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DOES TELEVISION VIEWING AFFECT CHILDREN'S BEHAVIOUR?

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Abstract. Using three-period panel data drawn from the National Longitudinal Survey of Youth 1979, we investigate whether television (TV) viewing at ages 6–7 and 8–9 years affects children's social and behavioural development at ages 8–9 years. Dynamic panel data models are estimated to handle the unobserved child-specific factor, endogeneity of TV viewing, and the dynamic nature of the causal relation. Special emphasis is placed on this last aspect, focusing on how early TV viewing affects interim child behavioural problems and in turn affects future TV viewing. Overall, we find that TV viewing during ages 6–7 and 8–9 years increases child behavioural problems at ages 8–9 years, and that the effect is economically sizable.

1. INTRODUCTION

Since the early days of television (TV), there have been concerns among the public and researchers about the impact of TV on child development. Research over the past 50 years, however, has not yet settled the issue, although the conventional wisdom is that TV viewing should be limited to below 2 h per day for small children (Pecora *et al.*, 2006 and Murray and Murray, 2008). This recommendation does not seem to be well heeded in reality. For example, an average 5-year-old in the National Longitudinal Survey of Youth 1979 child sample in the USA spends over 3 h per day in front of the TV; among children aged 8–9 years, approximately 80% of them watch TV for at least 2 h per weekday and 35% for at least 4 h. For US children, TV viewing is the most time-consuming activity after attending school (Jester and Stafford, 1991). Despite the increasing use of computers and the internet in recent decades, TV still remains the dominant form of media for children. Although US children are on the higher end in terms of the amount of time spent watching TV, their TV watching habits are not too different from children in other countries. The average TV viewing time of 11–15 years old across 35 countries surveyed in February 2001 was at least 2 h per day and was as high as 3.7 h daily in some countries (Vereecken *et al.*, 2006).

The goal of this paper is to determine the effects of TV viewing on children's social and behavioural development measured by the 'Behaviour Problems Index (BPI)'. This is an important issue because early child development results, including both cognitive and non-cognitive skills, have been shown to be important determinants of later schooling and socioeconomic success (Keane and Wolpin, 1997; Heckman, 2000; Heckman and Rubinstein, 2001; McLeod and

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Kaiser, 2004; Blanden *et al.*, 2006; Currie and Stabile, 2006, 2007; Heckman *et al.*, 2006). For example, children who had behavioural problems at early ages (6–8 years) are less likely to graduate from high school or to attend college. In this paper, we use three-period panel data ($t = 0, 1, 2$) drawn from the National Longitudinal Survey of Youth 1979, where $t = 0, 1, 2$ correspond to ages 4–5, 6–7 and 8–9 years, respectively. With some $t = 0$ variables used as instruments, essentially, we will be using two-period panel data models.

Little research has been undertaken on the effects of TV viewing on child behavioural problems using large, national samples. This is probably because of various difficulties in establishing the causal link between TV watching and child development. First, inappropriate home and school inputs (e.g. economically and intellectually deficient environments) may induce both TV watching and behavioural problems. This is an omitted variable (or 'unobserved confounder') problem, which can be resolved using detailed data with sufficient environmental control variables. Second, children and their parents might share predispositions for certain habits and behaviour that cannot be measured. This is an 'individual-specific effect' problem, which might be overcome with panel data. Third, TV watching can affect child social and behavioural development, which can in turn affect future TV watching. This is an issue of 'dynamic treatment effects with feedback', calling for an appropriate dynamic treatment effect model and an estimation method thereof.

The present paper makes the following contributions to the literature. First, we use a rich childhood longitudinal sample that includes not only child characteristics and family background variables but also detailed home and school inputs in current and earlier periods to mitigate the aforementioned omitted variable problems. Second, a new dynamic treatment effect estimation procedure developed in Huang and Lee (2010) is used to explicitly allow for the effects of TV viewing on child behavioural problems at interim ages, which then affects future TV viewing time and behavioural problems at later ages. Third, the new dynamic treatment effect estimation procedure is further refined to avoid some of the incoherent features in Huang and Lee.

Whereas Huang and Lee (2010) examine TV's effects on test scores, the present paper focuses on TV's effect on behavioural problems. There would be no dispute that both response variables, test scores and behavioural problems, are of great interest and concern for parents and scholars. The emphasis of Huang and Lee (2010) is on the methodological development of a dynamic treatment effect analysis and a subsequent comparison of their new method with the existing ones. Their empirical findings on TV's effect on test scores turn out to be 'weak', as the magnitude of the effect is economically small. In contrast, in the present paper, our empirical results are much stronger, with substantial effect magnitudes.

There has been little research in the economics literature on the effects of TV watching on child social and behavioural development. An exception is Waldman *et al.* (2006), whose findings suggest that early childhood TV viewing may be an important trigger for autism. Other than this narrow-scope finding for autism, Zavodny (2006) and Gentzkow and Shapiro (2008) examine the

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effects of TV on child cognitive development measured by math and reading scores.

The non-economic literature, especially child development and other psychological domains, tends to focus more on the effects of specific contents of TV programs and detailed neurological mechanism by which TV viewing may affect child development. However, their statistical analyses are mostly on correlations rather than causal relations. Many non-economic studies show that TV viewing is associated with more behavioural outcomes and poor performances among children and teenagers (Christakis *et al.*, 2004; Van Evra, 2004; Johnson *et al.*, 2007; Mistry *et al.*, 2007), although there are also a few studies reporting a weak or no relation at all (Christakis *et al.*, 2004; Van Evra, 2004; Stevens and Mulsow, 2006). The fact that there are more studies showing the bad effects of TV on behaviour than studies showing weak or no effects might be due to the publication bias that 'sensational' empirical findings are more likely to be published.

We find that more time spent viewing TV tends to increase children's behavioural problems and the effects are economically sizable. The results are coherent across various specifications and statistically significant in most cases. The results indicate that the total effect of TV watching during ages 6–7 and 8–9 years is positive and slightly concave for the BPI at ages 8–9 years, where the 'indirect effect' of TV viewing at the younger ages 6–7 years transmitted through the BPI at ages 6–7 years could be much larger than the direct effects. In our preferred estimates, for example, the marginal effect of 1 h of TV viewing daily at ages 6–9 years relative to 0 h viewing is 1.25 points or 8.3% of one standard deviation (SD) of the BPI at ages 8–9 years, which is similar in scale to the effect of 1 year of additional education of the child's mother (Carneiro *et al.*, 2008); 2 h TV viewing daily at ages 6–9 years increases BPI at ages 8–9 years by 2.37 points or 16% of one SD. Compared with less than 2 h of TV per day during ages 6–9 years, watching TV for 5 or 6 h daily increases one's BPI at ages 8–9 years by 3.27 points or 22% of one SD. All of these effects are statistically significant.

The rest of this paper is organized as follows. Section 2 describes a simple economic model to illustrate the determination of child TV viewing time and the implications for empirical estimation of its effect on child development results. Section 3 presents a dynamic treatment effect framework with feedback and lagged-response effects, and then introduces the aforementioned estimation procedure and its refinements. Section 4 describes our data. Section 5 presents the empirical findings. Finally, Sections 6 concludes.

2. A SIMPLE MODEL OF TV VIEWING AND CHILD DEVELOPMENT

The following two-period optimization model serves as an illustration of the general conceptual framework in which our estimation is embedded. In order to focus on parent–child interaction, a family is assumed to be composed of a mother and a child, where the mother is the planner for the family and there is no bargaining among family members. To simplify the discussion here, 'he' is used for child and 'she' for mother.

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In each period $t \in \{1, 2\}$, a mother is faced with a time constraint

$$W_t + H_t + L_t = 1, \tag{1}$$

where her total time is normalized to 1 and divided among working hours $W_t \geq 0$, 'quality time' with child $H_t \geq 0$, and leisure time $L_t \geq 0$. This means that a mother could spend her non-working time either pursuing her own interests (say, watching TV programs for adults) or actively interacting with her child to improve his development (such as reading to him).

Another time constraint for the mother is

$$H_t + d_t = F_t, \tag{2}$$

where $d_t \geq 0$ is the TV viewing time for the child and $0 < F_t < 1$ is the total free time of the child that has to be supervised or accompanied by an adult at home (i.e. by the mother in this simple model). A preschool child, for example, has more free time and, therefore, consumes more of his mother's time than a school-aged child; in countries such as the USA where school hours are relatively shorter, children have more time to spend at home. This condition formalizes the notion that a child engaged in TV viewing is not demanding active attention from the mother and, therefore, frees her time to do other things.

The budget constraint for the mother is

$$c_t + p_k x_t = w_t W_t + I_t, \tag{3}$$

where $c_t \geq 0$ is household consumption, $x_t \geq 0$ denotes a vector of market goods and services relevant in child development (e.g. books, toys, child care and enriching activities), $p_k \geq 0$ is the price vector of x_t, $w_t \geq 0$ mother's wage, and $I_t \geq 0$ the household income net of mother's wage. We assume that child TV viewing has a positive fixed cost reflected in c_t, including the price of the TV set and an annual or monthly subscription fee for cable service, but involves zero marginal cost; this assumption is fairly realistic and simplifies the exposition, although it is not necessary for our purposes.

The underlying production functions for child development results are the same across children. Let y_t denote an indicator of child development result at period t, which in our case is a child's BPI. A child's performance in the first period, y_1, is affected by his TV viewing time, d_1, and other home inputs, x_1 (including H_1), in addition to his innate character, δ, which is stable across the two periods. The second period response, y_2, is affected not only by current inputs x_2 and d_2, but also by historical inputs x_1 and d_1, as well as the last period response, y_1. Specifically, we assume

$$y_1 = f(d_1, x_1, \delta), \tag{4}$$

$$y_2 = g(d_2, d_1, x_2, x_1, y, \delta). \tag{5}$$

Estimating the dynamic effects of TV viewing (d_2, d_1) on y_2 is the main goal of the present paper. There are presumably many ways in which TV viewing affects

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child behavioural problems. For example, a child who spends more time watching TV at home tends to devote less time actively interacting with others and developing his skills in socialization, although he might receive some useful information and knowledge from TV programs. More time in front of TV might also lead to various problems such as attention deficit and to being overweight, which in turn contribute to child behavioural problems (Christakis *et al.*, 2004; Van Evra, 2004; Vereecken *et al.*, 2006).

