The effects of old and new media on children's weight*

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Abstract

Childhood obesity rates have recently been rising in many countries. It has been suggested in the literature that changes in children's media exposure may contribute to explaining this trend. I investigate whether or not this hypothesis is supported by data. I contribute to the literature by focusing not only on television, but also on new media - computers and video games. The Child Development Supplement to the Panel Study of Income Dynamics is used for the analysis. To address the endogeneity of children's media exposure, I use dynamic and panel data models. This is another improvement upon the existing literature. Additionally, an extensive list of control variables is included in the regressions. I find that video game playing or computer use has no effect on children's body weight. On the other hand, television viewing may increase children's body weight slightly.

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1 Introduction

Childhood obesity rates have recently been rising in many countries. For example, in the U.S., the proportion of obese children increased from around 5 percent in 1970s to 15 percent in late 1990s. The proportion of overweight children increased from 15 percent to 30 percent during the same period (Paxson et al., 2006). Childhood obesity has both short-term and long-term effects on health. Obesity is linked to many health problems, such as cardiovascular diseases, diabetes, asthma, and sleep disorders (Daniels, 2006). The health care costs of childhood obesity are substantial and rising. For example, in the US, the costs of treating obesity-associated illnesses in children increased from $35 million in 1979-81 to $127 million in 1997-99 (in 2001 dollars) (Daniels, 2006).

According to the literature, changes in children's media exposure may help to explain the increasing trend in children's body weight (Paxson et al., 2006). There are two reasons to believe that there may be a link between children's media exposure and body weight. First, children's media exposure has increased since the beginning of 1980s. Although children's television time has been rather stable during this period, children now also spend a substantial amount of time on video games and computers (Roberts and Foehr, 2008). Second, children have been increasing targeted by advertisements in media. These advertisements are dominated by foods that are high in calorie content, such as sugar-coated cereals, fast-food restaurants, candy, and soft drinks, (Calvert, 2008). Studies confirm that advertising has effects on children's preferences for food (Escobar-Chaves and Anderson, 2008; Andreyeva, Kelly and Harris, 2011).

To date the economics literature has only focused on the effects of television advertising on childhood obesity (Chou, Rashad and Grossman, 2008; Andreyeva, Kelly and Harris, 2011, and Grossman, Tekin and Wada, 2012). The findings of this literature suggest that there may be a positive relationship between television advertising and children's weight. The effects of video games and computers on children's body weight have not been analyzed so far. I contribute to this literature by providing evidence on the effects of both the old media (television and movies) and the new media (video games and computers) on children's body weight. As another contribution, I use more advanced methods than the other studies to address the endogeneity of media exposure. The panel nature of the data used for the analysis (The Child Development Supplement to the Panel Study of Income Dynamics) makes it possible to control not only for observed but also for unobserved confounders.

Media can affect children's body weight in two ways. First, media activities may displace other activities that require more energy, such as playing sports, exercising, or doing household chores, and reduce children's total energy expenditure. Second, exposure to media may affect children's energy intake. Media activities, especially television watching, may be accompanied by eating. Additionally, children's exposure to the advertisements of fast food, soft drinks, sugar-coated cereals, and candy may lead to higher consumption of these high-calorie foods. On the other hand, media activities, especially video game playing and computer use, can be highly engaging and, therefore, require children's full attention. As a result, children may be unwilling to do other activities, including eating, at the same time. Furthermore, thinness is often associated with positive qualities such as attractiveness and success in media and thus may encourage children, especially adolescents, to lose weight. Therefore, an increase in children's media time may increase their body weight, but not necessarily.

There are several reasons to expect differential effects of the old and new media on children's body weight. There are a few differences between the old and the new media. First, the new media are more interactive and engaging than the old media. It is unclear, however, how the interactivity of the new media affects the relationship between children's media exposure and body weight. On the one hand, the more engaging an activity is, the less likely children are to do other activities, including eating, at the same time. On the other hand, children can avoid advertisements on television by, for example, switching to other channels, whereas it is more difficult to avoid advertisements in video games and on the Internet. Second, advertising in the new media may be more effective than advertising in the old media due to less strict regulations (Calvert, 2008). Third, video game playing may be associated with higher energy expenditure than other sedentary activities, including television or movie watching, because of increased stress levels (Escobar-Chaves and Anderson, 2008). Overall, it is uncertain which type of media may have a larger effect on children's body weight.

