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

Agne Suziedelyte

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Agne Suziedelyte†

School of Economics, University of New South Wales, Australia

Australian School of Business Building, Level 4, 447, UNSW Sydney NSW 2052, Australia

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Abstract

The aim of this paper is to determine if there is a causal relationship between children's time spent on media related activities and their weight. Since the beginning of 1980s, childhood obesity rates in the U.S. and other developed countries have been increasing. It has been suggested in the literature that changes in children's media use is an important explanation for the observed increase in children's weight. I investigate whether or not this hypothesis is supported by data. Additionally, I compare the effects of television, or old media, with the effects of computers and video games, or new media. The Child Development Supplement to the Panel Study of Income Dynamics is used for the analysis. To address the endogeneity of children's media use, I use the child fixed effects and correlated random effects models. I find no evidence that media use contributes to weight gain among children. On average, a one hour per week increase in a child's video game or computer time is estimated to decrease his/her body mass index slightly and to not affect significantly the probability of being overweight or obese. The estimated effects of television time on weight are not significantly different from zero. These findings, especially the results related to children's computer or video game time, are robust to a number of sensitivity checks. Additionally, there is heterogeneity in the effects of media time by child and family characteristics.

JEL: D13; I12; J13

Keywords: obesity; body weight; media use; time use; children

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†Tel.: + 61 2 9385 2660. *E-mail address:* agne@unsw.edu.au

1 Introduction

Childhood overweight is considered to be an important issue, primarily because it has both short-term and long-term effects on health. Today, many obese children have health problems that previously affected only adults, for example, type 2 diabetes (Paxson et al., 2006). Such health problems as heart disease are likely to begin earlier in life in obese children compared to normal weight children (Paxson et al., 2006). Additionally, overweight and obese children are more likely to be obese in adulthood compared to non-overweight children (Paxson et al., 2006). Adulthood obesity is linked to such health problems as heart disease, high blood pressure, hardening of the arteries, type 2 diabetes, metabolic syndrome, high cholesterol, asthma, sleep disorders, liver disease, orthopedic complications, and mental health problems (Paxson et al., 2006).

The health care costs of obesity are substantial. According to one estimate, the costs of treating obesity-associated illnesses in children were $127 million in 1997-99 compared to $35 million in 1979-81 (in 2001 dollars). In 1998, US health care expenditures related to adult overweight and obesity were estimated to be $51.5-$78.5 billion (Paxson et al., 2006). Additionally, obese adults are more likely to become disabled before retirement, which further raises the costs of obesity (Paxson et al., 2006). There are also indirect costs of obesity due to reductions in economic opportunities and/or productivity, which are estimated to be around $23 billion per year in the US (Daniels, 2006). Indirect costs of childhood obesity include time away from work for parents and time away from school for children due to obesity caused illnesses (Daniels, 2006).

Childhood obesity rates have been recently rising. The rate of childhood obesity in the U.S. was around 5 percent in 1970s. In 1980s, the obesity rate among children started increasing and reached 15 percent in 1999-2002 (Paxson et al., 2006). The proportion of children who are either overweight or obese increased from 15 percent to 30 percent during the same period (Paxson et al., 2006). Other developed countries, for example, Germany and the UK have also recorded increases in childhood obesity rates (Anderson and Butcher, 2006). In developing countries, obesity coexists with malnutrition. For example, during the period of 1989 to 1997, the obesity rate among young children (2-6 years old) increased in urban China, but fell in rural China (Anderson and Butcher, 2006).

In the literature, the recent increase in children's weight has been partly attributed to electronic media, more specifically television, video games, and more recently, computers and the Internet (Paxson et al., 2006). Media use is considered as an explanation for growing childhood obesity rates for a number of reasons. First, there are multiple channels how media may affect children's weight. Media use may displace more physically intensive activities. Moreover, children may increase their consumption of high-calorie foods, such as soft drinks, snacks, candy, and fast food, due to the exposure to the advertisements of such foods on television, video games, and the Internet. Media use may also be accompanied by snacking. Finally, there are some studies suggesting that children's metabolic rate while watching television may be lower than while resting (Anderson and Butcher, 2006).

Second, children's media exposure has increased since the beginning of 1980s. Although children's television time has been rather stable in this period, new forms of media, such as video games and computers, emerged and became increasingly popular among children. In 1999, 8-18 year old children were estimated to spend on average 3 hours and 5 minutes watching television, 26 minutes playing video games, and 27 minutes using a computer per day (Roberts and Foehr, 2008). In 2004, children's average time spent watching television did not change, but their time spent playing video games and using a computer increased to 49 minutes and 1 hour per day respectively (Roberts and Foehr, 2008). Thus, the new electronic media did not displace the old media, rather the total media time increased.

Third, advertising targeted at children has increased over time. Advertisers' interest in children has grown because of an increase in children's discretionary income and power to influence their parents (Calvert, 2008). Additionally, the development of modern technologies opened new marketing opportunities (Calvert, 2008). The amount of television advertising targeted at children is regulated by law in the US. Thus, the total amount of advertisement time on children's television programs has not changed over time. Nonetheless, the number of television commercials children see has increased, because advertisements have become shorter (Calvert, 2008). In the new media, advertising targeted at children is less regulated. There are no limits on the number of advertisements that can be included in video games or Internet websites. To make advertising to children more effective, marketers have developed new techniques such as stealth advertising, which blurs the boundary between the advertisement and the content of the media (Calvert, 2008). An example of stealth advertising is embedding products within television programs, movies, websites and video games. Advertisements targeted at children are dominated by foods that are high in calory content, such as sugar-coated cereals, fast-food restaurants, candy, and soft drinks (Calvert, 2008). Furthermore, studies confirm that advertising has effects on children's preferences for food (Escobar-Chaves and Anderson, 2008; Andreyeva et al., 2011).

Additionally, there is evidence that a substantial proportion of the recent increase in childhood obesity rates cannot be explained by factors contributing to rising adulthood obesity rates. Anderson et al. (2007) conclude that the change in parents' body mass index between 1970s and 2000s can explain around 37% of the increase in children's body mass index. Thus, shared genetical and environmental factors are important, but there are other factors, specific to children's environment, that are contributing to the growth in children's weight. As media use, especially video game playing and computer use, is usually a child-specific activity, the variation in children's media time may potentially contribute to explaining the remaining variation in childhood obesity rates.

There are reasons to expect that old media, or television and videos, have different effects on children's weight than new media, which includes video games, computers, and the Internet. First, the new media are more interactive than the old media. As a result, children may be more focused and engaged while playing video games or using a computer than while watching television. It is unclear, however, how the interactivity of the new media would affect the relationship between children's media use and weight. On the one hand, the more focused a child is, the less likely he/she may be to engage in other activities, including snacking and eating in general. On the other hand, the more engaged in an activity a child is, the more likely he/she may be to notice and be affected by food advertisements. Additionally, children can avoid advertisements on television by switching to other channels or doing something else, whereas it is more difficult to avoid advertisements in video games and online. Second, advertising in the new media may be more effective than advertising in the old media due to less regulations and more effective stealth advertising techniques (Calvert, 2008). Third, there is some evidence that video game playing may be associated with higher energy expenditure than other sedentary activities due to stress that children experience while playing video games (Escobar-Chaves and Anderson, 2008). Overall, it is difficult to predict which type of media may have a larger effect on children's weight.

I contribute to the literature on childhood obesity by providing evidence on the effects of both new and old media on children's weight. Although there are studies that analyze the effect of television watching on childhood obesity, for example, Chou et al. (2008) and Andreyeva et al. (2011), and the effect of passive activities in general (Wilson, 2006), the effect of computer use or video game playing on children's weight has not been analyzed in the economics literature to date. Additionally, the model estimated in this analysis controls for other activities, which is an improvement upon the current literature on the relationship between media use and weight. Controlling for a child's time spent on other activities allows me to separate the effect of media use from the effects of these activities.

I find no support for the hypothesis that exposure to media increases children's weight. To the contrary, there is some evidence that the time spent on computer activities or video game playing affects children's weight negatively. The effect of television watching is neither economically nor statistically significant. Moreover, the effects of media use on children's weight are not significantly different from the effects of other common children's activities, including sports and other active leisure. These findings may be explained by children compensating the increase in their energy expenditure associated with more intense activities with an increase in their energy intake.

2 Literature review

This section reviews the literature on the effects of media use on children's weight. The findings of this literature suggest that there may be a positive relationship between television viewing and weight. Moreover, advertising appears to be an important channel via which television may be contributing to increasing childhood obesity rates. The evidence on the effect of computer use or video game playing on weight is scarce. A few studies report that there is no correlation between these activities and children's weight. The findings of these studies cannot be used, however, to draw causal inferences, because the endogeneity of media use is not addressed.

Chou et al. (2008) investigate if advertisements of fast food restaurants affect children's weight and obesity. The number of hours of fast food advertising aired in a child's local area and the number of hours spent watching television are used to construct the number of hours of fast food advertising that a child potentially sees per week. Chou et al. find that the more fast food advertising children see on television, the higher is their weight and the more likely they are to be obese. This result holds for boys and girls as well as for younger and older children. Andreyeva et al. (2011) use a different sample of children and source of advertising data to answer the same question as Chou et al. (2008). Andreyeva et al. also find that fast food advertising has a positive effect on children's weight. This effect is only statistically significant, however, for already overweight or obese children. Additionally, Andreyeva et al. provide evidence that advertising affects children's weight via an increase in their calorie intake. Exposure to advertising is positively related to children's consumption of fast food and soft drinks.