The preferences of mothers in terms of child development results, household consumption level and her leisure are represented by an instant utility function $u(y_t, c_t, L_t; a, \alpha)$, where $a \in R_+$ is a mother's altruism level, and α is a vector of parameters. At each period, she will choose optimal inputs to maximize her remaining lifetime utility discounted by β, subject to the constraints of time, budget and production functions listed above in equations 1–5. The three constraints (eqns 1–3) together imply

$$d_t = F_t + W_t + L_t - 1 = F_t + \frac{c_t + p_k x_t - I_t}{w_t} + L_t - 1. \tag{6}$$

If the preferences of all mothers $u(y_t, c_t, L_t; a, \alpha)$ are identical, equation 6 suggests that a child spends more time watching TV if he has more free time (F_t larger), if the other home inputs are more expensive (p_t larger), if the mother's market wage w_t is lower, and if the family income, I_t, is lower, among other things. The first two factors may vary across regions and countries, while the last two vary across families. If mothers differ in preferences, then the TV viewing time would also be affected by relevant preference parameters a and α.

Although this model is extremely simple, it characterizes some fundamental features relating to how home inputs that are chosen by parents affect child development results, and delivers important implications for empirical estimation. Because all inputs are correlated with each other through the budget, time and production constraints faced by a family, any omitted inputs must be correlated with the included ones and, therefore, cause biases in the estimated effects of the latter. A strong positive correlation between more TV viewing time and worse behavioural problems may not be caused by TV viewing per se, but by lack of important home inputs such as quality time with parents and other enriching activities. If the latter are not controlled, the estimated coefficients of TV viewing would be biased upwards in the regression of BPI.

When there is unobserved heterogeneity in preferences across parents or nonlinear interactions among inputs, the mapping from family background variables to home input choices is no longer one-to-one.[1] In other words, identical family backgrounds now lead to different inputs, so controlling the former no longer means that the latter is effectively controlled. This means that detailed home inputs have to be controlled in the regressions in addition to family backgrounds in order to obtain unbiased estimates. The dynamic feature of home input choices should also be adequately treated in the estimation. Our

[1] See Huang (2008) for a formal analysis.

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estimation methods and data in this paper are specifically chosen to handle these problems.

3. DYNAMIC TREATMENT EFFECTS AND PANEL DATA

3.1. *Dynamic model with feedback and lagged-response effect*

Suppose a vector of treatments (TV viewing time), covariates (home inputs) and outcomes (BPI scores)

$$(x'_{i0}, y_{i0}, x'_{i1}, d_{i1}, y_{i1}, x'_{i2}, d_{i2}, y_{i2}), i = 1, \ldots, N$$

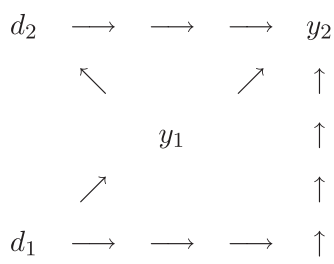
are observed, which are iid across $i = 1, \ldots, N$. We will often omit the subscript i in the rest of this paper in view of the iid assumption. The key treatment and response variables are

d_1 and y_1: Daily TV viewing time and BPI score at ages 6–7 years,

d_2 and y_2: Daily TV viewing time and BPI score at ages 8–9 years.

In each period, x_t is the 'period-t baseline' covariate, which can affect the treatment d_t and response y_t, and d_t then may affect y_t. *Our main interest is the effect of the treatment 'profile' (d_1, d_2) on the final response y_2 when there is a dynamic feedback feature $y_1 \rightarrow d_2$ and a lagged response effect $y_1 \rightarrow y_2$*, which can be seen in Diagram I that omits 'x_t's.

Diagram I – Full Dynamics



In Diagram I, there are several arrows. Those from d_1 and d_2 to y_2 are the 'direct effects'. As much as d_2 affects y_2 (contemporary effect), d_1 should be also allowed to affect y_1, which explains $d_1 \rightarrow y_1$. The lagged-response effect $y_1 \rightarrow y_2$ can be genuine (e.g. state dependence) or spurious, with y_1 proxying for some unobserved confounders. The feedback $y_1 \rightarrow d_2$ means that d_2 gets adjusted after the interim response y_1 has been observed. This is natural as parents do (and should) adjust their children's TV watching hours, d_2, after seeing their children's BPI y_1. Although d_1 and d_2 can affect y_2 directly, the feedback combined with the lagged-response effect results in the indirect effect of d_1 on y_2 through y_1:

$$d_1 \rightarrow y_1 \rightarrow y_2.$$

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Therefore, the total effect of (d_1, d_2) on y_2 consists of the direct and indirect effects:

$$\text{Direct and indirect effects of } d_1 \text{ on } y_2\text{: } d_1 \to y_2 \text{ and } d_1 \to y_1 \to y_2$$

$$\text{Direct effect of } d_2 \text{ on } y_2\text{: } d_2 \to y_2.$$

The key to the dynamic treatment effect framework is the two ingredients, $y_1 \to d_2$ (feedback) and $y_1 \to y_2$ (lagged-response effect). Without these, we can re-cast d_1 and d_2 in a static framework. For instance, suppose that d_1 and d_2 are binary, taking on 0 and 1. Then $d_1 = 0$, 1 and $d_2 = 0$, 1 together define a multinomial treatment with $4 = 2 \times 2$ categories, which can be handled with static treatment effect estimators developed for multinomial treatments; see, for example, Imai and Van Dyk (2004), Lee (2005) and the references therein.

Diagram II – Past Effects Only

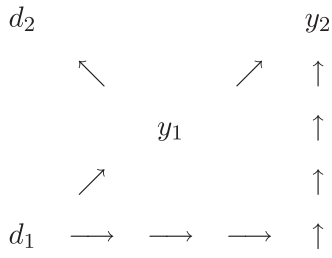
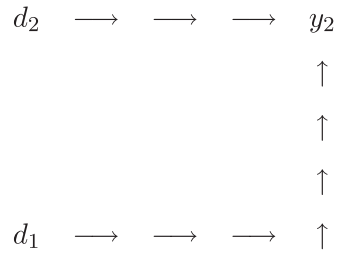


Diagram III – Direct Effects Only



The feedback feature $y_1 \to d_2$ makes d_2 non-randomized even if d_1 was random. This is a relatively minor problem. To see a major problem, examine Diagram II, where there is no true effect $d_2 \to y_2$. However, if y_1 is not controlled (i.e. omitted), then y_1 becomes a 'common factor' for d_2 and y_2; i.e. despite no true effect of d_2 on y_2, d_2 might look influential for y_2 due to y_1 affecting both d_2 and y_2. Suppose we control y_1 (in Diagram I) to avoid this problem. Then we get essentially Diagram III, which cannot identify the indirect effect $d_1 \to y_1 \to y_2$. This demonstrates the *fundamental dilemma: control y_1 to miss the indirect effect, or not control y_1 to incur the omitted variable bias*. The usual panel data estimators in the literature (as reviewed in Lee, 2002, for instance) will commit either mistake depending on whether y_1 is controlled or not.

To illustrate the dilemma and problems it generates, consider the following scenario. Suppose a child spent much time watching TV at ages 6–7 years (so d_1 is high) for an exogenous reason. As a result, he did not have adequate time left to interact with other kids, and, hence, was lagging behind in the development of adequate social skills or in establishing friendships with other children (which means that BPI y_1 is high). Seeing what has happened, his parents restrict his TV viewing time at ages 8–9 years (so d_2 is low), but this might not be effective enough to improve his relationship with other kids (which means that y_2 is still high). In other words, there is no appreciable true effect $d_2 \to y_2$. However, if we do not control y_1 in the regression of y_2 on d_2 and d_1, we may find a negative

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relationship between d_2 and y_2 (i.e. less TV viewing time appears to cause more behavioural problems) because $COR(d_2,\ y_1) < 0$ and $COR(y_2,\ y_1) > 0$ even though there is no effect. When y_1 is controlled in the regression, the indirect effect from d_1 to y_2 through y_1 cannot be found because it is absorbed by the effect of y_1 (i.e. conditional on the fact that the child was already having behavioural problems at ages 6–7 years, TV viewing time at ages 6–7 years does not appear to have much effect on behavioural problems at ages 8–9 years). Therefore, whether controlling or omitting the interim outcome y_1, biases arise in the estimation and wrong conclusions can be easily reached.

3.2. *Two-stage procedure of Huang and Lee (2010)*

Consider two equations for y_2 and y_1:

$$y_{i2} = \beta_1 + \beta_{y1} y_{i1} + \beta_{d1} d_{i1} + \beta_{d1q} d_{i1}^2 + \beta_{d2} d_{i2} + \beta_{d2q} d_{i2}^2 + \beta'_{x1} x_{i1} + \beta'_{x2} x_{i2} + v_{i2} \quad (M_1)$$

$$y_{i1} = \alpha_1 + \alpha_{y0} y_{i0} + \alpha_{d0} d_{i0} + \alpha_{d0q} d_{i0}^2 + \alpha_{d1} d_{i1} + \alpha_{d1q} d_{i1}^2 + \alpha'_{x0} x_{i0} + \alpha'_{x1} x_{i1} + v_{i1},$$

where the β parameters are for period 2 and the α parameters are for period 1. Because children grow, allowing for non-stationarity captured by different parameters across $t = 1, 2$ is important. Model M_1 also allows quadratic effects from d_1 and d_2 in case TV has a positive effect at low levels of watching hours and a negative effect at high levels. Although we did not use d_0 in the preceding subsection, d_0 appears in the y_1 equation of M_1. Excluding d_0 from the y_2 equation seems unavoidable because, otherwise, the y_1 equation would need d_{-1}, which is not available in our data although d_0 is.