2 Identification strategy

The potential endogeneity of children's media exposure makes the identification of the causal effects of media on body weight difficult. The first source of endogeneity is the unobserved time-invariant determinants of body weight, such as basal metabolic rate [1] or family background. For example, children with a lower basal metabolic rate may prefer sedentary media activities to physical activities. Children from lower socioeconomic status families may have both limited after-school activity options and lower-quality diets. I deal with this type of endogeneity by estimating three different models. The consistency of each of these models relies on somewhat different assumptions about the unobserved heterogeneity.

The first model is the value added (VA) model given by the following equation:

$$
\begin{aligned}
W_t &= \gamma_t W_{t-1} + Z_t' \beta_t + \delta_t \nu + e_t, \qquad (1)\\
Z_t &= (t_{tvmo,t}, t_{vgpc,t}, X_t),\\
\nu &= \xi + \mu,
\end{aligned}
$$

where t denotes a time period and child subscript is suppressed. A child's weight in the current period W_t is a function of his/her weight in the past period W_{t-1},

[1] Basal metabolic rate is the amount of energy consumed at rest.

time spent on television or movie watching $t_{tvmo,t}$, time spent on video game playing or computer activities $t_{vgpc,t}$, a vector of control variables X_t, unobserved heterogeneity ν, and the error term e_t. The unobserved heterogeneity term ν consists of time-invariant family-specific variables ξ and child-specific variables μ. By controlling for the past period weight, the VA model can take into account the potential correlation between children's media time and the unobserved heterogeneity ν. However, the consistency of the VA model estimates relies on the assumption that the effect of ν declines over time at a rate equal to the coefficient on the lagged dependent variable: $\delta_t = \gamma\delta_{t-1}$. Additionally, it is assumed that children's media time are uncorrelated with the error term e_t.

In addition to the VA model, I estimate the child and sibling fixed effects (FE) models. The child FE model is estimated using the time-demeaned variables:

$$(W_t - \overline{W}) = (Z_t - \overline{Z})'\beta + (e_t - \overline{e}), \tag{2}$$
$$Z_t = (t_{tvmo,t}, t_{vgpc,t}, X_t).$$

Therefore, the child FE model eliminates any time-invariant variables ν under the assumption that the impact of these variables is constant over time: $\delta_t = \delta_{t-1}$. The consistency of the child FE estimator relies on the strict exogeneity assumption: the explanatory variables are assumed to be uncorrelated with the unobserved time-variant factors e in the past, current, and future periods.

The differences in body weight (ΔW_t) and explanatory variables (ΔZ_t) between siblings are used to estimate the sibling FE model:

$$\Delta W_t = \Delta Z_t'\beta + \Delta\mu + \Delta e_t, \tag{3}$$
$$Z_t = (t_{tvmo,t}, t_{vgpc,t}, X_t).$$

In the siblings FE model, the unobserved family-specific variables ξ are eliminated under the assumption that these variables affect each sibling's weight in the same way $\delta_k = \delta_l$ (where k and l denote siblings). A child's media time and other explanatory variables are assumed to be uncorrelated with the unobserved own and sibling's characteristics μ and e.

Each of the three models has strengths and weaknesses. The child FE model eliminates any time-invariant unobservables, whereas the sibling FE model controls only for those time-invariant unobservables that are common to siblings. On the other hand, the sibling FE model also eliminates any time-variant family-specific unobserved variables. The strict exogeneity assumptions required for the consistency of the FE estimators are stronger than the contemporaneous exogeneity assumption required for the consistency of the VA model estimates. Furthermore, it is not possible to include the past period weight in the child and sibling FE models, because this reduces the sample size substantially. In the end, the choice of a preferred model depends on what the main source of endogeneity is and how the effect of the unobserved heterogeneity changes over time. Because the answers to these questions are not known, rather than choosing a preferred model, I present the estimates of all three models. Importantly, any of the three models has an advantage over the Ordinary Least Squares (OLS) model that does not control for the unobserved child heterogeneity at all.

In the VA and child FE models, the second source of endogeneity is the time-varying variables X_t and e_t. For example, a change in the mother's employment status may simultaneously affect a child's diet and time use. In the sibling FE model, there may be weight-related variables that vary across siblings. To control for both types of confounders, I include an extensive list of child and family characteristics in equations (1) - (3). Because changes in children's calorie intake and time spent on physical activities are the two mechanisms how media can affect body weight, these variables are not included in the models. However, the models should control for children's calorie intake that is exogenous to their media time. For this purpose, I include the parents' body weight in the models.

A change in the parents' body weight may reflect a change in the family's food choices, which is likely to affect a child's calorie intake as well.

