X		X	
breastfeed		X		X	
Z_t^B: birthweight				X	
Z_t^B: activity				X	
Z_t^X: Naccount	X				
Z_t^N: knowledge		X			
Z_t^W: avewage					X

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Table 3: Counterfactual Simulation Results

	Obesity	screen time	quality of nutrition	part-time employment	full-time employment	log wage
Baseline						
	0.204	3.54	5.87	0.114	0.460	1.61
Additional one hour of daily screen time						
	0.221		5.487	0.116	0.478	1.61

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Appendix

A. The survey questions

Q1. What is your age?

Q2. What is your marital status
a) married b) divorced c) widowed d) others

Q3. What is your educational attainment?
a) below high school b) high school c) bachelar's degree d) above bachelar's degree

Q4. What is your child's age?

Q5. What grade is your child in?

Q6. What is the gender of your child?
a) boy b) girl

Q7. Are you currently living with your child's biological father?
a) Yes b) No

Q8. How many children do you have?

Q9. How many younger siblings does your child have?

Q10. Are you currently working?
a) Yes b) No

Q11. If yes, do you work full-time or part-time?
a) full-time b) part-time c) N/A

Q12. If you work, what is your hourly wage?

Q13. What is your occupation?

Q14. What is your combined total family income?

Q15. How many hours does your child spend using screen devices per day in a typical weekday?

Q16. How many hours does your child spend using screen devices per day in a typical weekend?

Q17. What is your child's height? (in cm)

Q18. What is your child's weight? (in kg)

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Q19. Does your child have any chronic disease related to obesity?
a) Yes b) No

Q20. If yes, what is it?

Q21. Does your child eat breakfast?
a) Yes b) No

Q22. Does your child drink soft drinks more than 3 times per week?
a) Yes b) No

Q23. Does your child eat fast food more than 3 times per week?
a) Yes b) No

Q24. Does your child eat out or eat take-out meal more than 3 times per week?
a) Yes b) No

Q25. Does your child eat vegetables six or more times per week?
a) Yes b) No

Q26. Does your child eat pastries or sweets less than 5 times per week?
a) Yes b) No

Q27. Does your child eat fish one or more times per week?
a) Yes b) No

Q28. Does your child eat red meats and meat products less more than four times per week?
a) Yes b) No

Q29. Do you use any sugar substitutes when you cook to reduce the sugar intake?
a) Yes b) No

Q30. Does your child sleep more than 7 hours per day?
a) Yes b) No

Q31. What is the number of bad life event happened in the past year?

Q32. Does your child diagnosed with or show symptom of depression?
a) Yes b) No

Q33. What is the number of social media account your child has?

Q34. What is the duration of breastfeed of your child? (in month)

Q35. What is the birth weight of your child? (in kg)

Q36. What is the hours of physical activity in school per day?

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B. Parameter Estimation Results

Table B1: Parameter Estimation Result for maternal decision

	screen time		quality of nutrition	
	Coeff.	Std.Err.	Coeff.	Std.Err.
const	1.24***	(0.004)	0.56***	(0.027)
obesity	0.47***	(0.010)	0.63***	(0.074)
screen time			-0.32***	(0.041)
quality of nutrition	0.42***	(0.001)		
part-time employment	0.36***	(0.007)	-0.29***	(0.069)
full-time employment	0.78***	(0.004)	-0.20***	(0.001)
age	1.34	(0.101)	0.08	(0.069)
age^2	0.58	(0.303)	-0.4	(0.412)
age^C	0.52***	(0.004)	0.22***	(0.031)
gender	0.45***	(0.005)	-0.46***	(0.039)
father	-0.48	(0.510)	0.43***	(0.023)
Nsib	0.35	(0.278)	-0.08***	(0.037)
Nyounger	-0.24	(0.616)	0.98	(0.983)
educ	-0.56***	(0.009)	0.58***	(0.040)
condition	-0.68	(1.425)	-0.18	(0.28)
famincome	-0.99***	(0.002)	0.8***	(0.029)
sleep	-0.44 ***	(0.005)		
stress	0.6***	(0.005)		
depression	0.86***	(0.009)		
Z_i	0.62***	(0.006)	0.73	(0.472)

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Table B2: Parameter Estimation Result for maternal decision (Cont.)

	part-time employment		full-time employment	
	Coeff.	Std.Err.	Coeff.	Std.Err.
Const	-4.41***	(0.184)	-8.15***	(0.068)
obesity	0.12	(0.185)	0.69	(0.066)
screen time	0.05***	(0.014)	0.47***	(0.031)
quality of nutrition	-0.41***	(0.015)	-0.48***	(0.005)
experience	0.99***	(0.058)	0.92***	(0.053)
age	0.43***	(0.046)	0.15***	(0.049)
age^2	-0.21	(0.141)	-0.55	(0.090)
age^C	0.26	(0.189)	0.54	(0.073)
male	0.93	(0.622)	-0.88	(0.031)
father	0.82	(0.549)	-0.92***	(0.052)
Nsib	0.13***	(0.046)	-0.84***	(0.098)
Nyounger	-0.94***	(0.028)	-0.05***	(0.086)
educ	0.43***	(0.031)	0.19***	(0.089)
condition	-0.27	(0.289)	-0.05	(0.091)
famincome	0.37***	(0.024)	0.04***	(0.067)

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Table B3: Parameter Estimation Result for Obesity

	Coeff.	Std.Err.
Const.	-0.45***	(0.087)
screen time	0.04***	(0.009)
quality of nutrition	-0.25***	(0.003)
part-time employment	-0.22***	(0.002)
full-time employment	0.46***	(0.048)
male	0.68***	(0.091)
age^C	-0.69***	(0.087)
famincome	-0.67***	(0.008)
father	-0.73***	(0.022)
Nsib	0.44***	(0.037)
educ	-0.84***	(0.087)
condition	0.62***	(0.032)
stress	0.65***	(0.067)
depression	0.35***	(0.011)
sleep	-0.25***	(0.019)
breastfeed	-0.04	(0.041)
bweight	0.27***	(0.055)
Z_i	-0.33	(0.029)

Table B4: Parameter Estimation Result for Wage

	Coeff.	Std.Err.
Const.	-3.03***	(0.072)
full-time employment	-0.8	(0.629)
experience	0.19***	(0.062)
age	0.36***	(0.009)
age^2	-0.68***	(0.093)
age^C	0.9***	(0.020)
father	0.08	(0.061)
Nsib	-0.33***	(0.047)
Nyounger	0.84	(0.797)
educ	0.76***	(0.030)
condition	0.28	(0.052)
Z_i	0.12	(0.187)

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