In M_1, the direct effect of d_1 on y_2 is $\beta_{d1} + 2\beta_{d1q} d_1$ and the direct effect of d_2 on y_2 is $\beta_{d2} + 2\beta_{d2q} d_2$, whereas the indirect effect of d_1 *on* y_2 through y_1 is $\beta_{y1}(\alpha_{d1} + 2\alpha_{d1q} d_1)$. Putting these together, the total effect of (d_1, d_2) on y_2 consists of:

$$\text{Direct and indirect effects of } d_1 \text{ on } y_2\text{: } \beta_{d1} + 2\beta_{d1q} d_1 + \beta_{y1}(\alpha_{d1} + 2\alpha_{d1q} d_1)$$

$$\text{Direct effect of } d_2 \text{ on } y_2\text{: } \beta_{d2} + 2\beta_{d2q} d_2.$$

Hence, the total effect can be found by estimating each equation separately using the least squares estimator (LSE) or the instrumental variables estimator (IVE).

Because LSE/IVE is applied in the first stage to the two equations in M_1 and then the total effect is found in the second stage, this approach proposed by Huang and Lee (2010) is a two-stage procedure. This linear-model-based two-stage procedure is much simpler than the other approaches developed for dynamic treatment effects in biostatistics (see e.g. Robins, 1986, 1998, 1999), which require nonparametric smoothings and multiple integrals.

As for instruments, Angrist and Krueger (2001) present an ingenious list of instruments in various studies, but having these instruments is not always possible. In typical panel data, it is generally unavoidable that one finds

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instruments within the data, lagged regressors in particular. Because the y_2 equation in M_1 already involves y_1, d_1, d_2, x_1 and x_2, the only source left for instruments is x_0. As for the y_1 equation, because x_0 is already included, there is no alternative but to apply LSE to the y_1 equation. However, applying IVE to the y_2 equation and LSE to the y_1 equation is incoherent, unless the y_1 equation is taken as a 'reduced form'. A coherent procedure would be to apply LSE to both equations, which is our first approach.

One role of the lagged response $y_{i,t-1}$ is to capture the 'inertia' in the model. The same role can be played by a time-constant error (or 'individual-specific effect'), δ_i. Of course, we do not have to have both of them in the model. However, if we do, then the presence of δ_i leads to the endogeneity of $y_{i,t-1}$, and possibly some other right-hand-side variables. The usual specification for the error term v_{it} including δ_t is:

$$v_{it} = \delta_i + u_{it},$$

where u_{it} is a time-varying error or, more generally,

$$v_{i2} = \beta_\delta \delta_i + u_{i2} \text{ and } v_{i1} = \alpha_\delta \delta_i + u_{i1}.$$

Here, δ_i is allowed to be related to y_{i1} and y_{i2} differently with different slopes α_δ and β_δ. The following subsection takes a detailed look at this kind of endogeneity and specification issues, and then summarizes our discussions on various modelling and estimation strategies.

3.3. *Modifications and summary of methods to be used*

A model suitable for IVE for both equations in M_1 is the following one without the lagged covariates on the right-hand side because this 'frees up' the lagged covariates to be used as instruments:

$$y_{i2} = \beta_1 + \beta_{y1} y_{i1} + \beta_{d1} d_{i1} + \beta_{d1q} d_{i1}^2 + \beta_{d2} d_{i2} + \beta_{d2q} d_{i2}^2 + \beta'_{x2} x_{i2} + v_{i2} \qquad (M_2)$$

$$y_{i1} = \alpha_1 + \alpha_{y0} y_{i0} + \alpha_{d0} d_{i0} + \alpha_{d0q} d_{i0}^2 + \alpha_{d1} d_{i1} + \alpha_{d1q} d_{i1}^2 + \alpha'_{x1} x_{i1} + v_{i1}.$$

One may object to this model, however, because the lagged response and lagged treatment appear on the right-hand side, but not the lagged covariates: an incoherent feature.

In view of the last concern, consider yet another model

$$y_{i2} = \beta_1 + \beta_{y1} y_{i1} + \beta_{d2} d_{i2} + \beta_{d2q} d_{i2}^2 + \beta'_{x2} x_{i2} + v_{i2}$$

$$y_{i1} = \alpha_1 + \alpha_{y0} y_{i0} + \alpha_{d1} d_{i1} + \alpha_{d1q} d_{i1}^2 + \alpha'_{x1} x_{i1} + v_{i1}.$$

On the right-hand side, the only lagged variable is the lagged response. This type of model is widely used in econometrics. However, because M_2 includes this as a special case, we may as well use M_2 only. It looks as if the last display has no

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particular role to play, but it does play a nontrivial role in the following 'difference-based' model.

If we assume that endogeneity occurs only through δ_i, then we can deal with the endogeneity by eliminating δ_i from the model, which is another widely adopted practice. For this, assume the last model holds with $v_{i2} = \beta_\delta \delta_i + u_{i2}$ and $v_{i1} = \alpha_\delta \delta_i + u_{i1}$:

$$y_{i2} = \beta_1 + \beta_{y1} y_{i1} + \beta_{d2} d_{i2} + \beta_{d2q} d_{i2}^2 + \beta'_{x2} x_{i2} + \beta_\delta \delta_i + u_{i2} \qquad (M_3)$$

$$y_{i1} = \alpha_1 + \alpha_{y0} y_{i0} + \alpha_{d1} d_{i1} + \alpha_{d1q} d_{i1}^2 + \alpha'_{x1} x_{i1} + \alpha_\delta \delta_i + u_{i1}.$$

Do the quasi-differencing $y_{i2} - (\beta_\delta/\alpha_\delta) y_{i1}$ for M_3 as in Holtz-Eakin *et al.* (1988) to remove δ_i:

$$\begin{aligned} y_{i2} &= \left(\beta_1 - \frac{\beta_\delta}{\alpha_\delta}\alpha_1\right) - \frac{\beta_\delta}{\alpha_\delta}\alpha_{y0} y_{i0} + \left(\beta_{y1} + \frac{\beta_\delta}{\alpha_\delta}\right) y_{i1} - \frac{\beta_\delta}{\alpha_\delta}\alpha_{d1} d_{i1} - \frac{\beta_\delta}{\alpha_\delta}\alpha_{d1q} d_{i1}^2 \\ &\quad + \beta_{d2} d_{i2} + \beta_{d2q} d_{i2}^2 - \frac{\beta_\delta}{\alpha_\delta}\alpha'_{x1} x_{i1} + \beta'_{x2} x_{i2} + u_{i2} - \frac{\beta_\delta}{\alpha_\delta} u_{i1} \\ &= \gamma_1 + \gamma_{y0} y_{i0} + \gamma_{y1} y_{i1} + \gamma_{d1} d_{i1} + \gamma_{d1q} d_{i1}^2 + \gamma_{d2} d_{i2} + \gamma_{d2q} d_{i2}^2 + \gamma'_{x1} x_{i1} + \gamma'_{x2} x_{i2} + \varepsilon_{i2}, \end{aligned}$$

where the γ parameters are defined appropriately so that the second equality holds and $\varepsilon_{i2} \equiv u_{i2} - (\beta_\delta/\alpha_\delta) u_{i1}$.

This model appears to be the same as the y_2 equation in M_1 except for the presence of $\gamma_{y0} y_{i0}$, but the γ parameters are of reduced-form type derived from the 'deeper' α and β parameters. Although the endogeneity through δ is taken care of and LSE can be applied to this model, if desired, we can undertake IVE with the excluded x_0 as instruments to allow for further endogeneity working through u_2 or u_1. This IVE would be the most 'endogeneity-conscious' estimator among those considered in the present paper. However, this IVE has a shortcoming, and a corrective action taken to overcome the shortcoming as in the following will lead to a model encompassing both M_2 and M_3; the resulting model, not M_2 nor M_3, will be used later.

In M_3, both $\beta_\delta/\alpha_\delta$ and α_{y0} are likely to be positive. If so, then $\gamma_{y0} = -(\beta_\delta/\alpha_\delta)\alpha_{y0}$ has to be negative. However, in most dynamic models, the lagged responses have positive slopes: this is an empirical regularity. Hence, γ_{y0} being negative would be incompatible with reality. Also, $\gamma_{d1} = -(\beta_\delta/\alpha_\delta)\alpha_{d1}$ and $\gamma_{d1q} = -(\beta_\delta/\alpha_\delta)\alpha_{d1q}$ should have opposite signs from α_{d1} and α_{d2} so long as $\beta_\delta/\alpha_\delta > 0$, which implies that, if $\alpha_{d1} = \beta_{d2}$ and $\alpha_{d1q} = \beta_{d2q}$ (parameter stationarity for contemporaneous effects), then the signs of γ_{d1} and γ_{d1q} should be opposite to those of γ_{d2} $(= \beta_{d2})$ and γ_{d2q} $(= \beta_{d2q})$, which is also unlikely to hold in reality. To avoid this kind of a priori constraint on the signs on γ parameters, we need to add all regressors (y_0, d_1, d_1^2, and x_1) to the y_2 equation to obtain:

$$\begin{aligned} y_{i2} &= \beta_1 + \beta_{y0} y_{i0} + \beta_{y1} y_{i1} + \beta_{d1} d_{i1} + \beta_{d1q} d_{i1}^2 + \beta_{d2} d_{i2} + \beta_{d2q} d_{i2}^2 + \beta'_{x1} x_{i1} + \beta'_{x2} x_{i2} \\ &\quad + \alpha_\delta \delta_i + u_{i2} \qquad (M_4) \\ y_{i1} &= \alpha_1 + \alpha_{y0} y_{i0} + \alpha_{d1} d_{i1} + \alpha_{d1q} d_{i1}^2 + \alpha'_{x1} x_{i1} + \alpha_\delta \delta_i + u_{i1}. \end{aligned}$$

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Quasi-differencing then yields

$$y_{i2} = \gamma_1 + \gamma_{y0} y_{i0} + \gamma_{y1} y_{i1} + \gamma_{d1} d_{i1} + \gamma_{d1q} d_{i1}^2 + \gamma_{d2} d_{i2} + \gamma_{d2q} d_{i2}^2 + \gamma'_{x1} x_{i1} + \gamma'_{x2} x_{i2} + \varepsilon_{i2} \quad (\mathrm{M}_q)$$

$$\text{where} \quad \gamma_1 = \beta_1 - \frac{\beta_\delta}{\alpha_\delta}\alpha_1, \quad \gamma_{y0} = \beta_{y0} - \frac{\beta_\delta}{\alpha_\delta}\alpha_{y0}, \quad \gamma_{y1} = \beta_{y1} + \frac{\beta_\delta}{\alpha_\delta}$$

$$\gamma_{d1} = \beta_{d1} - \frac{\beta_\delta}{\alpha_\delta}\alpha_{d1}, \quad \gamma_{d1q} = \beta_{d1q} - \frac{\beta_\delta}{\alpha_\delta}\alpha_{d1q}, \quad \gamma_{d2} = \beta_{d2}, \quad \gamma_{d2q} = \beta_{d2q}$$

$$\gamma_{x1} = \beta_{x1} - \frac{\beta_\delta}{\alpha_\delta}\alpha_{x1}, \quad \gamma_{x2} = \beta_{x2}.$$

A typical applied economist/econometrician would estimate the y_2 equation M_q to find the direct effects while omitting the indirect effect; this is similar to the commonly used 'value-added specification' (Todd and Wolpin, 2003). Also, using LSE for M_q to test for H_0: $\gamma_{d1} = \gamma_{d1q} = \gamma_{d2} = \gamma_{d2q} = 0$ is a well known way of implementing Granger non-causality (Granger, 1969, 1980). Alternatively, IVE can be applied to M_q, with x_0 as a source for instruments.