I also investigate whether children's media time affects their overweight status. A child is overweight if his/her weight exceeds a threshold ω. The correlated child random effects (RE) probit model (also known as Mundlak's or Chamberlain's RE probit) is used to answer this question. This model has an advantage over the standard probit model, because it relaxes the assumption that there is no correlation between the explanatory variables Z_t and unobserved heterogeneity μ. Specifically, this model allows for correlation between μ and the time averages of the explanatory variables $\overline{Z}$:

$$\begin{aligned} W_t &= Z_t'\alpha + \lambda + u_t, \\ overweight &= 1 \ \ if \ \ W_t > \omega, \\ \lambda &= \psi + \overline{Z}'\pi + a, \\ a|Z &\sim Normal(0, \sigma_a^2). \end{aligned} \tag{4}$$

In the correlated RE probit model, the consistency of the coefficient estimates relies on the strict exogeneity and independence assumptions. The independence assumption requires a child's overweight status to be independent over time conditional on the explanatory variables Z and unobserved heterogeneity λ. As the focus of this analysis is to estimate the average partial effects (rather than the partial effects at the mean of λ), the independence assumption can be relaxed, as shown by Wooldridge (2010). In practice, the correlated RE probit model is estimated by including the time averages of the time-varying variables Z_t as regressors in the pooled probit model (Wooldridge, 2010). In addition, I present estimates of the correlated sibling RE probit model.[2]

[2] I also attempted to estimate a dynamic correlated RE probit to account for persistence in overweight status, but unfortunately it was not possible to achieve convergence (likely due to small sample size).

3 Data

3.1 The Child Development Supplement to the Panel Study of Income Dynamics

The data used for this analysis come from the Child Development Supplement (CDS) to the Panel Study of Income Dynamics (PSID) (The Survey Research Center, 2012). The purpose of the PSID-CDS is to collect data on children's health, cognitive development, and behavior problems and factors affecting these outcomes, including family environment, neighborhood characteristics, and school environment (The Survey Research Center, 2010). In 1997, all PSID families with children under 13 were included in the CDS. If there were more than two children under 13 years of age in the family, two children were randomly selected into the sample. In total, 2,394 families were interviewed (88% of the selected families) and data on 3,563 children were collected.

The PSID-CDS is especially suitable for the purpose of this study for three reasons. First, the PSID-CDS is a panel data set. After the first interviews in 1997, the children and their primary caregivers were interviewed two more times in 2002 and 2007. Panel data is necessary to estimate the value added and child fixed effects models. The presence of siblings in the data allows estimating the sibling fixed effects model. Second, the PSID-CDS has a time diary component, in which children record all activities that they do during the day. Time diary data provides more precise measures of time use variables than recall questions available in surveys (Stafford and Yeung, 2004). It is also important that television viewing, movie watching, video game playing, and computer use are recorded as separate activities, which allows comparing the effects of the old and new media on children's body weight. Third, the PSID-CDS provides a relatively precise measure of children's body weight, because the children were measured and weighed by the interviewers in most cases. Finally, the CDS can be linked to the PSID, which allows obtaining data on parent's weight and family characteristics.

Children aged 3 to 18 years old are used for the analysis. In the initial sample, there were 8,888 observations. Due to attrition, non-response, and missing values[3], 3,707 observations were deleted from the sample. A few observations (100) had to be excluded from the sample because of biologically implausible body mass index (BMI) values. Further only children observed in at least two consecutive waves can be used for the estimation of the value added and child fixed effects models. For this reason, further 1,187 observations were excluded from the sample. The final analysis sample contains 3,894 observations on 1,751 children. Most of these children (around 78 percent) are observed two times in the data.

3.2 Main variables

The main dependent variable in this analysis is a child's body mass index (BMI). When a child's height is measured in inches and weight is measured in pounds, as in the PSID-CDS, BMI is calculated as follows:

$$BMI = \frac{weight}{height^2} * 703. \tag{5}$$

A child's BMI is then standardized by age and gender to account for the changes in body fatness as children grow and the differences in weight development between girls and boys. Following the literature, I use the growth charts developed by the Centers for Disease Control and Prevention (CDC) for the standardization (Centers for Disease Control and Prevention, 2002). The CDC growth charts provide age and gender specific BMI distributions based on the data from the US

[3] All observations with missing information on weight, height, or media time are omitted from the sample. I deal with missing values of control variables in two ways. If a variable has less than 1 percent of values missing, the observations with missing information on this variable are omitted from the sample. If a variable has more than 1 percent of values missing, a dummy variable for missing values is created and included in the regressions (to preserve sample size).