Chang and Nayga Jr (2009) analyze the effect of television viewing on fast food and soft drink consumption and obesity among children in Taiwan. The results of this study show that the unobserved determinants of children's television time and fast food and soft drink consumption are positively correlated. Chang and Nayga Jr do not investigate, however, whether there is a causal relationship between children's television viewing and fast food consumption. Furthermore, the authors find that television time has a positive effect on weight and the probability of being overweight, but not on the probability of being obese. Since children's fast food consumption is included as a regressor in the estimations, these findings imply that television viewing may be affecting children's weight via other channels besides increased consumption of fast food and soft drinks. The results of Chang and Nayga Jr (2009) are in contrast to those of Chou et al. (2008), discussed above, who find that television time has no significant effect on children's weight, once their exposure to fast food advertising on television is held constant. Thus, it is unclear whether television watching affects children's weight via multiple channels or fast food advertising only.

Marshall et al. (2004) conduct a meta-analysis of the studies in medicine that analyze the relationships between a child's time spent watching television and playing video games and his/her body "fatness", as measured by body mass index and/or subcutaneous fat (skin-fold) thickness. The mean correlation coefficient between children's television viewing and body fatness is found to be positive and small (based on 52 studies). There are no significant differences between boys and girls, but it appears that the correlation between television viewing and body fatness is stronger for younger children (under 7 years of age) than for older children (7-18 years of age). The mean correlation coefficient between a child's body fatness and video game playing is also positive and small, but the hypothesis that it is zero is not rejected (based on 6 studies). Most of the studies included in the analysis are based on cross-sectional data and do not control for possible confounding variables. Therefore, these results do not allow making any causal conclusions about the relationship between media use and children's weight. On the other hand, a positive relationship between media use and body weight was also found in an experimental study of 8-9 year old children, which evaluated the effects of an intervention designed to reduce children's media time (Marshall et al., 2004). Given that this intervention was randomly assigned, the findings of this study suggest that there may indeed be a causal link between children's media time and weight.

A number of studies find that the mother's employment has a positive effect on a child's weight (Anderson et al., 2003; Ruhm, 2008; Cawley and Liu, 2007). Fertig et al. (2009) investigate whether this relationship may be due to maternal employment affecting children's eating patterns and/or activities, including media use. Their findings show that a change in a child's television time may be one of the channels via which the mother's hours of work positively affect a child's weight. Maternal employment is found to be positively associated with a child's television time, which in turn is positively associated with a child's body mass index. On the other hand, changes in a child's time spent playing video games or using a computer do not appear to explain the positive effect of the mother's working hours on a child's weight. Fertig et al. find no statistically significant correlation between maternal work hours and children's video game or computer time. Moreover, there is no correlation between a child's weight and his/her computer use or video game playing[1].

Wilson (2006) analyzes a broader question of what factors may have contributed to the recent increase in the prevalence of childhood obesity in the U.S. Wilson concludes that rising child obesity rates cannot be explained by the changes in children's calorie intake. On the other hand, increasing participation in passive activities and decreasing participation in physical activities could explain a substantial proportion of the variation in child obesity rates, according to Wilson. The time spent on passive activities, including media use, is found to have a positive effect on the probability of obesity relative to the time spent on physical activities. Wilson's findings are in contrast to those of Cutler et al. (2003) who conclude that the recent rise in adult obesity rates is more likely to be explained by an increase in calorie intake rather than by a decrease in energy expenditure among adults. The conclusions of Wilson are also inconsistent with the results of this study, which finds no evidence that such passive activities as television watching, computer use, and video game playing contribute to children's weight gain. I discuss how these differences may be explained in Section 7.

3 Underlying economic model

This section presents the conceptual framework, on which the empirical analysis is based[2]. In this model, parents care about their children's utility u_c as well as about the weight of their children W_t and their own consumption $c_{p,t}$. Parents' utility is increasing in the number of children N_t at a decreasing rate ($\lambda < 1$). A child's utility at time t depends on his/her weight W_t, consumption of food $c_{f,t}$ and non-food goods $c_{nf,t}$, and time spent watching television $t_{tv,t}$, playing video games $t_{vg,t}$, using a computer $t_{pc,t}$, and doing other activities $T_t = (t_{1,t}, \ldots, t_{J,t})$. Parents maximize their utility subject to the

[1]Note that Fertig et al. (2009) only examine whether or not there is a correlation between different activities, including media use, and children's body mass index and do not investigate whether these activities have causal effects on weight, because their variable of interest is maternal employment.

[2]This framework is largely based on Wilson (2006), Cutler et al. (2003), and Baum II and Ruhm (2009).

budget constraint, a child's time constraint, and weight production function:

$$
\begin{aligned}
\max \;\; & u_p(c_{p,t}, W_t) + N_t^{\lambda}[u_c(c_{f,t}, c_{nf,t}, t_{tv,t}, t_{vg,t}, t_{pc,t}, T_t, W_t)] && (1)\\
s.t. \;\; & c_{p,t} + N_t(p_{f,t}c_{f,t} + p_{nf,t}c_{nf,t}) = M_t, && (2)\\
& t_{vg} + t_1 + \ldots + t_J \leq \overline{T}, && (3)\\
& W_t = W_{t-1} + f_W(c_{f,t}, t_{tv,t}, t_{vg,t}, t_{pc,t}, T_t, B(W_t, X_t, \mu)) + e_t, && (4)
\end{aligned}
$$

where $p_{f,t}$ and $p_{nf,t}$ are prices of children's food and non-food consumption, respectively, and M_t is family income, all normalized with respect to the price of parents' consumption. The sum of children's time spent on different activities cannot exceed an upper bound $\overline{T}$.

The change in a child's weight $\Delta W = W_t - W_{t-1}$ depends on the difference between his/her energy intake, via food consumption $c_{f,t}$, and energy expenditure in period t. Children expend energy in three ways. First, the body consumes energy to keep it alive. This basal metabolism rate B depends on a child's body weight W_t, demographic characteristics X_t, and genetic factors μ. The basal metabolism accounts for around 60 percent of the total energy expenditure for most people (Cutler et al., 2003). Second, the body consumes energy to process food, which is estimated to account for around 10 percent of the total energy expenditure (Cutler et al., 2003). Third, a child's body consumes calories when a child engages in different activities. Calorie consumption associated with a given activity depends on how intense this activity is. For example, such activities as television watching, video game playing, computer use, and other passive activities require not much more energy than resting. On the other hand, such intense physical activities as playing soccer, basketball, or other similar sports require 7 to 10 times more energy than resting. Therefore, a child's weight depends on the amount of time spent on different activities. If a the total energy expenditure in period t exceeds the total energy intake in the same period, a child's weight decreases, and vice versa. Parameter e_t captures random shocks to a child's weight, such as health problems. Note that this model is characterized by joint production, that is, the inputs in the weight production function also affect children's utility directly.

Electronic media use could affect children's weight in two ways. First, television watching, video game playing, and computer use may displace other activities that require more energy than media use, such as playing sports, exercising, or doing household chores, and therefore, reduce children's total energy expenditure. Second, exposure to electronic media may affect children's energy intake. As discussed in the introduction, media use, 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 use, 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 engage in other activities, including eating. In extreme cases, children may even skip meals. Additionally, activities displaced by media may also increase children's calorie intake. For example, a child is likely to feel more hungry than usual after playing sports and, as a consequence, may have an extra snack or meal. The energy value of this meal may be higher than the energy expended during the sports activity. 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 use may lead to higher total calorie consumption, not affect it at all, or even decrease it. Consequently, the direction of the effect of media use on children's weight is ambiguous.

The time spent on television watching and the time spent on computer use or video game playing may have different effects on children's weight. As mentioned earlier, there is some evidence that video game playing requires more energy than resting, whereas energy consumption associated with television watching may be lower than at rest. Children may also be differently affected by advertising on the new and old media. In addition, children may be less likely to eat while playing video games or using a computer than while watching television, because the new media are more interactive and engaging than the new media.

4 Identification strategy

The aim of this study is to estimate a causal effect of children's media use on their weight. As mentioned above, media use can affect children's weight via two mechanisms, by displacing more intense physical activities and by increasing (or reducing) food consumption. To allow for the latter mechanism, the model should allow a child's food intake to change as his/her media time and other activity time changes. In other words, the model should not control for the child's food consumption. On the other hand, a child's media time could be affected by his/her food consumption, as calorie intake affects the child's weight and heavier children could be more likely to engage in sedentary activities, including media use, and less likely to participate in sports and other intense physical activities. Therefore, the model ideally would control for a child's food consumption exogenous to media use, but not for a child's food consumption endogenous to media use. In practice, it is difficult to separate children's food consumption in this way. Since a change in food consumption is an important channel via which media use may affect weight, a child's calorie intake is not included in the model in this analysis[3]. To control for a child's food consumption that is unlikely to be affected by media time, the model includes parents' weight. A part of the variation in parents' weight is due to the changes in the family's environment, including the family's food consumption. Furthermore, parents' weight is unlikely to be affected by children's media use (unless changes in children's food preferences influence parents' food preferences). Thus, the consistent estimation of the effect of media use on children's weight relies on the assumption that children's media use is exogenous to child specific calorie intake, which is not captured by parents' weight.

The baseline model estimated in this analysis is given by the following equations:

$$W_t = Z_t'\beta + \mu + e_t, \tag{5}$$

$$Z_t = (1, t_{tv,t}, t_{vgpc,t}, t_{1,t}, \ldots, t_{J,t}, W_0, X_t), \tag{6}$$

where $t_{tv,t}$ and $t_{vgpc,t}$ denote the time spent on television watching and the time spent on video game playing or computer activities, respectively. The model includes a child's initial period weight W_0, that is, his/her birth weight. Vector X_t contains a child's demographic characteristics, such as gender, race, and age, which may be correlated to his/her basal metabolic rate. Variables $t_{1,t}, \ldots, t_{J,t}$ denote the time spent doing other activities. Unobserved genetic factors are denoted by μ and e_t is the idiosyncratic error term. The model estimated in this analysis only includes current period inputs in the weight production function. Although a child's current period weight W_t also depends on past period inputs (via past period weight W_{t-1}), it is infeasible to estimate a dynamic model in this analysis due to data limitations. Since children's current media use is likely to be correlated to their past media use, the reported coefficient estimates are likely to capture not only the effects of current media use, but also the effects of past media use on children's weight.