So far we have introduced many estimators except probably the most popular panel-data estimator: the 'within-subject' fixed-effect estimator, which is the LSE (or IVE) applied to the first-differenced model of M_1 imposing the parameter stationarity: under $\beta = \alpha$ and $v_{it} = \delta_i + u_{it}$,

$$\Delta y_{i2} = \beta_1 + \beta_{y1}\Delta y_{i1} + \beta_{d1}\Delta d_{i1} + \beta_{d1q}\Delta d_{i1}^2 + \beta_{d2}\Delta d_{i2} + \beta_{d2q}\Delta d_{i2}^2 + \beta'_{x1}\Delta x_{i1} + \beta'_{x2}\Delta x_{i2} + \Delta u_{i2} \quad (\mathrm{M}_f)$$

where $\Delta y_{it} \equiv y_{it} - y_{i,t-1}$. Note that the intercept non-stationarity is still allowed in this model with the intercept β_1 kept.

In summary, we will try the following estimation schemes with some pros and cons:

(i) LSE to y_1 and y_2 equations in M_1; no endogeneity, but coherent and general model.
(ii) LSE to y_1 equation and IVE to y_2 equation in M_1; some endogeneity, but incoherent.
(iii) IVE to y_1 and y_2 equations in M_2; full endogeneity, but no lagged covariates on right-hand side.
(iv) Single-stage LSE to M_q (value-added approach or Granger non-causality); superb handling of endogeneity only through δ, but the indirect effect is missed.
(v) Single-stage IVE to M_q, superb handling of endogeneity through δ and full endogeneity overall, but the indirect effect is missed.
(vi) Single-stage LSE to M_f; endogeneity only through δ, parameter stationarity imposed.
(vii) Single-stage IVE to M_f; full endogeneity overall, and parameter stationarity imposed.

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In Huang and Lee (2010), essentially (i) was used for the two-stage procedure and (iv) was used for Granger causality. It will be thus interesting to implement the rest and compare the findings as 'model and estimator sensitivity analyses'. The specific form of instruments will be shown later after our data set is introduced.

4. DATA DESCRIPTION

The National Longitudinal Survey of Youth 1979 child sample contains rich information on children born to the women respondents of the National Longitudinal Survey of Youth in the USA, which included a nationally representative sample of 12 686 young people who were between ages 14 and 21 years when the survey began in 1979. They were interviewed annually through 1994 and are currently interviewed on a biennial basis. Although a primary focus of the National Longitudinal Survey of Youth 1979 survey is labour force behaviour, the content of the survey is considerably broader, containing information related to many important life events. Starting from 1986, a set of questionnaires were developed to collect information about the cognitive, social and behavioural development of children. The surveys for children are conducted every 2 years and collected variables include detailed information about home inputs and family backgrounds. These data are publicly available and more information can be obtained at http://www.bls.gov/nls/nlsy79ch.htm.

The BPI measures the frequency, range, and type of childhood behavioural problems for children of age 4 years and over. BPI is based on responses from the mother to 28 questions about specific behavioural problems that children might have exhibited in the previous 3 months. The questions were chosen to represent relatively common behavioural problems in children rather than rare ones indicative of serious pathology. Specifically, the questions include difficulties in interacting with other children, difficulties in concentrating, being too dependent/clingy, having a strong temper and being argumentative. Three response categories were used in the questionnaire: 'often true', 'sometimes true' and 'not true'. These responses were then dichotomized: 'often' and 'sometimes true' are recorded as one, and 'not true' as zero. Therefore, a higher BPI represents more behavioural problems. The dichotomous answers were then summed and scale-adjusted to produce BPI using a norming sample with mean 100 and SD 15 based on data from the 1981 National Health Interview Survey.

Based on children surveyed from 1986 to 1998, we constructed a longitudinal sample of approximately 2770 children with no missing values in both BPI and TV watching hours at ages 6–7 and 8–9 years. There are no discernible differences in terms of these key variables between this sample and the original sample of approximately 4000 children, which suggests that the missing values, which occur mostly in the TV variables at ages 6–7 years, are likely to be random. The first period is ages 6–7 years, and the second period is ages 8–9 years; the ages 4–5 years are then used as the base period (period 0). Each mother is asked how many hours of TV her child watches on a typical weekday and weekend day. A measure of daily TV viewing hours is constructed as:

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$$\frac{1}{7}\{5\times(\text{average weekday watching hours}) + 2\times(\text{average weekend}-\text{day watching hours})\}.$$

While examining the data, we found that some answers do not seem valid: the reported hours sometimes go well beyond 24 h. This might be due to some confusion between the daily measure and the weekly measure of TV watching hours. Therefore, we excluded children reportedly spending more than 10 h watching TV on a typical day at any age. This left us with a sample of 2314 children, based on which all of our empirical analyses were conducted. The summary statistics of the complete set of variables are provided in the Appendix.

The BPI in our sample has mean 105.8 (SD 15.1) for children ages 8–9 years and mean 104.9 (SD 14.6) for children ages 6–7 years. As shown in Figure 1, there is a strong positive correlation between BPI across time.

In the sample, the average child spends 3.4 h per day watching TV at ages 8–9 years and 3.3 h per day at ages 6–7 years. In terms of proportion, approximately 80% of children aged 8–9 years watch TV for at least 2 h per weekday, and 35% for at least 4 h. The histogram of TV viewing hours by children of ages 8–9 years in our sample is shown in Figure 2. These patterns are similar to those at ages 6–7 years, although younger children usually watch slightly less TV. It is clear from Figure 3 that the correlation of TV viewing hours across time is positive.

Table 1 illustrates the close relationships between TV viewing hours, BPI, home inputs and family backgrounds. White children on average watch

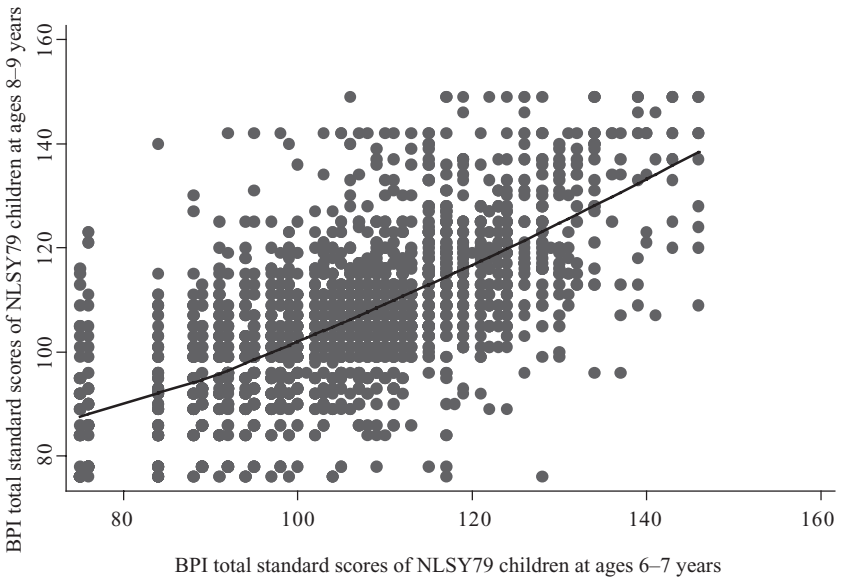

Figure 1. Behavioural problems index (BPI) scores between ages 8–9 and 6–7 years (bandwidth = 0.8). NLSY79, National Longitudinal Survey of Youth 1979.

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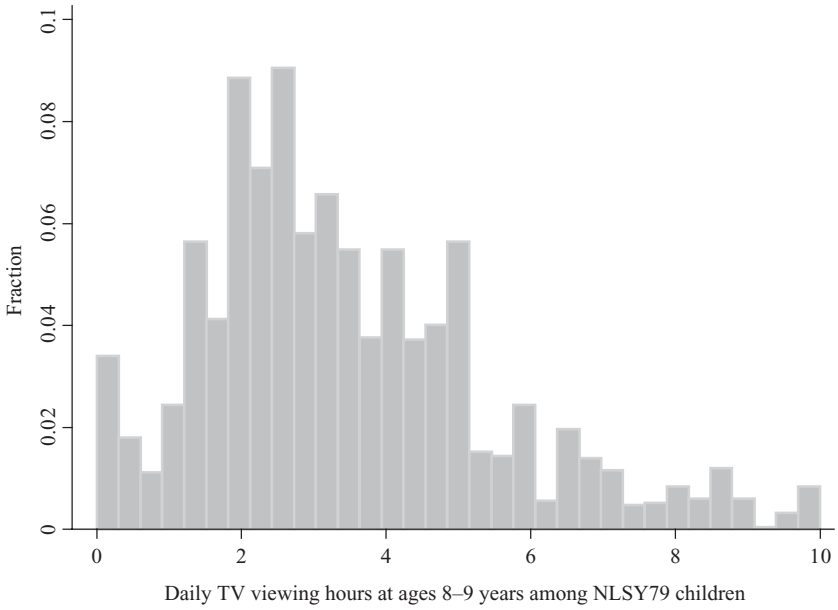

Figure 2. TV viewing hour histogram at ages 8–9 years. NLSY79, National Longitudinal Survey of Youth 1979 (bandwidth = 0.8).