National (and Nutrition) Health Examination Surveys from 1963 to 1994.[4] The weighted mean of the standardized BMI in the analysis sample is 0.42, which corresponds to the 66th percentile of the standard normal distribution. The weighted median (0.45) corresponds to the 67th percentile. Thus, both an average and a median child in the analysis period (1997-2007) were heavier than a median child in the reference period (1963-1994). If a child's standardized BMI is greater than or equal to the 85th percentile, the child is defined as overweight. In the analysis sample, around 32 percent of children are considered to be overweight. This figure is consistent with the other sources (Paxson et al., 2006).

A disadvantage of using BMI as a measure of body weight is that BMI cannot differentiate between an increase in body fat and an increase in muscle mass (Anderson and Butcher, 2006). However, BMI is the only available measure of body weight in the PSID-CDS. Moreover, other studies on media and childhood obesity find consistent results, when they use alternative measures of body fatness (percentage body fat) in addition to BMI (Grossman, Tekin and Wada, 2012).

Children's media exposure is measured by the time spent watching television or movies and the time spent playing video games or using a computer or a cell phone (excluding phone conversations). In the PSID-CDS, the child, or the primary caregiver of the child if the child is too young, is asked to complete two 24 hour diaries, one on a randomly selected weekday and one on a randomly selected weekend day. These two time diaries are used to calculate the number of hours spent on each activity per week in the following way:

$$t_j = 5 * t_{j,wd} + 2 * t_{j,we}, \tag{6}$$

[4]A child's standardized BMI is calculated according to the following formulas: $BMI_z = \frac{((BMI/M)^L)-1}{LS}$ if $L \neq 0$ and $BMI_z = \frac{ln(BMI/M)}{S}$ if $L = 0$, where M is the median of the BMI distribution corresponding to a child's age and gender, S is the generalized coefficient of variation, and L is the power in the Box-Cox transformation, which accounts for the skewness of the BMI distribution (Centers for Disease Control and Prevention, 2002).

where $t_{j,wd}$ is the time spent doing an activity j on the weekday and $t_{j,we}$ is the time spent doing an activity j on the weekend day.

Almost all children (97 percent) spend at least some time watching television or movies during the week. Television watching (16.27 hours per week) accounts for most of the time spent on the total old media (16.5 hours per week). Close to 60 percent of children play video games or use computer for at least some time during the week. On average, more time is spent on video game playing (more than 3.5 hours per week) than on computer activities (more than 2.5 hours per week). There is variation in media exposure by day of the week and child and family characteristics. More time is spent on media activities on weekends than on weekdays. Boys and girls spend a similar number of hours watching television or movies, but boys spend almost twice as much time on computer activities or video games as girls. Black and Hispanic children spend more time watching television or movies, but less time playing video games or using a computer compared to white children. There is little variation in the exposure to the old media by age. Even children as young as 3 to 4 years old spend 16-17 hours per week watching television. To the contrary, new media time increases with age (from 1-2 hours per week for young children to 10-12 hours per week for adolescents). Children's new media time is positively correlated with household income and primary caregiver's education, but the opposite is true for old media time. The variation in media exposure by child and family characteristics suggests that it is unlikely that children's media exposure is exogenous.

Figure 1 shows how children's body weight and media exposure changed over the analysis period (1997 to 2007). To control for the age effects, the sample is restricted to the children of the same age (10-12 years old) in each year. Children became on average heavier over time. In 1997, the standardized BMI of an average 10-12 year old child was around 0.25, which corresponds to the 60th percentile of the BMI distribution. In 2007, an average child's BMI increased to 0.57, which corresponds to the 72nd percentile. From 1997 to 2002, the proportion of children defined as overweight also increased. Interestingly, there was no change in the overweight rate from 2002 to 2007, although the average BMI increased over the same period. This implies that the changes in BMI were not uniform across the BMI distribution. Children's exposure to the new media also increased over time. Children spent twice as much time on video game playing or computer activities in 2007 compared to 1997. On the other hand, children's exposure to the old media increased from 1997 to 2002, but there was a decline in the time spent on television and movies between 2002 and 2007. Although Figure 1 shows that both children's BMI and their media exposure increased over the analysis period, it does not tell anything about causality. Other variables may be driving the observed changes in both variables.

3.3 Control variables

Turning to the control variables, parents' BMI is calculated using the self-reported weight and height data from the PSID. Only the observations on those parents who reside in the same household as the child are used for the analysis, because parents' BMI is a proxy for the environment common to parents and children. In order not to limit the sample to children from two-parent families, I combine the information about the mother and father's BMI into one measure. If data is available for both parents, the average of their BMI is calculated. If data is only available for one of the parents, the BMI of that parent is used.