The identification of the effects of media use on children's weight is complicated by the endogeneity of children's media time. The first issue is that the time spent watching television, playing video games, using a computer, and doing other activities is likely to be correlated with the unobserved genetic factors μ, which affect children's metabolic rate and in turn their weight. Children who have lower metabolic rate are heavier than children who have higher metabolic rate, even if they consume the same amount of calories and participate in the same physical activities. For this reason, children with lower metabolic rate may prefer more sedentary activities, including media use, to more intense physical activities, such as sports. The presence of these unobserved factors makes the usual

[3]This modeling choice is also affected by data availability. The data used for this analysis contains limited information on children's calorie intake.

estimators such as ordinary least squares (OLS) inconsistent. To address this issue, I use the child fixed effects (FE) model for the estimation of the child weight regression. This estimation method eliminates genetic factors and other child-specific time-invariant variables via the within transformation of the data. The identification of the coefficients β in this model comes from the within child variation in the independent variables over time. In the child FE model, the consistency of the coefficient estimates relies on the strict exogeneity assumption: $E(e_k|Z_l, \mu) = 0, \forall k, l = 1, \ldots, T$.

As it is overweight and especially obese children who face the highest health risks and are most likely to become obese in adulthood, it is also important to investigate whether media use affects children's overweight status. Therefore, the effects of media use on the probability of a child being overweight or obese and the probability of a child being obese are also estimated. As the dependent variables in these regressions are binary, a probit model is used for their estimations. More specifically, I use the correlated random effects (RE) probit model (also known as Mundlak's or Chamberlain's random effects probit). This model has an advantage over the standard probit model, because it relaxes the assumption of the independence between the explanatory variables Z_t and the unobserved heterogeneity μ by allowing for correlation between μ and the time averages of these variables $\overline{Z}$:

$$\mu = \psi + \overline{Z}'\xi + a, \tag{7}$$

$$a|Z_t \sim Normal(0, \sigma_a^2), \tag{8}$$

$$\mu|Z_t \sim Normal(\psi + \overline{Z}\xi, \sigma_a^2), \tag{9}$$

$$\overline{Z} = \sum_{t=1}^{T} Z_t. \tag{10}$$

In this 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_t and unobserved heterogeneity μ. As the focus of this analysis is to estimate the average partial effects, that is, the effects of media use on the probability of a child being overweight (or obese), the independence assumption can be relaxed, as shown by (Wooldridge, 2011). In practice the correlated RE probit model is estimated by including the time averages of the time varying variables Z_t as regressors and estimating a pooled probit model (allowing for correlation across the observations of the same child over time). The effects of the variables that do not vary over time, such as W_0 and some of the elements of X_t, cannot be estimated separately from the unobserved heterogeneity μ in the correlated RE model. The regressions of overweight and obesity are also estimated using the linear probability model (LPM) with child fixed effects. Comparing to the correlated RE model, the limitation of child FE LPM model is that it places unnatural restrictions on the unobserved heterogeneity μ. More specifically, this model implies that $-Z_t'\beta \leq \mu \leq 1 - Z_t'\beta$ (Wooldridge, 2011, p.608). On the other hand, the child FE LPM model allows for arbitrary correlation between the explanatory variables Z_t and the unobserved heterogeneity μ, unlike the correlated RE model, which restricts this correlation, as described above.

The second issue related to the identification of the effects of media use on children's weight is the possibility of reverse causality. In other words, children's time use may be affected by their weight. Reverse causality violates the strict exogeneity assumption required for the consistent estimation of the child FE and correlated RE probit models, because it implies that the explanatory variables Z_t are correlated with the error term e_t. This error term contains a child's food consumption and shocks to weight, such as illnesses. If a child gains weight because of increased food consumption, he/she may spend more time on media activities and less time on physical activities. This would positively bias the estimated effects of media time on weight. On the other hand, an illness is most likely to reduce a child's weight and increase his/her time spent on sedentary activities, which would negatively bias the estimated effects of media use on weight. Thus, the direction of the overall bias is ambiguous. One strategy to address the possibility of reverse causality is instrumenting the time use variables. In practice, this strategy is difficult to implement due to the high number of exclusion restrictions required.

Instead, I use two other strategies to address the possibility of reverse causality. First, I include the future period media time variables $t_{tv,t+1}$ and $t_{vgpc,t+1}$ as regressors in equation (5). This is a test for the assumption that $E(e_t|t_{tv,t+1}, t_{vgpc,t+1}, Z_t, \mu) = 0$. There is no reason to expect future period media time to affect current period weight. Thus, if the coefficients on variables $t_{tv,t+1}$ and $t_{vgpc,t+1}$ are significant, this implies that the media use variables are correlated with the past period error term and that the strict exogeneity assumption is violated. Second, I include additional variables, which may be proxies for some of the unobserved variables, in equation (5). If reverse causality is indeed present, the estimated coefficients on the media time variables are expected to change once the additional controls are included in the weight regression. If the coefficient estimates are not significantly affected by the inclusion of the additional control variables, this provides some support for the strict exogeneity assumption.

5 Data and variables

For this analysis, I use the Child Development Supplement (CDS) to the Panel Study of Income Dynamics (PSID). The PSID is a panel survey of US families, which have been followed since 1968. The aim of this study is to collect data on changes in family income, wealth, welfare participation, employment, and housing. The original PSID sample consisted of a nationally representative subsample of around 3,000 households and an over-sample of around 2,000 low-income households. In 1997, an immigrant refresher sample was added to reflect the changes in immigration into the US since 1968. The re-interview rates of the PSID are high (96-98%). Consequently, the (weighted) sample remains nationally representative (The Institute for Social Research, 2010a). 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 the family environment, neighborhood characteristics, and school environment (The Institute for Social Research, 2010b). 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 suitable for the purpose of this study for three reasons. First, the PSID-CDS is a panel data set, that is, children are observed up to three times in 1997, 2002, and/or 2007. Panel data is necessary to estimate the child FE and correlated RE probit models. Second, the PSID-CDS has a time diary component, which provides the data on children's time spent doing different activities, which are necessary to estimate the effects of media use and other activities on children's weight. It is also important for this analysis that television viewing, 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 weight. Third, the PSID-CDS provides a precise measure of a child's weight. The height and weight of children is measured by the interviewers[4]. If it is not possible to take the measurements, the primary caregiver reports the height and weight of a child (as measured at the last visit to a doctor or the best estimate of the primary caregiver). Fourth, the CDS can be linked to the PSID, which allows obtaining data on parent's weight and family characteristics.

Finally, the PSID-CDS time diaries record both primary and secondary activities. This feature of the data is important for the analysis of the effects of media time on children's

[4] In wave I, the interviewer measured only the height of a child and the weight of a child was reported by the primary care giver.

weight, because media use, especially television watching and computer use, is often a secondary activity among children (Roberts and Foehr, 2008). Exposure to food advertising in media may affect a child's weight even when this activity is not the primary focus of a child. Thus, to capture the total effect of media use, both primary and secondary activities of children should be taken into account. Furthermore, the availability of the secondary activity data allows estimating the absolute effects of media use, that is, the effects of media time holding other activity time fixed. The estimates of the absolute effects can also be used to calculate the relative effects, which allow comparing the effects of media use to the effects of other activities. As a sensitivity check, I also estimate the relative effects using the primary activity data only.

The dependent variables in this analysis are a child's body mass index (BMI), a binary variable indicating whether or not a child is overweight *or* obese, and a binary variable indicating if a child is obese. In the PSID-CDS, a child's height, is measured in inches and weight is measured in pounds. Thus, a child's BMI is calculated as follows:

$$BMI = \frac{weight}{height^2} * 703. \tag{11}$$

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. For this purpose, I use the growth charts developed by the Centers for Disease Control and Prevention (CDC) (Centers for Disease Control and Prevention, 2002a). The CDC growth charts provide the parameters of the age and gender specific distributions of child BMI in the 1963-1994 period. The data from the US National Health Examination Surveys II and III (1963-1970) and National Health and Nutrition Examination Surveys I-III (1971-1994) are used to construct these growth charts. A child's standardized BMI is calculated according to the following formulas (Centers for Disease Control and Prevention, 2002a):

$$BMI_z = \frac{((BMI/M)^L) - 1}{LS}, \; L \neq 0, \tag{12}$$

$$BMI_z = \frac{ln(BMI/M)}{S}, \; L = 0, \tag{13}$$

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. The standard normal distribution tables can then be used to obtain the percentile corresponding to a particular BMI value. For example, if a child's standardized BMI is equal to 0, his/her BMI corresponds to the 50th percentile, or the median, of the BMI distribution.

To define whether or not a child is overweight or obese, the child's BMI is compared to the appropriate percentile of the BMI distribution from the CDC growth charts (specific to his/her age and gender). If a child's BMI is greater than or equal to the 85th percentile of this BMI distribution, the child is defined as overweight or obese. If a child's BMI is greater than or equal to the 95th percentile of the BMI distribution, the child is considered to be obese. It should be noted that the CDC growth charts are constructed using earlier period data than the analysis sample period (1997-2007). Since childhood obesity has been recently growing, the percentage of children who are overweight or obese in the analysis sample exceeds 15 percent, and the percentage of obese children exceeds 5 percent.

The time a child spends watching television and the time a child spends playing video games or using a computer are the variables of interest in this analysis. Television time includes movies watched on the television set. Video games may be played using a video game console, a computer, or a hand held device[5]. Computer activities include communication (emailing, chatting, sending instant messages, or talking over the Internet); recreational activities ("surfing" the Internet, listening to music, or watching movies); homework, studying, or research related to classes; and other activities (reading news, shopping, financial services, looking for specific information, installing software/hardware, media lessons in computers, and working for pay at home). Computer time also includes the time spent doing the above listed activities on a mobile phone, except for phone conversations.