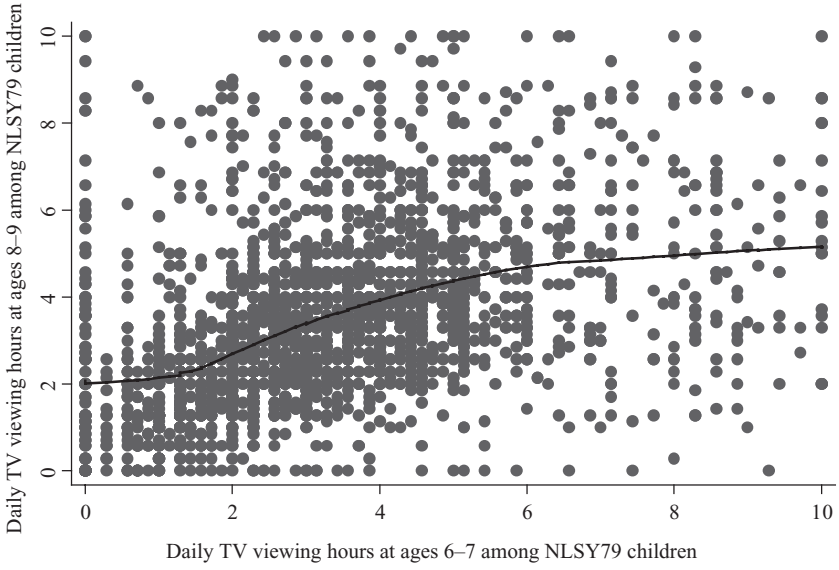

Figure 3. TV viewing hours at ages 8–9 and 6–7 years. NLSY79, National Longitudinal Survey of Youth 1979 (bandwidth = 0.8).

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Table 1. TV viewing and child Behavioural Problems Index (BPI): Summary statistics

	Daily TV viewing hours		BPI total standard scores		
	At age 8–9 years	At age 6–7 years	At age 8–9 years	At age 6–7 years	Group size
Main sample	3.4 (2.0)	3.3 (2.0)	105.8 (15.1)	104.9 (14.6)	2314
Race					
White	2.9 (1.7)	2.9 (1.8)	105.0 (14.7)	103.7 (14.2)	1230
Non-white	4.1 (2.1)	3.9 (2.2)	106.8 (15.4)	106.1 (14.7)	1084
Sex					
Boy	3.4 (2.0)	3.3 (1.9)	106.8 (15.3)	105.8 (14.9)	1164
Girl	3.5 (2.0)	3.4 (2.1)	104.8 (14.7)	103.9 (14.2)	1150
Birth order					
Firstborns	3.2 (1.9)	3.1 (1.9)	104.9 (14.4)	104.1 (13.8)	937
Others	3.6 (2.0)	3.5 (2.1)	106.5 (15.5)	105.4 (15.1)	1377
How many children books a child has at home at age 6–7 years					
≥10	3.3 (1.9)	3.1 (2.0)	92.6 (13.2)	94.6 (15.4)	1968
<10	4.6 (2.2)	4.1 (2.2)	104.9 (14.4)	104.1 (13.8)	340
Mother reads to child at age 6–7 years					
Often	3.3 (2.0)	3.2 (2.0)	105.0 (15.0)	103.8 (14.4)	1734
Not often	4.0 (2.0)	3.6 (2.0)	108.4 (14.9)	108.2 (14.7)	576
Whether parents discuss TV programs with a child					
Discuss	3.3 (1.9)	3.3 (2.0)	105.2 (14.9)	104.3 (14.6)	1901
Not discuss	3.8 (2.2)	3.6 (2.1)	109.0 (15.2)	107.7 (13.9)	400
School type					
Public	3.4 (2.0)	3.4 (2.0)	105.6 (15.5)	105.0 (15.2)	914
Private	2.5 (2.0)	2.2 (1.6)	100.3 (12.4)	100.1 (11.0)	78
Mother's highest grade					
≥16	2.7 (1.8)	2.6 (1.8)	103.2 (14.2)	103.0 (14.3)	595
<16	3.7 (2.0)	3.6 (2.1)	106.7 (15.2)	105.5 (14.6)	1719
Mother's AFQT score in 1981					
Above mean	2.7 (1.5)	2.7 (1.7)	104.7 (14.3)	103.1 (13.5)	1060
Below mean	4.1 (2.1)	3.9 (2.1)	106.8 (15.7)	106.3 (15.2)	1254
Breastfeed					
Yes	3.0 (1.9)	2.9 (1.9)	104.8 (14.7)	103.6 (14.0)	1148
No	3.8 (2.0)	3.8 (2.1)	106.9 (15.3)	106.2 (15.0)	1067
HOME scores at age 4–5 and 1–3 years					
Above mean	2.9 (1.8)	2.9 (1.9)	101.9 (13.8)	100.8 (13.5)	922
Below mean	4.2 (2.1)	3.9 (2.1)	110.0 (16.1)	109.7 (15.0)	592

The entries are group means and standard deviations (in parentheses). The main sample is composed of kids watching 10 h or less of TV per day between ages 6–9 years. AFQT, Armed Forces Qualification Test.

approximately 1 h less TV per day at both ages 6–7 and 8–9 years than the others, and their BPI is around 2 points lower than for non-whites. There is virtually no difference between boys and girls in TV watching hours, although boys have more behavioural problems: their BPI is on average 2 points higher than girls' BPI.

Firstborns watch about half an hour less than the others and have slightly fewer behavioural problems. A child with 10 or more children's books at home

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watches approximately 1.3 h less TV at ages 8–9 years and has a much lower BPI (12.3 points lower or 81% of one SD) than those with fewer books. Children whose mothers read to them frequently (at least three times per week) and whose parents discuss TV programs with them spend slightly less time watching TV and have fewer behavioural problems (around 3–4 points lower in their BPI). In general, TV watching times are significantly and negatively correlated with other activities such as going to museums and theatres.

Public school children watch approximately 1 h more TV on a daily basis at ages 6–7 and 8–9 years than those in private schools and their BPI is 5 point higher. Because school inputs were not available for children above 5 years old before 1992, there are many missing entries. The perceived quality of detailed school inputs (including the skills of the principal and teachers, how much teachers care about the students, whether parents are given enough information and opportunity to participate in school affairs, the safety and order of the school, and whether moral teaching is offered), however, do not seem to affect much TV watching time, although they are negatively associated with BPI. The correlation between TV watching hours and time spent on maths homework or reading and writing assignments is quite weak and sometimes positive, which is possibly due to multitasking where many children watch TV while doing homework (Rideout *et al.*, 2005).

Children with mothers with 16 or more years of schooling watch approximately 1 h less TV and have a BPI 3.5 points lower at ages 8–9 years. Similarly, children whose mothers have above average Armed Forces Qualification Test (AFQT) scores watch 1.4 h less TV at ages 8–9 years and around 1.2 h less at ages 6–7 years, and their BPI is 2.1 lower. Breastfed children watch 0.8 h less TV and their BPI is 2.1 lower at ages 8–9 years. Finally, children with a higher quality home environment at ages 1–5 years measured by the age-specific home observation measurement of the environment variable (*HOME*), which is often used in child development research as an aggregate quality indicator of home environment, have 1 h less TV viewing time and about 9 points lower BPI than the others. In summary, children with high quality home inputs and better educated mothers watch less TV and experience less behavioural problems.

A salient feature in Table 1 is that more time spent viewing TV is almost always associated with higher BPI. This is also illustrated in Figure 4. The potentially harmful effects of TV watching on child behavioural problems, however, might be overestimated if detailed home inputs are not controlled, because a child watching more TV may also lack important home inputs. The strength of our data is that a rich set of home inputs from birth up to age 9 years as well as key family background variables are available; for some children, there are also many detailed school inputs available. This would greatly reduce potential biases due to omitted variables. Most home and school input variables were categorical with multiple levels, and were converted to dummy variables according to the sample medians.

Recall that we assumed the time sequence $x_t \to d_t \to y_t$ in each period; x_t works as the time-t baseline covariates which affect d_t and possibly y_t, and then the treatment d_t affects y_t. In out data, this temporal order is plausible for several

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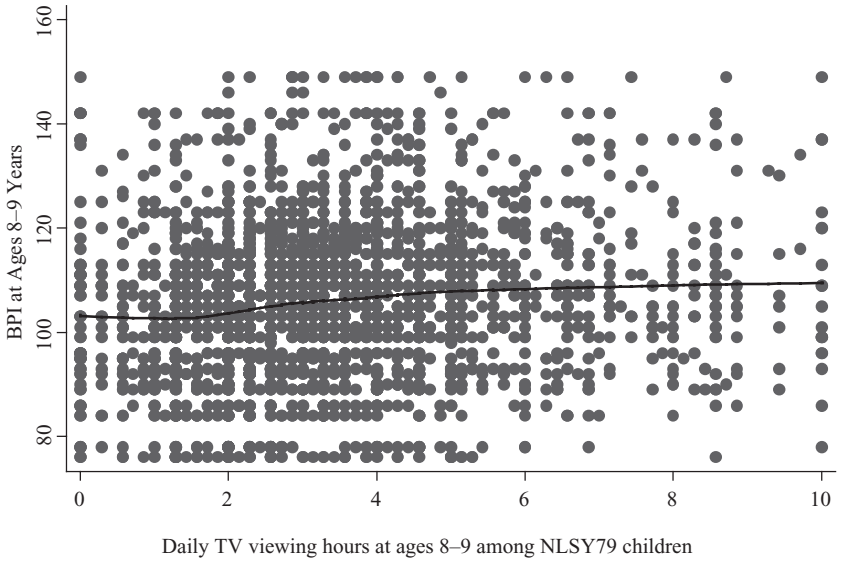

Figure 4. BPI and TV viewing hours at ages 8–9 years. NLSY79, National Longitudinal Survey of Youth 1979 (bandwidth = 0.8).

reasons. First, y_t is based on child behaviour in the past 3 months, while x_t and d_t are based on regular patterns in the entire past year. Hence, this strongly suggests that x_t and d_t precede y_t, although possible violations of this have been taken into consideration and treated accordingly in our estimation later. Second, many family characteristics in x_t are family routines that are likely to be determined independently of d_t. Third, overall, TV watching hours tend to be the 'residual' usage of time, and are therefore unlikely to influence the other time-consuming activities, although we cannot completely rule out TV watching taking precedence over the other activities.