Other control variables are grouped in three groups. The first group contains variables describing a child's environment and changes to it: the Home Observation for Measurement of the Environment - Short Form (HOME-SF) index (standardized to have mean 0 and standard deviation 1 in each wave), which is a measure of cognitive stimulation and emotional support provided to a child by his/her parents; parental warmth variables that indicate how frequently the primary caregiver expresses positive feelings towards a child and is involved in a child's activities; the primary caregiver's Kessler psychological distress scale (which varies from 0 = no distress to 24 = high distress); whether or not a child is negatively affected by anyone in the household's alcohol consumption; whether or not the family had any financial hardships in the past 12 months; neighborhood rating (which varies from 1 = poor to 5 = excellent); whether or not a child changed school, and whether or not the family moved.

The second group of control variables consists of family characteristics that may proxy for some of the unobserved determinants of children's body weight: family income (adjusted for family size and composition, in 1996 dollars); education, employment status, and age of the primary caregiver; whether or not both parents live in the household; the number of children in the family; and whether or not the family lives in a standard metropolitan statistical area (SMSA).

Finally, the models control for child health measures: whether or not a child has any health conditions; whether or not a child has any physical or mental disabilities; a child's number of doctor visits in the past 12 months; and primary caregiver-assessed child health status (which varies from 1 = poor to 5 = excellent). A child's gender, race, birth weight, a cubic function in age (measured in months), and year effects are also included in the model.[5] Table 1 presents the descriptive statistics of the control variables.

4 Results

Tables 2 and 3 report the estimates of the effects of weekly media hours on standardized BMI and overweight status, respectively. Standard errors are clustered at the family level in all estimations to account for the multiple observations per child and multiple children within a family. The first column of Table 2 presents the estimates of the ordinary least squares (OLS) model without any controls.

[5]Not all of these variables can be included in all models. For example, the coefficients on the time-invariant variables cannot be identified in the child FE model.

Both the time spent watching television or movies and the time spent playing video games or using a computer are found to be positively correlated with BMI, but only the time spent watching television or movies is statistically significant. A one hour per week increase in children's television and movie time is associated with 0.009 unit increase in their standardized BMI.

The next two columns of Table 2 present the estimates of the OLS and child random effects (RE) models that control for the observed child and family characteristics. Adding the control variables to the OLS model reduces the coefficients on weekly media hours substantially. The adjusted R-squared increases from 0.007 to 0.105. The control variables are highly joint statistically significant (F-statistics is 7.73). Controlling for the observed characteristics, a child's standardized BMI is found to increase by 0.005 when the time spent watching television or movies increases by one hour per week. There is no correlation between BMI and the time spent playing video games or using a computer.

The remaining columns of Table 2 present the estimates of the fixed effects (FE) and value added (VA) models. According to the adjusted overall R-squared[6], the child FE model has the best fit, but the observed variables in the VA model also explain quite a large proportion (35.9 percent) of the variation in BMI. As expected, there is persistence in children's BMI. A one unit increase in BMI in the past wave is associated with a 0.4 unit increase in BMI in the current wave.

The estimated effect of weekly video game and computer hours on standardized BMI varies from -0.006 in the sibling FE model to -0.001 in the child FE model and is not statistically significant in any of the three models. In the siblings FE model, the coefficient on weekly video game and computer hours is quite imprecisely estimated, but effects larger than 0.003 can be ruled out with a 95 percent confidence. The estimated effect of weekly television and movie hours on standardized BMI varies across the models. In the child FE model, the effect of

[6]The overall R-squared in the FE models is the R-squared of a "dummy variable" regression that includes the fixed effects as regressors.

weekly television and movie hours is found to be small (0.001) and statistically insignificant.[7] In the sibling FE and VA models, the estimated effect of weekly television and movie hours is larger (0.008 and 0.004, respectively) and statistically significant at the conventional significance levels. Although this effect is significantly different from zero, it is not quantitatively large. Taking the larger sibling FE estimate, a one hour per week increase in children's television and movie time would only increase their BMI from the mean of 66.28th percentile to 66.57th percentile. Overall, the results suggest that children's weight may be somewhat affected by television and move watching, but video game playing and computer use does not have any effect on their weight.

Turning to the models of overweight status, the first column of Table 3 presents the average partial effects of the probit model. Columns (2) and (3) report the estimates of the correlated child and sibling RE probit models, which relax the assumption of no correlation between weekly media hours and the unobserved heterogeneity. The results consistently show that the probability of a child being overweight is not affected by weekly video game and computer hours. A positive correlation is found between overweight status and weekly television and movie hours in the probit model. In the correlated RE models, the average partial effect of weekly television and movie hours is of similar size to the probit estimate (0.001 - 0.002) but statistically insignificant. Average partial effects larger than 0.4 percentage points (a small effect compared to the mean of 32 percent) can be ruled out with a 95 percent confidence.