Other activities are grouped into categories as follows[6]:

1. other passive leisure besides media use, such as listening to music, reading, phone or face-to-face conversations, and relaxing;
2. educational activities, including time at school or daycare center, homework, studying, and private tutoring;
3. active leisure, for example, participating in individual and team sports, fishing, camping, and other outdoor activities, walking, hiking, jogging, or playing social or outdoor games;
4. less active leisure, such as photography and other hobbies, crafts, painting, writing, and other creative activities, playing an instrument, singing, and playing card, board, dress-up, and other less active non-electronic games;

[5]In 2005-2006, the 7th generation video game consoles, such as Nintendo's Wii, were released. These consoles enable playing physically active video games, making video game playing a non-sedentary activity. Nonetheless, only children in Wave III had access to these consoles. Thus, it is unlikely that the results are driven by physically active video games.

[6]Travel time related to an activity was also coded as that activity.

5. entertainment, including sport or cultural events, movies, visiting museum or zoo, dancing, attending parties, and socializing with other people;
6. duties, work, and helping others, including household chores, obtaining goods and services, paid work, caring for other children and adults, and participating in activities of volunteer organizations;
7. basic needs of a child, such as sleeping and eating; and
8. missing time.

In the PSID-CDS, children (or their primary care givers) were asked to fill in two 24 hour diaries, one for a randomly selected weekday and one for 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:

$$t_j = 5 * t_{j,wd} + 2 * t_{j,we}, \tag{14}$$

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. The data on both primary and secondary activities is used to measure the time spent in each activity. For example, if a child spent 2 hours watching television as a primary activity and 6 hours per week watching television as a secondary activity, the television time for this child is 8 hours. As a result, the total time per week sums up to a number greater than 168 hours per week.

A child's age, parents' BMI, and time effects are included in all regressions. Age is measured in years, months, and days at the time a child's height and weight measurements are taken. I include a dummy variable for each year of age (except one) as well as age in days. Parents' BMI is calculated using the self-reported weight and height data from the PSID. This data is available for parents who are heads or wives of the household[7]. I use only the observations on these parents' who reside in the same household as the child, 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's 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. A child's gender, race, and birth weight are included in all regressions, except for the child FE model, in which both observed and unobserved time-invariant variables are eliminated. The measure of a child's birth weight is constructed using both the PSID and the CDS data. In the PSID, the birth

[7]Parent height and weight data is available for selected years only. In wave I, I use parents' BMI in 1999, and in wave II, I use the average of parents' BMI in 2001 and 2003. In wave III, parent's BMI data is available for the same year as for children.

weight of a child is recorded closer to the birth compared to the CDS[8]. Thus, the PSID survey should provide a more precise measure of the birth weight. For this reason, I use mainly the PSID data to obtain a child's birth weight. Missing values are replaced with the birth weight data from the CDS.

Children aged 3 years or older are used for the analysis. There are 6,959 observations with completed child assessment questionnaires, which contain weight and height measurements, in the data. I exclude the observations with missing values for any of the main variables from the sample (1,861 observations). Biologically implausible BMI values are also excluded from the analysis sample (104 observations). Biologically implausible BMI values are determined using a methodology suggested by the Centers for Disease Control and Prevention (CDC). Following this methodology, a modified z-score for BMI is calculated using the parameters of the BMI distribution from the CDC growth charts (Centers for Disease Control and Prevention, 2002b). If this modified z-score is lower than -4 or greater than 5, a child's BMI is defined as biologically implausible. Furthermore, the observations for which the total primary activity time does not sum up to 168 hours per week (15 observations) or missing time inputs account for more than 25% of the total weekly time (17 observations) are not included the sample. The sample also excludes the children observed only once, as these observations are not used for identification in the panel data models (945 observations).

The final analysis sample contains 4,017 child-year observations on 1,800 children. Most of the observations are from wave II (42.6%). Observations from wave I and III constitute 31.5% and 25.8% of the sample, respectively. In wave I, children are 3-13 years old; in wave II, children are 5-19 years old; and in wave III, they are 10-19 years old. Children who reached 19 years of age in wave III were not supposed to be part of the CDS survey anymore. Nevertheless, a few 19 year-old children were were still surveyed in 2007 and are included in the sample. On average, a child is observed 2.2 times. Most of the children (77%) are observed two times, and the rest are observed three times.

Table 1 presents the weighted means of the variables. The mean of standardized BMI is greater than zero in all years, indicating that an average child in the 1997-2007 period was heavier than an average child in the 1963-1994 period, on which the CDC growth charts are based. The BMI of an average child in the analysis period corresponds to the 62nd percentile of the BMI distribution in the reference (1963-1994) period. During the 1997-2007 period, children's weight increased, especially between 1997 and 2002. The observed increase in standardized BMI may reflect not only an increasing trend in child

[8]The PSID respondents are asked about the birth weight of their children born since the 1st of January of the past calendar year.

weight, but also age and cohort effects. As shown in Table 2, an average child in wave I (II) was younger than an average child in wave II (III). Additionally, wave I data has more children from the older cohort (born 1984-1991) and less children from the younger cohort (born 1991-97) compared to wave II. The same is true comparing waves II and III. It is estimated that 32 percent of children were overweight or obese in the 1997-2007 period, and 17 percent of children were obese. These figures are consistent with other sources (Paxson et al., 2006). Overweight and obesity rates increased over time. Parents' BMI increased as well during the same period. The BMI of an average parent (26.87) exceeds the overweight threshold (25). Thus, an average parent would be defined as overweight.

Table 1: Weighted means of main variables

	1997	2002	2007	All years
BMI (standardized)	0.21	0.48	0.55	0.43
BMI (percentile)	0.57	0.63	0.64	0.62
Overweight/obese	0.29	0.33	0.35	0.32
Obese	0.15	0.18	0.20	0.17
Parents' BMI	26.29	26.80	27.58	26.87
Hours per week spent on:				
Computer or games	2.21	5.80	10.89	6.18
TV	15.31	16.89	16.07	16.22
Other passive act.	25.04	25.47	26.62	25.66
Educational act.	30.32	35.76	38.97	35.09
Active leisure	9.77	5.11	5.79	6.62
Less active leisure	14.76	7.83	4.53	8.89
Entertainment	3.03	3.80	4.02	3.64
Duties	8.75	11.20	10.76	10.38
Basic needs	93.06	86.17	82.16	87.03
Missing	1.02	0.64	0.76	0.78
Total	203.27	198.67	200.56	200.49
Observations	1,266	1,713	1,035	4,014

Notes: In 2007, the sampling weight is missing for three observations; therefore, the sample used for the estimation of the weighted descriptive statistics is smaller than the analysis sample.

There were changes in children's exposure to media over time[9]. Children's time spent on video game playing or computer activities more than doubled between 1997 and 2002, and further increased by 88 percent between 2002 and 2007. On average, children are estimated to have spent more than 6 hours per week on video game playing or computer activities. In an average year, children spent more time playing video games than using a computer, but computer use increased faster than video game playing. In 2007, children's

[9]As discussed above these changes may reflect not only changes in children's time use over time, but also be related to changes in children's age and cohort differences.

time spent using a computer exceeded their time spent playing video games. On the other hand, children's television time hardly increased over the sample period. The time spent watching television, in fact, decreased between 2002 and 2007. Nonetheless, television watching is still more popular activity than video game playing or computer activities among children. On average, more time is spent on television watching than on video game playing or computer use. Additionally, more children report a positive number of hours spent watching television (97 percent) compared to video game playing or computer use (59 percent). As expected, the time diary data shows that media use is not always a primary activity. Computer use is most likely to be a secondary activity (24 percent of the total computer time), followed by television watching (16 percent of the total television time), and video game playing (5 percent of the total video game time).

Not surprisingly, more time is spent on media on weekends than on weekdays. On an average weekday, children spent approximately 2 hours watching television and 44 minutes playing games or using a computer. On an average weekend day, children spent just above 3 hours watching television and 1 hour and 15 minutes playing games or using a computer. There are also differences in media use by child and family characteristics. Although the difference in television time between boys and girls is small, boys spend almost twice as much time on computer activities or video games as girls. Black and Hispanic children spend more time watching television than white children, but less time playing video games or using a computer. There is little variation in television time by age. On the other hand, computer or video game time is increasing with age. The differences in media time by birth cohort are small. Children's computer or video game time increases with family income and primary care giver's education, but the opposite is true for television time. There are no differences in media time by whether a child lives in a standard metropolitan statistical area or not.

Table 1 allows comparing children's media time to their other activity time. Children spend more time on other passive leisure, such as listening to music, reading, and talking to other people, than on media, but these passive activities are mostly secondary (83 percent of the total passive activity time). Educational activities take up most of children's time after sleeping and other basic needs. Children's television time exceeds time spent on active and less active leisure and entertainment. Children's computer or video game time compares to the time spent on sports and other physical activities. More time is spent on video game playing or computer activities than on entertainment activities, such as attending sports or cultural events and socializing with other people. Children's time spent on different activities sums up to approximately 200 hrs/week on average, which implies that an average child spent 32 hours per week multitasking, that is, doing two (or more) activities at the same time. In any given year, most of the children (97-99 percent) spent at least some time multitasking.

The sample means of demographic characteristics are presented in Table 2. There are equal numbers of female and male children observations in the sample. More than 50% of the sample observations are of white children, more than a third are of black children, around 11% are of Hispanic and other race children. Once the data is weighted to account for the over-sampling of low income families in the PSID, the race distribution in the sample resembles the race distribution in the U.S. population. The average age is equal to 11.40 years. Around half of the sample observations were born in 1984-1991. The other half were born in 1991-97.