The availability of a rich set of control variables in our data is crucial for the application of the two-stage dynamic effect estimation, which relies on the credibility of the 'no unobserved confounder' (i.e. no omitted variable bias) assumption. As listed in the Appendix, our control variables contain four groups: (i) a child's demographic information including race, sex and birth order; (ii) home inputs at different ages 4–5, 6–7 and 8–9 years, which cover many aspects of child life at home, such as the numbers of child books at home, how often the mother reads to the child, how often the child is taken to a museum, performance, outdoor activities, meeting with relatives and having meals with parents; (iii) school inputs at ages 6–7 and 8–9 years, including the number of hours spent on maths and writing homework, whether the school is public or private, the mother's rating of school quality such as the skills of the principal and teachers, and the safety and order of the school; (iv) family background details, including the mother's AFQT score, highest grade, mar-

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riage status, age at the child's birth, whether the child was breast-fed, and family income. These variables constitute a highly comprehensive set of controls for our purpose of determining the dynamic effects of TV viewing on BPI at ages 8–9 years. After controlling these variables, there are no other obvious important unobserved confounders that may affect both TV viewing time and BPI. That said, a better data set should also include more information about the child's father, such as his AFQT score and education level, and more objective variables on school quality.

5. EMPIRICAL RESULTS

5.1. *Fixed-effect estimation*

Table 2 contains the results of the 'within-child' fixed effect estimator for M_f (including specification (vi) using LSE and (vii) using IVE), where the difference in BPI between ages 8–9 and 6–7 years is the dependent variable. The various specifications differ mainly in the control variables used, where the variables of squared TV viewing hours are used in all specifications as well as the basic group of controls, including the child's race, sex and birth order. The total effects of TV viewing during ages 6–9 years are listed in the lower half of the table.

In the first column 'FE1', the earlier BPI y_0 at ages 4–5 years is used as a proxy for the child fixed factor, such as his innate characteristics, which should be included if its effects on behavioural problems vary over time. The estimated coefficient of y_0, however, is small and statistically insignificant, which suggests that the influences of the child fixed factor on BPI are constant over time and, therefore, can be removed by the within-child fixed-effect estimator. The specification in this column also includes current and lagged home inputs at ages 8–9 and 6–7 years as well as family background variables (mother's AFQT score, her age at the child birth, whether the child was breast-fed, her marriage status, her highest grade, and family income), because our econometric model allows these invariant variables to have different effects on child BPI at different ages. The estimated effects of TV viewing hours at both ages 8–9 and 6–7 years are positive and concave, where the marginal effect of TV viewing for a child watching d hours of TV per day at ages 8–9 years is $0.95 - 2 \times 0.09\, d$ and $0.74 - 2 \times 0.05\, d$ at ages 6–7 years.

As listed in the lower half of the table in the same column 'FE1', the estimated total effect of watching 6 h of TV daily during ages 6–9 years versus not watching TV at all is 5.11, which is 34% of one SD of BPI at ages 8–9 years, and it is statistically significant at the 10% level. Watching 3 h of TV daily, which is just below the mean level of TV viewing time of all children in the sample, is estimated to increase BPI at ages 8–9 years by 3.82 points or 25% of one SD. Because most children (over 99%) watch some TV on a daily basis, a more realistic comparison might be between those who watch a lot and those who watch only a little. The bottom two rows of the table show the difference between watching 1 h or 2 h of TV daily (labelled as '*Low TV*') versus watching

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Table 2. TV viewing and child Behavioural Problems Index (BPI): Within-child fixed effect estimation

	BPI scores differenced between ages 8–9 and 6–7 years				
	FE1	FE2	FE3	FE4	FEIV1
Daily TV hours differenced between ages 8–9 and 6–7 years	0.95 (0.71)	0.99 (0.71)	0.54 (0.57)	0.71 (0.66)	0.85 (1.42)
Squared daily TV hours differenced between ages 8–9 and 6–7 years	–0.09 (0.07)	–0.10 (0.07)	–0.03 (0.06)	–0.06 (0.07)	–0.10 (0.15)
Daily TV hours differenced between ages 6–7 and 4–5 years	0.74 (0.62)	0.88 (0.64)	0.69 (0.53)	0.98 (0.58)	1.19 (0.84)
Squared daily TV hours differenced between ages 6–7 and 4–5 years	–0.05 (0.07)	–0.06 (0.07)	–0.05 (0.06)	–0.07 (0.07)	–0.10 (0.10)
BPI score at age 4–5 years	0.013 (0.027)	0.011 (0.028)		0.010 (0.024)	0.010 (0.027)
Family backgrounds	Yes	Yes		Yes	Yes
Current home inputs at age 8–9 years	Yes	Yes	Yes		
Lagged home inputs at age 6–7 years	Yes	Yes	Yes		Yes
Earlier *HOME* scores at ages 1–5 years		Yes			Yes
Sample size	1025	964	1343	1134	1036
R^2	0.04	0.04	0.03	0.01	0.03
Mean difference in BPI scores (bootstrapped standard deviation in parentheses)					
Daily TV hours at ages 6–9 years	FE1	FE2	FE3	FE4	FEIV1
1 h versus 0 h	1.55 (1.00)	1.70* (0.98)	1.14 (0.80)	1.55* (0.95)	1.84 (1.75)
2 h versus 0 h	2.82 (1.77)	3.06* (1.73)	2.10 (1.42)	2.83* (1.68)	3.29 (3.07)
3 h versus 0 h	3.82* (2.31)	4.09* (2.27)	2.89 (1.89)	3.84* (2.19)	4.35 (3.97)
4 h versus 0 h	4.53* (2.63)	4.78* (2.61)	3.50 (2.21)	4.58* (2.52)	5.01 (4.49)
5 h versus 0 h	4.96* (2.76)	5.14* (2.78)	3.93* (2.40)	5.05* (2.67)	5.28 (4.72)
6 h versus 0 h	5.11* (2.74)	5.17* (2.82)	4.18* (2.49)	5.24* (2.70)	5.16 (4.80)
3–4 h versus 1–2 h	1.98* (1.05)	2.06* (1.11)	1.57* (0.96)	2.02* (1.07)	2.11 (1.89)
5–6 h versus 1–2 h	2.85* (1.52)	2.78* (1.61)	2.43* (1.45)	2.95* (1.54)	2.65 (2.84)

*$P < 0.1$; **$P < 0.05$; ***$P < 0.01$. Standard deviations are in parentheses. The sample is composed of kids watching 10 h or less of TV per day between ages 6 and 9 years. The controlled inputs also include a child's race, sex and birth order; family backgrounds include mother's Armed Forces Qualification Test score, her age at child birth, her marriage status, highest grade, family income, whether the child was breastfed and whether the child had a low birth weight.

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3 or 4 h of TV (*Middle TV*) and versus 5 or 6 h (*High TV*). The estimated difference in BPI between Middle TV and Low TV is 1.98 and that between High TV and Low TV is 2.85; both are significant just below 5% level.

These results are very close to the results in the second column 'FE2' when *HOME* scores at ages 2–3 and 4–5 years are further controlled. Because the fixed factors such as BPI at ages 4–5 years and family backgrounds as well as home inputs before age 5 years are not significant in this within-child fixed effect model, we exclude them in the third column 'FE3'; the estimated effects of TV viewing are smaller than before and the effects of earlier TV viewing at ages 6–7 years are now larger than those at ages 8–9 years, but the overall pattern is the same where more TV viewing time increases child behavioural problems. These results are similar to the fourth column 'FE4', where only family backgrounds are included whereas all the other home inputs are excluded; the explanatory power is lower than before, while the estimated effects of TV viewing are larger. This suggests that the detailed inputs at different ages, although having sizable effects on BPI as shown by the much lower R^2, have little impact on the estimated effects of TV viewing in the within-child fixed-effect model once a good set of family background variables is controlled.

The last column 'FEIV' presents the fixed-effect IVE results, where TV viewing hours at ages 8–9 years are instrumented by those at ages 4–5 years and the other current home inputs at ages 8–9 years are excluded. This specification is meant to deal with the potential problems of endogeneity and reverse causality. The *F*-statistic in the first-stage regression is 20.18, which suggests that the problem of weak instruments is not a serious concern. The estimators are quite similar to the other columns without instrumental variables, where the marginal effect of TV viewing at ages 8–9 years is $0.85 - 2 \times 0.10d$, smaller than that at ages 6–7 years, which is $1.19 - 2 \times 0.10d$. Specifically, the estimation shows that, compared with Low TV, BPI is increased by 2.11 points with Middle TV and by 2.65 points with High TV. These numbers are very similar to those in the other columns, suggesting that the endogeneity problem, if any, is of minor influence on the estimates of TV effects. The Hausman test indeed failed to reject the null hypothesis of no difference between the LSE and IVE specifications. The total estimated effects under instrumental variables specification are in general slightly larger than those without instrumental variables, which is caused by the relatively larger effects of earlier TV viewing at ages 6–7 years. These effects, however, are not significant at the conventional levels due to low precision in estimation.

We also tried other specifications (not reported in the table) that yielded similar estimation results. For example, when detailed school inputs are controlled, the estimated TV effects are only slightly smaller, but the sample size shrinks a lot because school inputs were not available before 1992, as mentioned previously. When we use detailed home inputs at ages 4–5 years as instruments for current home inputs at ages 8–9 years, the estimated TV effects are even larger but the estimation is less precise. These results also apply to the other tables described below and thus will not be mentioned again.

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5.2. *Value-added estimation*

Table 3 presents results for the value-added estimation based on model M_q (including specifications (iv) using LSE and (v) using IVE), which can be also used to test Granger causality. The various specifications differ mainly in the control variables used, where the basic group of controls that are common to all include child race, sex, birth order, lagged home inputs at ages 6–7 years, and family background variables. In all of these specifications, Granger non-causality of TV viewing at ages 6–9 years on BPI at ages 8–9 years is rejected above the 5% significance level, which is mostly driven by the significant effects of TV viewing at ages 6–7 years.