In Table 4, I investigate if there is heterogeneity in the effects of weekly media hours on children's weight. The model presented in panel A relaxes the assumptions that video game playing has the same effect on weight as computer use and that television viewing has the same effect on weight as movie watching. The estimates of all three models (child and sibling FE and VA) show that both

[7]The differences in the estimates across models are not explained by the differences in the samples. Estimating the child FE model on the same samples as the other models provides results that are very similar to the child FE estimates obtained using the full sample.

weekly video game hours and weekly computer hours have no statistically significant effects on BMI. The estimated effect of weekly television hours on BMI is positive (0.001-0.008), but only statistically significant in the sibling FE and VA models. According to the sibling FE model estimates, an increase in weekly movie hours may increase standardized BMI quite substantially (by 8.1 percent of the standard deviation). However, this result is not robust. In the child FE and VA models, the coefficient on weekly movie hours is negative and statistically insignificant.

In panel B of Table 4, weekly media hours are interacted with a child's age, the primary caregiver's education, and family income. Older children may receive more pocket money than younger children and have more discretion in how they spend their money. Therefore, older children may be more likely to respond to the advertisements of high-calorie foods. On the other hand, older children may be more aware than younger children that these foods are harmful. The effects of media exposure may also vary by the education level of the parents. More educated parents may be less likely to buy high-calorie foods advertised on media for their children. Holding parents' education fixed, higher income households may spend more money on advertised high-calorie foods (if these foods are normal goods). Additionally, these child and family characteristics may be correlated with the types of activities being displaced by media. Two (tentative) conclusions can be drawn from the results presented in panel B. First, although the interactions between weekly media hours and age are largely statistically insignificant, we cannot rule out that some younger children (under 12 years of age) may be negatively affected by both types of media. Second, the effect of video game playing and computer use is found to be smaller for children with more educated primary caregivers, as expected. The rest of the heterogeneity results are imprecisely estimated and not consistent across the models.

Finally, Panel C of Table 4 tests the hypothesis that media has different effects on children on weekdays and weekends.[8] On weekdays, children may spend more time unsupervised by parents and therefore have more opportunities to snack while watching television, playing games, or using a computer than on weekends. The results show that video game and computer time does not have any effect on children's body weight either on weekdays or weekends. The results for television and movie watching vary across models. In the child FE model, no statistically significant effect of television and movie time is found on either weekdays or weekends. According to the sibling FE model estimates, the time spent watching television or movies has a larger effect on children's weight on weekdays than on weekends. The VA model estimates show the opposite. Given these contradictory results, it is not possible to reach any definite conclusions about whether children are more affected by television and movie watching on weekdays or weekends.

5 Discussion and conclusion

To summarize, I find that the time spent on video game playing or computer activities has no effect on children's body weight. Even modest size effects of weekly video game and computer hours on BMI and overweight status can be ruled out. The time spent on television or movie watching is found to modestly increase BMI. Thus, television and movies may indeed decrease children's energy expenditure or increase their calorie intake, either via exposure to high-calorie food advertising, as shown by Chou, Rashad and Grossman (2008), Andreyeva, Kelly and Harris (2011), and Grossman, Tekin and Wada (2012), or snacking or both. However, weekly television or movie hours do not have any statistically significant effect on children's overweight status.

[8]The coefficients in panel C, are interpreted as the effects of a one hour *per day* increase in media time on standardized BMI. In Table 2 and panels A and B of Table 4, the coefficients are interpreted as the effects of a one hour *per week* increase in media time. That explains why the coefficients in panel C are larger in magnitude.

The results provide support the hypothesis that the new media affects children's weight differently from the old media. This finding may be explained by the more engaging nature of video game playing and computer activities, which may take a child's mind off food, and/or higher energy expenditure associated with video game playing relative to television and movie watching. Additionally, children may be less affected by advertising in video games and on the Internet than on television and movies.

Although the estimated models control for the unobserved heterogeneity and an extensive list of time-varying variables, it is not possible to control for all time-variant variables. If the omitted variables were correlated with children's media exposure, the effects of media would be confounded with the effects of these variables. However, any remaining biases in the coefficients on the media use variables are more likely to be positive than negative. The main threat to the internal validity is that an increase in children's media time may coincide with other changes in children's lives that increase their body weight. For example, if the mother of a child starts working longer hours, she may have both less time to cook nutritious meals for children and monitor children's media time. In this case, the results presented in this paper can be interpreted as upper bounds of the true effects of media time on body weight. Since media time is found to have very small effects on children's weight, the true effects may be even smaller.