Table 2: Sample means of demographic characteristics

	Wave I	Wave II	Wave III	All waves
Male	0.50	0.49	0.51	0.50
White non-Hispanic	0.56	0.53	0.53	0.54
Black non-Hispanic	0.35	0.36	0.34	0.35
Hispanic	0.06	0.07	0.08	0.07
Other race	0.04	0.04	0.04	0.04
Age, years	7.97	12.07	14.47	11.40
Born in 1984-1991	69.59	51.90	23.22	50.06
Born in 1991-1997	30.41	48.10	76.78	49.94
Observations	1,266	1,713	1,038	4,017

6 Results

6.1 Main results

Table 3 reports the estimates of the absolute effects of media use and other activities on a child's standardized body mass index (BMI), the probability of a child being overweight or obese, and the probability of a child being obese[10]. The absolute effects show how the standardized BMI or the probability of overweight (or obesity) changes when a child's time spent on a certain activity increases by one hour per week and his/her time spent on all other activities is held constant. The estimated models allow for all the activities to affect children's weight via changes in energy expenditure and energy intake, as calorie consumption is not held fixed in these models (besides the calorie consumption correlated with parent's BMI). The child fixed effects (FE) model is used to estimate the BMI

[10]To simplify the discussion of the results I refer to children who are overweight or obese as overweight in this section.

regression. The overweight and obesity regressions are estimated using the correlated random effects (RE) model. Table 3 reports the average partial effects based on these estimations. Standard errors are clustered at the family level in all the estimations to allow for correlation between siblings and correlation across the observations of the same child over time.

The small within R-squared value of the BMI regression shows that only a small fraction of children's BMI variation is explained by the within-child variation in their time spent on different activities and parents' BMI. On the other hand, child fixed effects, which account for child-specific time-invariant variables, such as genetic factors, explain a substantial proportion of the variation in children's BMI, as shown by the overall R-squared value of 0.721[11]. The low pseudo R-squared values of the overweight and obesity regressions indicate that the variables used in this analysis contribute little to explaining the variation in children's overweight and obesity status.

The estimates reported in Table 3 show that there is no evidence that media use contributes to children's weight gain. Holding other activity time fixed, the estimated effect of television time on children's standardized BMI is statistically insignificant, whereas the estimated effect of computer or video game time is negative and marginally statistically significant. With a 95 percent confidence, any positive effects of computer use or video game playing and positive effects of television watching larger than 0.003 can be ruled out. Neither television viewing nor computer use or video game playing is found to affect the probability of being overweight or the probability of being obese.

I have further investigated whether there are any differences in the effects on children's weight between video game playing and computer activities. In the BMI regression, the estimated effects of these two activities are of similar size, although only the effect of computer use is statistically significant. In the overweight and obesity regressions, the estimated effects of video game playing are close to zero, whereas the estimated effects of computer activities are negative and marginally significant, although quantitatively small. Thus, neither video game playing nor computer use seems to contribute to children's weight gain. Moreover, the negative effect of the time spent on video game playing or computer use on children's weight appears to be driven by the latter activity.

The effects of other activities on children's BMI are largely negative, suggesting that, on average, energy expenditure exceeds energy intake associated with these activities. Most of these effects are, however, imprecisely estimated. More insights in the effects of the statistically insignificant activities could be gained by disaggregating these activities.

[11]The overall R-squared is the R-squared of a "dummy variable" regression that includes dummy variables for all children but one as regressors

Table 3: Absolute effects of media use and other activities on standardized BMI and overweight status

	(1) BMI	(2) Prob(overweight/obese)	(3) Prob(obese)
Computer or games	-0.005^{*}	-0.001	-0.001
	(0.003)	(0.001)	(0.001)
Television	-0.002	-0.000^{a}	0.000^{a}
	(0.002)	(0.001)	(0.001)
Other passive act.	-0.001	0.000^{a}	-0.000^{a}
	(0.001)	(0.001)	(0.000)
Educational act.	-0.006^{**}	-0.001	-0.001
	(0.003)	(0.001)	(0.001)
Active leisure	-0.003	-0.001	-0.001
	(0.004)	(0.001)	(0.001)
Less active leisure	-0.003	-0.000^{a}	0.000^{a}
	(0.003)	(0.001)	(0.001)
Entertainment	-0.008^{**}	-0.001	-0.001
	(0.004)	(0.001)	(0.001)
Duties	-0.002	-0.001	-0.001
	(0.003)	(0.001)	(0.001)
Basic needs	-0.002	-0.001	-0.001
	(0.003)	(0.001)	(0.001)
Missing	0.005	0.001	0.002
	(0.007)	(0.004)	(0.003)
Parents' BMI	0.019^{*}	0.004	0.001
	(0.011)	(0.004)	(0.003)
Within R-squared	0.055		
Overall R-squared	0.721		
Pseudo R-squared		0.082	0.088
Observations	4,017	4,017	4,017

Notes: Standard errors (clustered at the family level) in parentheses. Regressions control for age and time effects. *denotes statistical significance at the 10% level and **denotes statistical significance at the 5% level. ^{a} indicates that $|\hat{\beta}| < 0.001$.

Some of the activities within each group may have significant effects on children's weight, although the average effect across all activities is not significantly different from zero. The only two activities that are found to have statistically significant effects on children's weight are entertainment[12] and educational activities. The negative effect of educational activities is driven by after school activities, such as homework or being tutored[13]. None of the activities significantly affect the probabilities of being overweight or obese. Children's BMI is related to their parents' BMI. A 10 percent increase in parents' BMI is associated with almost 12 percent increase in children's BMI, holding a child's activities constant. The probabilities of overweight and obese are also positively affected by parents' BMI, but these effects are not statistically significant. Age and time effects on weight are imprecisely estimated.

It may be somewhat surprising that the effect of active leisure on weight is found to be statistically insignificant. Participation in sports and other physical activities may, however, increase not only children's energy expenditure, but also energy intake, resulting in a net zero effect on children's weight. Additionally, physical activities may increase a child's muscle mass and total body weight, although his/her body fat may in fact decrease. BMI cannot capture these changes, which is one of the disadvantages of this measure of body fatness (Anderson and Butcher, 2006). Moreover, certain sports may have significant negative effects on children's weight, even though the average effect of all activities included in the active leisure category is not significantly different from zero.

Next, I present the estimates of the relative effects of media time on children's weight, which allow comparing the effects of media use to the effects of other activities. The relative effect of an activity shows how a child's weight (or the probability of being overweight or obese) changes, when this activity increases by one hour per week and another activity decreases by the same amount, holding the other variables fixed. There are two ways in which these relative effects can be estimated. The first one is taking a difference between the absolute effects of two activities, presented in Table 3. The second approach is to use the primary activity data only, that is, to include only the time an activity is reported as primary in measuring the time spent on this activity. As mentioned in Section 5, this approach ignores the fact that media use is often a secondary activity. Thus, by discarding secondary activity data one cannot estimate the full effect of media use. On the other hand, the identification of the absolute effects comes from the variation

[12]Entertainment includes attending sports and cultural events, socializing with other people, attending parties, and dancing.

[13]Since no other activities are recorded in time diaries while children are at school, there is no independent within-child variation in school time. Therefore, the absolute effects of time at school cannot be identified.

in a child's time spent multitasking, or doing two activities at a time. The effect of an activity may vary depending on whether or not a child performs another activity at the same time. For these reasons, I present both the relative effects derived from the absolute effects (columns 1, 3, and 5 of Table 4), and the relative effects obtained by using the primary activity data only (columns 2, 4, and 6 of Table 4).

Panel A of Table 4 presents the effects of computer use or video game playing relative to the other activities. The stars indicate whether the effect of computer or video game time is significantly different from the effects of another activity time. I first focus on the relative effects obtained using the primary and secondary activity data (columns 1, 3, and 5). Relative to television watching, the effect of computer use or video game playing on children's BMI is negative, implying that the net energy expenditure associated with the new media is higher than the net energy expenditure associated with the old media. However, this difference is not statistically significant. In the BMI regression, the effect of computer or video game time is positive relative to the time spent on educational activities and entertainment, suggesting that if children played games or used a computer instead of these activities their standardized BMI would increase slightly. The effects of computer or video game time relative to the time spent on the rest of the activities are negative, implying that if computer use or video game playing replaced these activities, children's weight would decrease slightly. Nonetheless, none of these effects are statistically significant. The relative effects of computer or video game time on the probabilities of being overweight or obese are neither economically nor statistically significant. Thus, I do not find evidence that children's weight would be affected significantly if computer activities or video game playing replaced other more intense activities, provided that children's calorie consumption associated with these activities is allowed to change as well. Columns 2, 4, and 6 present the relative effect estimates obtained using the primary activity data only. These estimates are qualitatively similar to the estimates presented in columns 1, 3, and 5, with one exception. In all the three regressions, the estimated effects of video game time relative to the other passive activity time are negative, statistically significant, and larger in absolute magnitude than the estimates of these effects obtained using both the primary and secondary activity data[14]. These differences may be explained by the fact that other passive activities are often secondary. Therefore, provided that the effects of such activities as reading, listening to music, talking to people, and relaxing vary depending on whether they are primary or secondary, discarding the secondary activity data may alter the estimated effects of these activities more than the effects of the other activities.

[14]Other passive activities include reading, listening to music, talking to people, relaxing, and doing nothing.