In the first column 'VA1', the earlier BPI y_0 at ages 4–5 years is used as well as home inputs at ages 8–9 years. The earlier *HOME* scores at ages 1–3 and 4–5 years are further controlled in the next column 'VA2', and the lagged BPI y_1 at ages 6–7 years is also controlled in the third column 'VA3'. The estimation results across these three columns are very similar, where more time spent on watching TV at ages 6–9 years is associated with higher BPI at ages 8–9 years, although the effects are slightly smaller when more control variables are included. Based on estimates in column 'VA2' listed in the lower half of the table, the estimated total effect of watching 6 h of TV daily during ages 6–9 years versus not watching TV at all is 5.73, which is 38% of one SD of BPI at ages 8–9 years and statistically significant above the 1% level; the estimated difference in BPI between Middle TV and Low TV is 1.88 and that between High TV and Low TV is 3.88; both are significant above the 5% level. These estimates are also similar in scale to those of Table 2.

When two variables of child temperament at ages 1–3 years (measuring the degrees of a child's insecurity and compliance) are used as a proxy for child fixed characteristics in the fourth column 'VA4', the sample shrinks to half the original size due to many missing values, and the explanation power is dramatically reduced. The estimated total TV effects are much larger than before, indicating that BPI at ages 4–5 years are quite different from the early temperament variables at ages 1–3 years and may already be affected by or affect TV viewing hours. When current home inputs at ages 8–9 years are excluded to avoid possible endogeneity problems in column 'VA5', the estimated total TV effects are slightly smaller than those in 'VA4'. The last column 'VAIV' shows the instrumental estimation results where TV viewing hours at ages 8–9 years are instrumented by those at ages 4–5 years while the other controls are the same as in 'VA5'. The two TV variables are strongly correlated with each other, which rules out any weak instruments problem (the first stage *F*-statistic is well over 100). The estimated TV effects become insignificant due to imprecise estimation, and their scales are smaller than those in 'VA5' but still comparable to estimates in the first three columns. This suggests that, as in Table 2, the endogeneity problem is not a serious concern for the total TV effects (confirmed by the Hausman test), although it might affect some coefficient estimates such that the estimated effects of TV viewing at ages 6–7 years become slightly larger than those at ages 8–9 years.

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Table 3. TV viewing and Child Behavioural Problems Index (BPI): Value-added estimation

	BPI scores at age 8–9 years					
	VA1	VA2	VA3	VA4	VA5	VAIV
Daily TV hours at age 8–9 years	1.20* (0.72)	1.07 (0.73)	1.04 (0.66)	0.15 (1.17)	–0.62 (1.18)	–2.66 (5.70)
Squared daily TV hours at age 8–9 years	–0.10 (0.07)	–0.09 (0.08)	–0.68 (0.07)	0.03 (0.12)	0.16 (0.12)	0.30 (0.71)
Daily TV hours at ages 6–7 years	–0.19 (0.69)	–0.21 (0.71)	–0.31 (0.58)	1.31 (1.19)	1.39 (1.20)	2.51 (2.44)
Squared daily TV hours at age 6–7 years	0.10 (0.07)	0.10 (0.07)	0.08 (0.06)	0.04 (0.13)	0.003 (0.13)	–0.08 (0.22)
Joint significance of TV at ages 6–9 years	0.002***	0.002***	0.047**	0.000***	0.000***	0.003***
Joint significance of TV at ages 8–9 years	0.190	0.278	0.307	0.563	0.054*	0.897
Joint significance of TV at ages 6–7 years	0.007***	0.004***	0.078*	0.000***	0.004***	0.042**
BPI score at age 4–5 years	0.58*** (0.030)	0.58*** (0.030)	0.26*** (0.032)			
BPI score at age 6–7 years			0.57*** (0.031)			
Child temperament at ages 1–3 years				Yes	Yes	Yes
Current home inputs at age 8–9 years	Yes	Yes	Yes	Yes		
Earlier *HOME* scores at 1–3 and 4–5 years		Yes	Yes	Yes	Yes	Yes
Lagged home inputs at age 6–7 years	Yes	Yes	Yes	Yes	Yes	Yes
Family backgrounds	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	1063	1000	964	485	529	529
R^2	0.40	0.41	0.58	0.20	0.16	0.15
BPI Scores at age 8–9 years (bootstrapped standard deviation in parentheses)						
Daily TV hours at ages 6–9 years	VA1	VA2	VA3	VA4	VA5	VAIV
1 h versus 0 h	1.01 (0.67)	0.88 (0.74)	0.71 (0.68)	1.53 (1.23)	0.93 (1.32)	0.08 (15.7)
2 h versus 0 h	2.01* (1.20)	1.78 (1.30)	1.35 (1.19)	3.21 (2.17)	2.19 (2.33)	0.59 (25.6)
3 h versus 0 h	3.01* (1.57)	2.72 (1.70)	1.93 (1.53)	5.02* (2.84)	3.78 (3.05)	1.54 (29.6)
4 h versus 0 h	4.00** (1.82)	3.69* (1.95)	2.45 (1.72)	6.98** (3.26)	5.67 (3.48)	2.92 (27.9)
5 h versus 0 h	4.98** (1.96)	4.70** (2.08)	2.92* (1.78)	9.07*** (3.49)	7.90** (3.68)	4.75 (21.0)
6 h versus 0 h	5.96*** (2.02)	5.73*** (2.13)	3.31* (1.74)	11.31*** (3.60)	10.46*** (3.70)	7.00 (11.4)
3–4 h versus 1–2 h	1.99** (0.78)	1.88** (1.11)	1.17* (0.71)	3.63*** (1.40)	3.16** (1.47)	1.90 (8.38)
5–6 h versus 1–2 h	3.96*** (1.52)	3.88*** (1.25)	2.09** (0.96)	7.81*** (2.13)	7.62*** (2.11)	5.55 (10.56)

*$P < 0.1$; **$P < 0.05$; ***$P < 0.01$. Standard deviations are in parentheses. The sample is composed of kids watching 10 h or less of TV per day between ages 6 and 9 years. The controlled inputs also include a child's race, sex and birth order; family backgrounds include mother's Armed Forces Qualification Test score, her age at child birth, her marriage status, highest grade, family income, whether the child was breastfed and whether the child had a low birth weight.

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5.3. *Two-stage procedure*

Table 4 presents results for the two-stage procedure with linear models in M_1 and M_2 (including specifications (i) to (iii)). The basic group of controls common across specifications include child race, sex, birth order and family background variables. The first two columns labelled 'TS1' estimate M_1, where current and lagged home inputs are included as further control variables. The next two columns labelled 'TS2' estimate M_2, where lagged home inputs are excluded. The estimated marginal and total TV effects are quite similar across these two specifications. Based on estimates in column 'TS1', which has the most comprehensive controls, watching 6 h of TV daily during ages 6–9 years increases BPI at ages 8–9 years by 5.56 points versus not watching TV at all; the estimated difference in BPI between Middle TV and Low TV is 1.77 and that between High TV and Low TV is 3.27; all these effects are significant above the 1% significance level and their scales are also similar to those in Tables 2 and 3. The estimated marginal effect of an extra hour of TV viewing daily at ages 6–9 years evaluated at zero-hour viewing time is 1.25 points or 8.3% of one SD of BPI at ages 8–9 years.

To get a sense of the relative importance of the indirect effect of TV watching at ages 6–7 years on BPI 2 years later, we did some calculations based on the estimates in columns 'TS2' where only the current home inputs are included. Compared with not watching TV at all, the effect of watching 3 h of TV at ages 6–7 years on BPI at ages 6–7 years is $0.6 \times 3 - 0.02 \times 9 = 1.62$, which leads to an indirect effect on BPI at ages 8–9 years, $1.62 \times 0.67 = 1.09$, while its direct effect is $0.06 \times 3 + 0.01 \times 9 = 0.27$. Hence, the indirect effect (1.09) of the earlier TV watching at ages 6–7 years is more than four times the direct effect (0.27). When the earlier home environment variables are controlled in columns 'TS1', similar calculations suggest that the indirect effect of TV viewing at ages 6–7 years is 0.95 and the direct effect is 1.17, while the direct effect of 3 h TV watching at ages 8–9 years is 1.17. Hence, the total effect of TV viewing at ages 6–7 years is almost twice that at ages 8–9 years.

The instrumental variables specifications in the rest of the table are again meant to deal with the potential problems of endogeneity and reverse causality. The two columns labelled 'TSIV1' present the IVE results for M_1 (specification (ii)), where current home inputs at ages 8–9 years are instrumented by those at ages 4–5 years for the y_2 equation, while those labelled 'TSIV2' contain the IVE results for M_2 (specification (iii)), where the home inputs at ages 8–9 and 6–7 years are instrumented by the lagged home inputs at ages 6–7 and 4–5 years, respectively. The estimated effects are much larger than before, but the estimation errors are also much larger, so the total TV effects are overall insignificant. Again, the Hausman test failed to reject the null hypothesis of no differences between the IVE and LSE results. As before, the total effect of 1 h of TV viewing at ages 6–7 and 8–9 years on BPI at ages 8–9 years (which is 3.37, as reported in the first row of column 'TSIV2' in the lower half of Table 4) can be decomposed into three components; the total effect of TV viewing time at ages 6–7 years is $(-0.24 + 0.04) + (2.32 - 0.24) \times 0.72 = -0.20 + 1.50 = 1.30$, where

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Table 4. TV Viewing and Child Behavioural Problems Index (BPI): Two-stage linear estimation