To conclude, the results of this study suggest that increased exposure to media, either new or old, is unlikely to be the main factor contributing to the recent increase in children's body weight. Although television and movie time is found to significantly affect children's weight, this effect is quantitatively small. Thus, researchers need to look for alternative explanations for rising childhood obesity rates.

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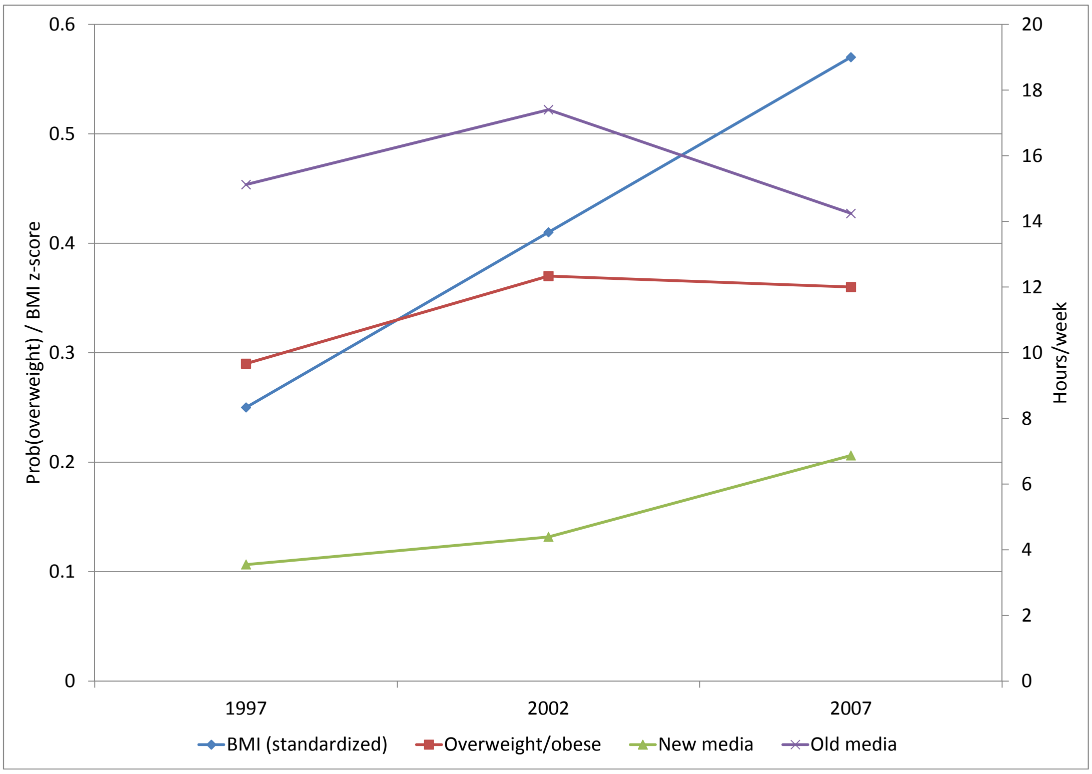

Figure 1: Trends in child body weight and media exposure, 1997-2007. *Notes*: The presented figures are weighted means estimated on the sub-sample of 10-12 year old children. Sample sizes in years 1997, 2002 and 2007 are 223, 356 and 187 observations, respectively.

Table 1: Weighted descriptive statistics of control variables

	Mean	Std.Dev.	Observations
Parents' BMI	26.869	4.869	3,653
HOME-SF index	0.108	1.001	3,894
Parental warmth[a]*:*			
I love you once/wk	0.051	-	3,894
I love you a few times/wk	0.151	-	3,894
I love you everyday	0.753	-	3,894
Acknowledges once/wk	0.17	-	3,894
Acknowledges a few times/wk	0.451	-	3,894
Acknowledges everyday	0.311	-	3,894
Joint activities once/wk	0.256	-	3,894
Joint activities a few times/wk	0.369	-	3,894
Joint activities everyday	0.171	-	3,894
Talk once/wk	0.139	-	3,894
Talk a few times/wk	0.407	-	3,894
Talk everyday	0.375	-	3,894
PCG's Kessler psychological distress scale	3.81	3.457	3,625
Alcohol problems in HH	0.117	-	3,625
Financial problems in HH	0.573	-	3,624
PCG neighborhood rating	3.902	1.052	3,624
Changed school	0.037	-	3,894
Moved	0.213	-	3,894
Equivalized HH income (thousand 1996 $)	28.828	32.564	3,704
PCG years of education	13.189	2.631	3,699
PCG employed	0.707	-	3,894
Age of PCG	38.632	7.175	3,894
Both parents in HH	0.709	-	3,894
Number of children in HH	2.342	1.073	3,894
Standard metropolitan statistical area	0.519	-	3,894
Ever diagnosed with a health condition	0.399	-	3,894
Doctor visits	2.309	3.823	3,894
Physical or mental disability	0.059	-	3,894
Parent assessed-health	4.411	0.771	3,894
Birth weight, oz	119.286	21.004	3,894
Male	0.493	-	3,894
Black non-Hispanic[b]	0.138	-	3,894
Hispanic[b]	0.129	-	3,894
Other race[b]	0.059	-	3,894
Age, months	139.65	46.511	3,894