Table 4: Relative effects of media use on standardized BMI and overweight status

	BMI		Prob(overweight/obese)		Prob(obese)	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Effects of computer use or video game playing relative to:						
Television	−0.004	−0.001	−0.001	−0.001	−0.001	−0.001
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Other passive act.	−0.004	−0.008*	−0.002	−0.003**	−0.001	−0.002
	(0.003)	(0.005)	(0.001)	(0.002)	(0.001)	(0.002)
Educational act.	0.001	0.001	0.000[a]	0.001	0.000[a]	−0.000[a]
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Active leisure	−0.003	−0.001	0.000[a]	0.000[a]	0.000[a]	0.001[a]
	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)
Less active leisure	−0.002	0.000[a]	−0.001	−0.000[a]	−0.001	−0.000[a]
	(0.004)	(0.004)	(0.001)	(0.002)	(0.001)	(0.001)
Entertainment	0.003	0.004	−0.000[a]	0.000[a]	−0.000[a]	−0.000[a]
	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)
Duties	−0.003	−0.002	−0.000[a]	0.000[a]	−0.000[a]	−0.000[a]
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Basic needs	−0.004	−0.005	−0.000[a]	0.000[a]	−0.000[a]	−0.000[a]
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
B. Effects of television watching relative to:						
Other passive act.	−0.000[a]	−0.007*	−0.000[a]	−0.003*	0.000[a]	−0.001
	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.001)
Educational act.	0.005**	0.002	0.001*	0.001	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Active leisure	0.001	0.000[a]	0.001	0.001	0.001	0.002
	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)
Less active leisure	0.002	0.001	0.000[a]	0.000[a]	−0.000[a]	0.001
	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)
Entertainment	0.006*	0.005	0.001	0.001	0.001	0.001
	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)
Duties	0.001	−0.001	0.001	0.001	0.001	0.001
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Basic needs	−0.000[a]	−0.004	0.001	0.001	0.001	0.001
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	4,017	4,017	4,017	4,017	4,017	4,017

Notes: Columns 1, 3, and 5 present the relative effects derived from the absolute effects. Columns 2, 4, and 6 present the relative effects obtained by using the primary activity data only. Standard errors (clustered at the family level) in parentheses. Regressions control for other activity time, parents' BMI, age, and time effects. *denotes statistical significance at the 10% level and **denotes statistical significance at the 5% level. [a] indicates that $|\hat{\beta}| < 0.001$.

Panel B of Table 4 presents the estimated effects of television watching relative to the other activities. These estimates suggest that television time would have a positive effect on children's BMI if television watching replaced educational activities or entertainment. This finding is consistent across both specifications of the model (columns 1 and 2). Relative to educational activities, television watching is also estimated to have a small, positive, and marginally statistically significant effect on the probability of being overweight. In the estimation based on the primary activity data (columns 2 and 4), television time is found to have negative significant effects on children's BMI and the probability of being overweight relative to the other passive activity time. As discussed above, this finding is likely to result from the failure to take into account the effect of secondary passive activities.

I also present the results of the other models that can be used to estimate the effects of media use on children's weight. The BMI regression is re-estimated using the ordinary least squares (OLS), child random effects (RE), and family fixed effects (FE) models. Table 5 reports these estimates. The OLS and child RE models do not allow for the endogeneity of media use. These models assume that the unobserved child heterogeneity is uncorrelated with children's media time and the other explanatory variables. The results of a Hausman test do not provide support for this hypothesis. The null hypothesis that the differences in the child FE and RE estimates are not systematic is rejected. The estimates presented in columns 1-3 of Table 5 show that failing to account for the correlation between media time and the unobserved child heterogeneity slightly underestimates the negative effect of computer or video game time on children's BMI. Ignoring unobserved child heterogeneity has more serious consequences for the inferences about the effect of television time on children's BMI. The OLS and RE estimates of this effect are positive, whereas the child FE estimate is negative. The differences between the OLS, RE, and FE estimates imply that children's television time is positively correlated with the time-invariant child characteristics that positively affect weight.

The availability of siblings[15] in the PSID-CDS data makes it also possible to estimate the family FE model, which eliminates any unobserved family-specific variables. The identification of the media use effects in this model comes from the differences in media time between children from the same family. The family FE estimates of the media use effects on standardized BMI are presented in column 4 of Table 5. To facilitate comparison of the results, the baseline (child FE) model is re-estimated using the sibling sample (column 5). The fit of the child and family FE models is similar in terms of both

[15]More specifically, the sample used for the estimation of the family FE model includes pairs of children who live in the same household, most of which are siblings.

Table 5: Other model estimates of media use effects on standardized BMI

	(1) Child FE (baseline)	(2) OLS	(3) Child RE	(4) Family FE	(5) Child FE (same sample)
Computer or games	−0.005*	−0.002	−0.003	−0.010*	−0.007
	(0.003)	(0.003)	(0.002)	(0.005)	(0.005)
Television	−0.002	0.005**	0.002	0.008*	−0.002
	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
Within R-squared	0.055			0.069	0.085
Overall R-squared	0.721	0.106	0.104	0.695	0.739
Observations	4,017	4,017	4,017	1,950	1,950

Notes: Standard errors (clustered at the family level) in parentheses. Regressions control for other activity time, parents' BMI, age, and time effects. The OLS and child RE regressions additionally control for child birth weight, gender, and race. The family FE regression additionally controls for birth weight and gender and excludes parent's BMI and time effects. *denotes statistical significance at the 10% level and **denotes statistical significance at the 5% level.

the within R-squared and the overall R-squared. The family FE estimate of the effect of computer or video game time is negative and qualitatively similar to the child FE estimate of this effect. On the other hand, the family FE estimate of the effect of television time is positive, statistically significant, and more similar to the OLS estimate than to the child FE estimate of this effect. On the one hand, this finding may be explained by the family FE effect model failing to capture the child-specific heterogeneity, as this model only eliminates the unobserved factors common to siblings or cousins. On the other hand, this result may indicate that the child FE model fails to account for time varying family characteristics, which are eliminated in the family FE model. All in all, these results weaken support for the hypothesis that television viewing does not contribute to children's weight gain. Nonetheless, the estimated effect of television time in the family FE model is still quantitatively small.

Panel A of Table 6 presents the estimated effects of media time on the probability of overweight based on the probit, child RE probit, and child FE linear probability (LPM) models. Panel B of this table reports the estimated effects of media time on the probability of obesity based on the same models. The probit and RE probit models assume that the unobserved child characteristics are not correlated with the explanatory variables, including children's media time. To check whether this assumption holds, I conduct a test for the joint significance of the time averages of the time varying variables, included in the correlated RE probit model. If there is no correlation between the explanatory variables and unobserved child heterogeneity, these time averages should be jointly insignificant. The hypothesis that all the time averages are zero is rejected for both overweight and obesity regressions (at the one percent and five percent level, respectively), suggesting that the probit and RE probit models are not appropriate in this case. The results presented in columns 1-3 of Table 6 show that failing to allow for the correlation between the unobserved child heterogeneity and computer or video game time does not affect the estimated effect of these activities on the probability of being overweight or the probability of being obese. On the other hand, the results confirm that it is important to take into account the correlation between the unobserved child heterogeneity and television time. In the probit and RE probit models, the effects of children's television time on the probabilities of overweight and obesity are estimated to be positive, whereas in the correlated RE probit, these effects are close to zero. Column 4 of Table 6 presents the estimates of the child FE linear probability model. These estimates are very similar to the correlated RE probit results, suggesting that the latter model captures the correlation between children's media time and the unobserved heterogeneity quite well, or that the restrictions on the unobserved heterogeneity implied by the child FE LPM do not affect the results, or both.

Table 6: Other model estimates of media use effects on overweight status

	(1) Corr RE probit (baseline)	(2) Probit	(3) RE probit	(4) Child FE LPM
A. Prob(overweight/obese)				
Computer or games	−0.001	0.000^{a}	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Television	0.000^{a}	0.002^{**}	0.001	0.000^{a}
	(0.001)	(0.001)	(0.001)	(0.001)
(Pseudo) R-squared	0.082	0.071	-	0.698
B. Prob(obese)				
Computer or games	−0.001	0.000^{a}	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Television	0.000^{a}	0.002^{**}	0.001^{*}	0.000^{a}
	(0.001)	(0.001)	(0.001)	(0.001)
(Pseudo) R-squared	0.088	0.075	-	0.686
Observations	4,017	4,017	4,017	4,017

Notes: Standard errors (clustered at the family level, except for the RE probit model) in parentheses. Regressions control for other activity time, parents' BMI, age, and time effects. *denotes statistical significance at the 10% level and **denotes statistical significance at the 5% level. ^{a} indicates that $|\hat{\beta}| < 0.001$.

6.2 Sensitivity analysis

In this subsection, I investigate robustness of the results. As the estimated effects of media use on the probability of being overweight or obese are similar to the effects on the probability of being obese, in the below discussed model specifications, I only report the first set of estimates. Given that there are no differences between the correlated RE and child FE LPM estimates in the baseline model specification, the results based on the latter model are presented in this subsection. Conclusions of the sensitivity analysis would not change, if the correlated RE probit model were used instead.

First, I use the two strategies described in Section 4 to check how plausible the strict exogeneity assumption is in this analysis. This assumption requires media time to be uncorrelated with the unobserved time varying variables. As a first test, a child's future period media time is included in the regressions. It is only possible to use the children who are observed in all three waves for the estimation of this model specification. Therefore, the sample size is smaller. Panel A of Table 7 reports the results of this test. The coefficient on the future period media time is not statistically significant in either the BMI regression or the overweight regression. As explained in Section 4, these findings provide support for the strict exogeneity assumption.

As a second test, I add additional control variables to the model. These variables are grouped in three groups: family characteristics, changes in a child's environment, and health. The following family characteristics are added: family income; the number of children in the family; a binary variable indicating whether or not both parents live in the household; education, age, and employment status of the primary care giver of a child; and a binary variable indicating whether or not the family lives in a standard metropolitan statistical area (SMSA). Variables describing changes in a child's environment include binary variables indicating whether or not a child changed school, whether or not a child moved, and whether or not the family has financial problems; parental warmth and discipline measures; and neighborhood rating. A child's health is described by binary variables indicating whether or not a child has any chronic conditions and whether or not he/she has any physical or mental disabilities; a child's number of doctor visits; and primary care giver assessed health status. The full list of these variables is provided in Appendix A. Many of the above listed variables may affect a child's weight via changes in calorie consumption. Additionally, some illnesses could affect a child's metabolic rate. The sample size is smaller in these estimations due to missing values. For comparison purposes, I re-estimate the baseline model using the same sample. The results presented in panel B of Table 7 show that the estimated effects of media time on children's weight are not affected by the inclusion of the additional controls. Overall, the results of these two exercises provide support for the strict exogeneity assumption. Note that the estimated effect of computer or video game time is positive in both the specification with additional control variables and the baseline specification re-estimated on the same sample. These findings suggest that there may be heterogeneity in the effects of media time, which is explored in the following subsection.

Table 7: Sensitivity checks, child FE estimates of media use effects on standardized BMI and overweight status

	BMI		Prob(overweight/obese)		Sample
	Computer or games	TV	Computer or games	TV	size
Baseline	-0.005^{*}	-0.002	-0.001	-0.000^{a}	4,017
	(0.003)	(0.002)	(0.001)	(0.001)	
A.					
$t_{j,t+1}$	0.002	-0.001	-0.001	0.002	834
	(0.006)	(0.006)	(0.002)	(0.002)	
$t_{j,t}$	-0.012	-0.013	-0.003	0.001	
	(0.015)	(0.009)	(0.005)	(0.003)	
B.					
Adding controls	0.004	0.000^{a}	-0.001	-0.001	1,993
	(0.004)	(0.004)	(0.001)	(0.001)	
New baseline	0.003	-0.001	-0.001	-0.001	1,993
	(0.004)	(0.003)	(0.001)	(0.001)	
C.					
Excluding	-0.004	-0.002	-0.001	0.000^{a}	3,888
outliers	(0.003)	(0.003)	(0.001)	(0.001)	
Excluding	-0.007^{**}	-0.005	-0.001	-0.001	2,826
atypical days	(0.003)	(0.003)	(0.001)	(0.001)	
Excluding non-	-0.005^{*}	-0.001	-0.001	0.000^{a}	3,843
consecutive obs	(0.003)	(0.002)	(0.001)	(0.001)	
D.					
$t_{j,t}$	-0.001	-0.001	-0.001	-0.000^{a}	4,017
	(0.004)	(0.005)	(0.002)	(0.002)	
$t^2_{j,t}$	-0.000^{a}	-0.000^{a}	-0.000^{a}	0.000^{a}	
	(0.000^{a})	(0.000^{a})	(0.000^{a})	(0.000^{a})	
Weights	-0.003	-0.004	-0.001	-0.000^{a}	4,017
	(0.003)	(0.003)	(0.001)	(0.001)	

Notes: Standard errors (clustered at the family level) in parentheses. Regressions control for other activity time, parents' BMI, age, and time effects. *denotes statistical significance at the 10% level and **denotes statistical significance at the 5% level. ^{a} indicates that $|\hat{\beta}| < 0.001$.

The second part of the sensitivity analysis summarizes the results of the additional robustness checks. First, I investigate whether excluding some of the observations from the sample affects the results. These estimates are presented in panel C of Table 7. The first row of this panel shows how the results are affected by the exclusion of the outliers of media time. An observation is considered to be outlier if a child's computer or video game time and/or television time exceeds the 99th percentile of the corresponding distribution. The exclusion of these outliers practically does not affect the results, besides making the effect of video game or computer time statistically insignificant in the BMI regression. The second row of panel C reports the estimates of the media use effects based on the subsample that excludes the observations with very atypical time diary days. Such days may not measure the time use of a child well. The exclusion of these observations further strengthens the conclusion that media use does not affect children's weight significantly and that the time spent on video game playing or computer activities may in fact decrease children's BMI. The final row of panel C presents the results based on the subsample that includes only the consecutive observations. This subsample excludes the children observed in wave I and III, but not in wave II. Restricting the sample this way does not affect the results either.

Next, I check whether there are any non-linearities in the effects of media time on children's weight by including a square of computer or video game time and a square of television time to the regressions. The results presented in the first and second rows of panel D of Table 7 suggest that the baseline estimates are not driven by the omitted non-linearities. The quadratic terms of computer or video game time and television time are economically and statistically insignificant. Finally, I investigate whether using sampling weights in the estimations affects the results. The estimates based on the weighted data are presented in the last row of panel D. The estimated effects of media time on children's weight are largely not affected by the use of weights. Overall, the baseline results remain robust.

6.3 Heterogeneity in the effects of media use

This subsection investigates whether there is heterogeneity in the effects of media on children's weight. Television programs, movies, video games, and computer and Internet activities are likely to vary by child and family characteristics. Therefore, the degree of engagement in media activities and exposure to food advertising on media may be different across children. I analyze whether the effects of media time on children's weight vary by such child and family characteristics as gender, race, year of birth, location, family income, education of the primary care giver of a child, and family structure. I split the sample by these characteristics and estimate the BMI and overweight regressions separately for each of the subsamples[16]. Tables 8 and 9 present the child FE estimates of

[16] The estimated effects of media time on the probability of obesity are not statistically significant in most of the subsamples, and therefore, are not reported.

these regressions. Sample sizes are smaller is some of the estimations due to the missing values of child and family characteristics. Additionally, only children observed at least twice in a given subsample are used for the estimations.

Table 8: Effects of media use on standardized BMI and overweight status by child characteristics, child FE estimates

	BMI		Prob(overweight/obese)		
	Computer or games	TV	Computer or games	TV	Sample size
Gender					
Female	−0.004	−0.001	−0.003	0.001	2,011
	(0.004)	(0.003)	(0.002)	(0.001)	
Male	−0.004	−0.002	−0.001	−0.001	2,006
	(0.003)	(0.003)	(0.001)	(0.001)	
Race[a]					
White	−0.001	−0.003	−0.001	0.001	2,167
	(0.004)	(0.003)	(0.001)	(0.001)	
Black	−0.012***	0.001	−0.003**	−0.001	1,410
	(0.005)	(0.004)	(0.002)	(0.002)	
Birth cohort					
1984-1988	−0.013**	−0.002	−0.003	−0.001	982
	(0.004)	(0.004)	(0.002)	(0.002)	
1988-1991	−0.006	−0.001	−0.003	−0.001	1,029
	(0.006)	(0.005)	(0.002)	(0.002)	
1991-1994	−0.005	−0.006	−0.001	0.000[b]	1,206
	(0.005)	(0.004)	(0.002)	(0.002)	
1994-1997	0.007	0.007	0.001	0.002	800
	(0.007)	(0.005)	(0.002)	(0.002)	

Notes: Standard errors (clustered at the family level) in parentheses. Regressions control for other activity time, parents' BMI, age, and time effects. **denotes statistical significance at the 5% level and ***denotes statistical significance at the 1% level. [a] The sizes of Hispanic and other race subsamples are too small to draw any inferences. [b] indicates that $|\hat{\beta}| < 0.001$.

The results presented in Table 8 show how the effects of media time on children's weight vary by the child characteristics. There are no differences in these effects by gender. The negative effect of computer or video game time on children's BMI seems to be driven by black children. In the white children subsample, this effect is smaller and not statistically significant. In the black children subsample, computer or video game time is found to negatively affect not only children's BMI, but also the probability of being overweight or obese, and both effects are statistically significant. The effect of television watching is statistically insignificant in both white and black children subsamples. For children of other races, the effects of media time on children's weight are not precisely identified due to small sample sizes. There is some evidence that the effect of computer or video game time on children's weight may vary by their birth cohort. For children born between 1984 and 1988, the estimated effect of video game playing or computer use on BMI is negative and statistically significant, whereas for the youngest cohort this effect is positive (although statistically insignificant). It should be noted that it is difficult to separate the variation in the media effects by birth cohort from the variation in these effects by children's age and/or time period.

Table 9: Effects of media use on standardized BMI and overweight status by family characteristics, child FE estimates

	BMI		Prob(overweight/obese)		
	Computer or games	TV	Computer or games	TV	Sample size
Standard metropolitan statistical area (SMSA)					
No	−0.004	−0.003	0.000[a]	0.000[a]	1,679
	(0.004)	(0.003)	(0.002)	(0.001)	
Yes	−0.007*	−0.001	−0.003**	−0.001	2,163
	(0.004)	(0.004)	(0.001)	(0.001)	
Family income					
≤ median	−0.003	0.002	−0.002	0.000[a]	1,573
	(0.004)	(0.004)	(0.002)	(0.002)	
> median	−0.002	−0.005	−0.002	0.000[a]	1,581
	(0.004)	(0.004)	(0.002)	(0.001)	
Education of PCG, years					
≤ 12	−0.004	0.001	0.000[a]	0.000[a]	1,734
	(0.004)	(0.004)	(0.001)	(0.001)	
13-15	−0.012**	−0.009	−0.005**	−0.001	1,049
	(0.006)	(0.005)	(0.002)	(0.002)	
≥ 16	0.004	−0.008	0.000[a]	−0.002	807
	(0.007)	(0.005)	(0.003)	(0.002)	
Child has a secondary care giver					
No	−0.005	0.010**	0.001	0.005***	728
	(0.005)	(0.005)	(0.002)	(0.002)	
Yes	−0.003	−0.004	−0.002	−0.001	2,677
	(0.003)	(0.003)	(0.001)	(0.001)	
Number of other children in the family					
0	0.006	0.003	0.002	0.001	509
	(0.008)	(0.007)	(0.002)	(0.003)	
1	−0.001	0.006	−0.002	0.002	1,332
	(0.005)	(0.004)	(0.002)	(0.002)	
≥ 2	−0.015***	−0.006	−0.004*	−0.003	996
	(0.005)	(0.005)	(0.002)	(0.002)	

Notes: Standard errors (clustered at the family level) in parentheses. Regressions control for other activity time, parents' BMI, age, and time effects. *denotes statistical significance at the 10% level, **denotes statistical significance at the 5% level, and ***denotes statistical significance at the 1% level. [a] indicates that $|\hat{\beta}| < 0.001$.