Notes: [a] omitted category is less than once a week. [b] omitted category is white non-Hispanic.

Table 2: Effects of weekly media hours on standardized BMI

	OLS	OLS	Child RE	Child FE	Sibling FE	VA
	(1)	(2)	(3)	(4)	(5)	(6)
New media(t)	0.002	−0.002	−0.001	−0.001	−0.006	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)
Old media(t)	0.009***	0.005**	0.003**	0.001	0.008**	0.004***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)
BMI(t-1)						0.402***
						(0.021)
Controls	No	Yes	Yes	Yes	Yes	Yes
Overall R^2	0.007	0.116	-	0.728	0.706	0.359
Adjusted overall R^2	0.007	0.105	-	0.496	0.396	0.345
Within R^2	-	-	-	0.056	0.081	-
Observations	3,894	3,894	3,894	3,894	1,866	2,143

Notes: Standard errors (clustered at the family level) in parentheses. Regressions in columns (2) to (6) control for all variables described in Section 3. Overall R^2 is the R-squared of a regression that controls for the fixed effects and within R^2 is the R-squared of a regression on the within-transformed data. ** denotes statistical significance at the 5% level and *** denotes statistical significance at the 1% level.

Table 3: Average partial effects of weekly media hours on overweight status

	Probit	Correlated child RE probit	Correlated sibling RE probit
	(1)	(2)	(3)
New media	0.000^a	-0.000^a	−0.002
	(0.001)	(0.001)	(0.002)
Old media	0.002***	0.001	0.002
	(0.001)	(0.001)	(0.001)
Pseudo R2	0.081	0.097	0.115
Observations	3,894	3,894	1,866

Notes: Standard errors (clustered at the family level) in parentheses. Regressions control for all variables described in Section 3. *** denotes statistical significance at the 1% level. [a] indicates that $|\hat{\beta}| < 0.0005$.

Table 4: Heterogeneity in media effects on standardized BMI

	Child FE		Sibling FE		VA	
	(1)		(2)		(3)	
A.						
Video games	0.000	(0.003)	−0.006	(0.006)	−0.001	(0.003)
Computer/cellphone	−0.002	(0.003)	−0.006	(0.006)	−0.003	(0.002)
Television	0.001	(0.002)	0.008**	(0.004)	0.004***	(0.002)
Movies	−0.011	(0.017)	0.081*	(0.044)	−0.007	(0.015)
B.						
New media	0.002	(0.004)	−0.001	(0.007)	0.000	(0.003)
New media*						
Child age < 12 years	0.007	(0.006)	0.015*	(0.009)	0.009	(0.008)
PCG education > 12 years	−0.007	(0.005)	−0.020*	(0.010)	−0.012**	(0.005)
HH income > median	−0.000	(0.005)	0.012	(0.010)	0.007	(0.005)
Old media	0.003	(0.003)	0.004	(0.006)	0.003	(0.003)
Old media*						
Child age < 12 years	−0.005	(0.003)	0.005	(0.007)	0.003	(0.004)
PCG education > 12 years	−0.002	(0.004)	0.003	(0.008)	0.007*	(0.004)
HH income > median	−0.000	(0.004)	0.002	(0.008)	−0.003	(0.004)
C.						
New media, weekday	−0.011	(0.015)	−0.021	(0.027)	−0.011	(0.015)
New media, weekend	0.006	(0.011)	−0.025	(0.024)	0.001	(0.010)
Old media, weekday	0.000	(0.013)	0.057***	(0.020)	0.008	(0.011)
Old media, weekend	0.009	(0.009)	−0.005	(0.018)	0.023***	(0.009)
Observations	3,894		1,866		2,143	

Notes: Standard errors are clustered at the family level. In panels A and B, media time is measured in hours per week. In panel C, media time is measured in hours per day. Regressions control for all variables described in Section 3. *denotes statistical significance at the 10% level, **denotes statistical significance at the 5% level, and ***denotes statistical significance at the 1% level.