The results reported in Table 9 show how the effects of media time vary by the selected family characteristics. The negative effect of computer or video game time on children's weight is mostly due to children living in standard metropolitan statistical areas. However, there are no differences between these two subsamples in the effect of television time. Although the estimated effect of television time on BMI is positive for children from lower income families and negative for children from higher income families, none of these effects are statistically significant. No differences are found in the effect of computer or video game time on children's weight by family income, but this effect appears to vary with the primary care giver's education. The effect of video game playing or computer activities on BMI is negative and statistically significant in the subsample of children whose primary care givers have 13-15 years of education. For children whose primary care givers have 12 years of educations or less, this effect is negative and statistically insignificant, whereas for children whose primary care givers are likely to have college education (16 years of education or more) this effect is positive and also statistically insignificant. A similar pattern is observed in the overweight regression. Turning to the family structure variables, there seems to be heterogeneity in the effects of media time, especially television time, by whether or not a child has a secondary care giver[17]. There is some evidence that television watching affects the weight of children without a secondary care giver positively, both in terms of BMI and the probability of overweight/obesity, whereas this effect is statistically insignificant in the subsample of children who have a secondary care giver. It should be noted that the first finding is based on a small sample of children. Finally, the results show that the effects of media time may vary by the number of children in the family. The effects of both types of media are positive for children with no siblings, and become negative as the number of other children in the household grows.

The observed variation in the media use effects by family characteristics helps to explain some of the variation in the media effects by race. The larger negative effects of computer or video game time on weight among black children than among white children may be explained by the fact that black children are more likely to live in standard metropolitan statistical areas, have a primary care giver with lower education, and have two or more siblings. These family characteristics are associated with larger negative effects of video game playing or computer use on weight.

[17]Most of the children who have only one biological or adoptive parent have another relative living in the household who helps caring for the child, such as a grandparent, step-father/mother, or sibling. Children without a secondary care giver are cared for by only one person.

7 Discussion

Overall, the results of this paper suggest that changes in children's time spent on media, either new or old, are unlikely to be the main factor contributing to the recent increase in children's weight. I find no evidence that computer use or video game playing increases children's weight. To the contrary, the effect of the time spent on video game playing or computer activities on children's BMI is estimated to be negative and marginally statistically significant (holding other activity time fixed). This result implies that the net energy expenditure associated with computer use or video game playing may be positive. In other words, children may not be consuming enough calories to compensate for the expended energy while being engaged in video games or computer activities. As discussed earlier, the interactive nature of the new media may make video game playing and computer activities highly engaging and even addictive. By capturing children's full attention, video game playing and computer activities may distract them from other activities and needs, including eating. Nonetheless, the estimated negative effect of computer or video game time on children's weight is quantitatively small. In the baseline specification, it is estimated that a one hour per week increase in a child's computer or video game time decreases his/her standardized BMI by 0.005, which corresponds to 1.1 percent of the mean.

Television time is also found not to significantly affect children's weight (holding other activity time fixed). In the baseline specification, positive television time effects on standardized BMI larger than 0.003 (0.7 percent of the mean) can be ruled out with a 95 percent confidence. The insignificant effects of television time on children's weight imply that a change in a child's time spent watching television does not affect the balance between his/her energy intake and expenditure. As television watching is not expected to affect children's energy expenditure relative to resting, these findings further suggest that children's calorie consumption is not increased by an increase in television time. Although in some of the estimations, television time is found to have positive effects on children's weight, these effects are quantitatively small. For example, in the subsample of children without a secondary care giver, it is estimated that a one hour per week increase in a child's television time increases his/her standardized BMI by 0.010, which corresponds to 2.3 percent of the mean.

Furthermore, the results of this analysis suggest that increasing childhood obesity rates cannot to be explained by media use replacing other activities. Although television watching is found to have positive effects on children's BMI relative to educational and entertainment activities, these effects are quantitatively small. Moreover, the average television time is estimated to have increased by only 0.76 hours from 1997 to 2007. The average standardized BMI increased by 0.34 during the same period. Thus, the increase in children's television time would explain only a small proportion (1.1-1.3 percent) of the increase in BMI even if all the increase in children's television time came at the expense of educational or entertainment activities. Furthermore, children's time spent on educational and entertainment activities did not decrease during the 1997-2007 period. The results of this analysis also show that a child's weight would not increase significantly if his/her time spent on computer use or video game playing displaced other more intense activities.

Turning to the differences between the new and old media, the baseline results do not support the hypothesis that computer use or video game playing affects children's weight differently from television viewing. Nevertheless, in some of the subsamples of children, the effects of computer or video game time are significantly different from the effects of television time. Computer or video game time is usually found to affect children's weight negatively, whereas the effect of television time is either also negative, but smaller in absolute magnitude, or positive. For example, in the black children subsample, the effect of computer or video game time on children's BMI is negative and statistically significant, whereas the effect of television time is positive and statistically insignificant[18]. The relatively larger negative effects of the new media may be explained by the more engaging nature of video game playing and computer activities, which may distract children from eating, and/or higher energy expenditure associated with video game playing than television watching. Additionally, children may be less affected by advertising in video games and on the Internet than on television.

Next, I compare the results of this analysis to the findings of the other studies cited in the literature review section. Chou et al. (2008) and Andreyeva et al. (2011) find that exposure to television advertising positively affects children's weight. The results of this paper show, however, that television time has no significant effects on children's weight. Nonetheless, my results can be expected to be different from those of Chou et al. and Andreyeva et al. First, my study focuses on children's time spent watching television and not on children's exposure to fast food advertising on television[19]. Thus, to compare the

[18]Computer or video game time is also found to affect children's BMI significantly differently from television time among children born in 1984-1988 and children without a secondary care giver. In addition, it is estimated that the new and old media have significantly different effects on the probability of overweight among girls, children whose care givers have 13-15 years of education, children without a secondary care giver, and children with one sibling.

[19]Children's exposure to fast food advertising on television is computed by multiplying the proportion of a child's time spent on television viewing by the number of fast food advertising hours aired on television in the child's local area.

results of this study to those of Chou et al. and Andreyeva et al., a measure of children's exposure to fast food advertising should be constructed. Second, the conclusions of the cited papers are based on the OLS estimates. In my analysis, the OLS estimate of the effect of television time on children's weight is also positive. Chou et al. show that children's exposure to fast food advertising on television can be treated as an exogenous variable in their analysis. To the contrary, I find evidence for the endogeneity of children's television time, which does not support using OLS for the estimations. Finally, children's other activity time is held constant in my analysis, but not in the studies of Chou et al. and Andreyeva et al. Relative to some of the other activities, I find a positive effect of television time on children's weight. Thus, my results are not necessarily inconsistent with the findings of Chou et al. and Andreyeva et al.

Chang and Nayga Jr (2009) find that television time has a positive effect on children's weight holding their consumption of fast food and soft drinks constant. As their model does not control for children's time spent in other activities, these findings show that television viewing may be affecting children's weight by replacing other more intense physical activities. It is difficult to compare my findings to those of Chang and Nayga Jr, because, in my analysis, fast food and soft drink consumption is not included in the model to allow media to affect children's weight via changes in their energy intake. Nonetheless, I find that relative to some of the other activities television viewing has positive effects on children's weight. It is likely that if calorie consumption were held fixed, the relative effects of television watching would remain positive and increase. Holding energy intake constant, the relative effects of television viewing measure the changes in children's weight due to the differences in energy expenditure between television viewing and other activities, and energy required for television watching is lower than energy required for many other activities. This suggests that the findings of my analysis may be in line with those of Chang and Nayga Jr.

Wilson (2006) reaches a conclusion that the recent rise in childhood obesity in the U.S. can be at least partly attributed to children spending more time on computer activities and video games. This claim is not supported by the findings of my analysis, although I use the same data as Wilson. I find a small negative effect of computer or video game time on the probability of being overweight. More detailed investigation of Wilson's findings casts doubt on the validity of his claim. Wilson indeed finds that, relative to intense activities, passive activities have a positive effect on the probability of being overweight. However, when the endogeneity of time use variables is addressed by using child FE and instrumental variable methods, this effect becomes highly statistically insignificant. Moreover, Wilson includes not only video game playing and computer activities, but also television watching, listening to music, reading, talking to other people, and relaxing, to the definition of passive activities. The results of my analysis suggest that Wilson's finding that passive activities affect the probability of overweight positively is driven not by video game playing or computer use, but by the other passive activities.

8 Conclusions

To summarize the results of this paper, I find that holding other activity time fixed, the time spent on video game playing or computer activities has a slight negative effect on children's BMI. This finding is robust to the use of alternative estimation methods, analysis samples, and model specifications as well as allowing the effect of computer or video game time to vary by child and family characteristics. The estimated effect of computer or video game time on the probability of being overweight (or obese) is statistically and economically insignificant. Television time is also found not to significantly affect children's BMI or the probability of overweight (or obesity), holding other activity time fixed. However, these findings are not completely robust. In some of the estimations, television time is found to have positive, although quantitatively small, effects on children's weight.

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A Additional controls

The following variables are added to the weight equation: family income (adjusted for family size and composition, in 1996 dollars); the number of adults in the family; the number of children in the family; whether a child has another care giver; whether or not a child's biological or adoptive parents live in the household; age, education, and employment status of the primary care giver; whether or not the family lives in a standard metropolitan statistical area (SMSA); whether a child changed schools; whether or not the family moved; the number of the primary care giver's activities with the child; parental warmth and discipline measures; interviewer observations about the interaction between the primary care giver and the child (whether or not the primary care giver spontaneously spoke with the child, responded to the child's questions, showed physical affection towards the child, slapped or spanked the child, physically restricted the child, conveyed positive feelings about the child, spontaneously praised the child, was warm and affectionate when interacting with the child); interviewer rating of the primary care giver based on hostility, pride, and warmth towards the child; interviewer rating of home environment (how monotonous, cluttered, clean, and safe the house is); whether or not the primary care giver reported ever spanking the child; whether or not a child is negatively affected by anyone in the household's alcohol consumption; the primary care giver's self-esteem, self-efficacy, and distress scales; how often the family gets together with friends or relatives; whether or not the family had any financial hardships in the past 12 months; neighborhood rating; whether or not a child has any chronic conditions; a child's number of doctor visits in the past 12 months (for illness or injury); whether or not a child has any physical or mental disability; and primary care giver assessed health status of a child.