	BPI Scores at age 8–9 years							
	TS1		TS2		TSIV1		TSIV2	
	At 8–9 years	At 6–7 years	At 8–9 years	At 6–7 years	At 8–9 years	At 6–7 years	At 8–9 years	At 6–7 years
Daily TV hours at age 8–9 years	0.48 (0.61)		0.45 (0.57)		0.85 (16.94)		2.24 (5.62)	
Daily TV hours at age 8–9 years squared	–0.03 (0.07)		–0.02 (0.06)		0.06 (2.19)		–0.18 (0.70)	
Daily TV hours at age 6–7 years	0.51 (0.52)	0.47 (0.58)	0.06 (0.51)	0.60 (0.54)	0.91 (6.37)	0.56 (0.68)	–0.24 (1.73)	2.32 (6.17)
Daily TV hours at age 6–7 years squared	–0.04 (0.06)	–0.002 (0.06)	0.01 (0.05)	–0.02 (0.06)	–0.13 (0.72)	–0.001 (0.07)	0.04 (0.16)	–0.24 (0.82)
BPI score at age 6–7 years	0.68*** (0.02)		0.67*** (0.02)		0.66*** (0.10)		0.72*** (0.03)	
BPI score at age 4–5 years		0.58*** (0.03)		0.59*** (0.02)		0.57*** (0.03)		0.55*** (0.04)
Home inputs at 8–9 years	Yes		Yes		Yes		Yes	
Home inputs at 6–7 years	Yes	Yes		Yes	Yes	Yes		Yes
HOME scores at ages 1–3 and 4–5 years	Yes	Yes						
Family backgrounds	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	1373	1311	1626	1504	1071	1043	1091	1036
R^2	0.50	0.41	0.48	0.41	0.	0.43	0.43	0.16

BPI scores at age 8–9 years (bootstrapped standard deviation in parentheses)				
Daily TV hours at ages 6–9 years	TS1	TS2	TSIV1	TSIV2
1 h versus 0 h	1.25 (0.62)**	0.90 (0.62)	2.05 (6.66)	3.37 (13.79)
2 h versus 0 h	2.37 (1.10)**	1.76 (1.08)	3.96 (11.55)	6.13 (23.53)
3 h versus 0 h	3.36 (1.44)**	2.59 (1.41)*	5.73 (14.72)	8.27 (29.32)
4 h versus 0 h	4.22 (1.65)***	3.38 (1.61)**	7.35 (16.27)	9.80 (31.34)
5 h versus 0 h	4.96 (1.75)***	4.14 (1.70)**	8.83 (16.43)	10.72 (30.02)
6 h versus 0 h	5.56 (1.77)***	4.86 (1.72)***	10.17 (15.65)	11.02 (26.51)
3–4 h versus 1–2 h	1.77 (0.71)**	1.66 (0.68)**	3.53 (6.57)	4.29 (12.01)
5–6 h versus 1–2 h	3.27 (1.06)***	3.17 (1.00)***	6.49 (8.54)	6.12 (13.72)

*$P < 0.1$; **$P < 0.05$; ***$P < 0.01$. Standard deviations are in the parentheses. The sample is composed of kids watching 10 h or less TV per day between ages 6 and 9 years. The controlled inputs also include a child's race, sex and birth order; family backgrounds include mother's AFQT score, her age at child birth, her marriage status, highest grade, family income, whether the child was breastfed or has low birth weight.

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the indirect effect 1.50 is much larger than the direct effect, which is almost zero.

5.4. *Discussion*

Assuming that the two-stage dynamic linear model is the correct specification, we checked whether the stationary assumptions in the within-child fixed effect model are correct. The bootstrap results (not presented in this paper but available from the authors upon request) showed that, at least for the TV effects on BPI at ages 8–9 and 6–7 years, the differences between the coefficients of TV viewing hours at these two different ages (represented by d_2 and d_1 in the regression of y_2 compared with d_1 and d_0 in the regression of y_1) are not significantly different from zero. When the coefficients on the treatment variables are stationary over time, the value-added model can be used to obtain dynamic effects. Hence, a convenient implication for practitioners is that when there is not enough information on earlier home inputs, assuming stationary coefficients and using either the within-child fixed-effect model or the value-added model can render the correct dynamic effects, as the two-stage dynamic model does. This is actually already reflected in the similarities between our estimation results across different models.

Another message from our estimation is that the endogeneity of the current home inputs does not seem to seriously affect the estimated coefficients of TV viewing on child behavioural problems. In contrast, the dynamic indirect effect of TV viewing at earlier ages through interim outcomes could be much larger than the direct effect on later child development results.

6. CONCLUSIONS

This paper studied the effect of TV viewing on child social and behavioural development measured by BPI scores using a rich childhood longitudinal sample from the National Longitudinal Survey of Youth 1979 in the USA. This is an important issue because early child behavioural problems are important determinants of later schooling and other human capital outcomes.

A variety of panel data model estimators, including the within-child fixed-effect estimator, the value-added model estimator and a two-stage linear dynamic treatment effect procedure, as well as instrumental variable methods, were used to handle the unobserved child-specific factor, endogeneity of TV viewing, and the dynamic nature of the causal relation. Special emphasis was placed on the last aspect, focusing on how early TV viewing affects interim child behavioural problems and in turn affects future TV viewing.

Overall, our estimation results provide coherent evidence suggesting that TV viewing during ages 6–7 and 8–9 years increases child behavioural problems at ages 8–9 years with economically sizable magnitudes. We also find that the indirect dynamic effect of early TV viewing at ages 6–7 years transmitted through BPI at ages 6–7 years can he much larger than its direct effect on BPI at ages 8–9 years. The importance of the earlier treatment is a rather surprising finding.

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To the extent that the process of child development is similar across countries, the validity of the estimation results obtained in this paper goes beyond the particular data (National Longitudinal Survey of Youth) used. One should be aware, however, that the exact magnitude of the effects might not be fully applicable to children in countries other than the USA due to, for example, differences in the length of school hours, the amount of time required to finish school homework, the pattern of care giving for kids after school and the availability and prices of other activities for children. Hence, more research is needed, especially using data from different countries, to achieve a better understanding of the effects of TV viewing on child behavioural problems and other child development indicators.

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APPENDIX

List of variables and summary statistics

Variable	Mean (SD)	Size
Behaviour Problems Index (BPI) at ages 8–9 years	105.8 (15.1)	2314
Behaviour Problems Index (BPI) at ages 6–7 years	104.9 (14.6)	2314
Behaviour Problems Index (BPI) at ages 4–5 years	104.6 (14.6)	2166
Child temperament score: insecure at ages 1–3 years	19.8 (4.32)	1177
Child temperament score: compliance at ages 1–3 years	21.9 (4.91)	1119
(G1) Child demographic information		
Race of child: Black or Hispanic	0.47 (0.50)	2314
Sex of child: boy	0.50 (0.50)	2314
Birth order of child	1.93 (1.00)	2314
(G2) Home inputs for 8–9 year olds		
Number of hours/day child watches TV	3.43 (2.00)	2314
Child has 10 or more children books at home	0.88 (0.32)	2307
How often mom reads to child: at least three times a week	0.59 (0.49)	2307
How often child reads for enjoyment: every day	0.36 (0.48)	2311
Family encourages hobbies	0.93 (0.26)	2306
How often child taken to museum: at least several times a year	0.42 (0.49)	2310

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Variable	Mean (SD)	Size
How often child taken to performance: at least several times a year	0.35 (0.48)	2306
How often family get with relatives/friends: at least 2–3 times/month	0.59 (0.49)	2311
How often child with dad outdoors: at least once a week	0.48 (0.50)	2208
How often child eats with mum and dad: at least once a day	0.56 (0.50)	2210
Parents discuss TV programs with child	0.83 (0.37)	2287
(G3) Home inputs for 6–7 years olds		
Number of hours/day child watches TV	3.33 (2.04)	2314
Child has 10 or more children books at home	0.85 (0.35)	2308
How often mom reads to child: at least three times a week	0.75 (0.43)	2310
How often child reads for enjoyment: every day	0.67 (0.47)	2303
Family encourages hobbies	0.90 (0.30)	2306
How often child taken to museum: at least several times a year	0.78 (0.41)	2310
How often child taken to performance: at least several times a year	0.61 (0.49)	2313
How often family get with relatives/friends: at least two to three times/month	0.61 (0.49)	2313
How often child with dad outdoors: at least once a week	0.51 (0.50)	2265
How often child eats with mum and dad: at least once a day	0.78 (0.42)	2306
Parents discuss TV programs with child	0.83 (0.38)	2301
(G4) Home inputs for 4–5 years olds		
Number of hours per day child watches TV	3.38 (2.97)	1562
Number of hours TV is on per day	5.28 (4.09)	2105
How many books does child have: 10 or more books	0.82 (0.38)	2143
How often mother read to child: at least three times a week	0.58 (0.49)	2143
How often child taken to museum: at least several times a year	0.71 (0.45)	2128
How many magazines does family get: three or more	0.61 (0.49)	2131
The child sees father or a father figure daily	0.79 (0.41)	2128
How often child taken on outing: at least several times a week	0.57 (0.50)	2124
How often child eats with mum and dad: at least once a day	0.76 (0.43)	2124
Home observation measurement of the environment variable (*HOME*)	206.0 (34.6)	2220
Home observation measurement of the environment variable (*HOME*) at ages 0–3 years	140.4 (22.7)	2029
(G5) Family background		
Mother's AFQT score taken in 1981	41.1 (28.2)	2234
Mother's highest grade at 1988	12.5 (2.2)	2251
Family salary income in 1988	6972.8 (8505.6)	2228
Mother was married in 1988	0.82 (0.38)	1912
Mother's age at child birth	25.0 (3.0)	2314
Child is breastfed	0.52 (0.50)	2215
Child is of low birth weight (5.5 pounds or less)	0.07 (0.25)	2194
(G6) School Inputs for 8–9 years old		
Hours/week a child spends on maths homework	2.14 (3.22)	989
Hours/week a child spends on writing homework	1.73 (2.96)	989
The school is public	0.92 (0.27)	992
Mother's rating of teacher caring: high	0.59 (0.49)	1040
Mother's rating of principal as leader: high	0.51 (0.50)	1039
Mother's rating of teacher skill: high	0.51 (0.50)	1038
Mother's rating of safety of school: high	0.64 (0.48)	1039
Mother's rating of school communicating with parents: high	0.56 (0.50)	1041
Mother's rating of parents participating with school: high	0.31 (0.46)	1039
Mother's rating of school teaching right and wrong: high	0.53 (0.50)	1042
Mother's rating of school maintaining order: high	0.56 (0.50)	1042
Mother's rating of teacher caring: middle	0.32 (0.47)	1040
Mother's rating of principal as leader: middle	0.34 (0.47)	1039
Mother's rating of teacher skill: middle	0.39 (0.49)	1038
Mother's rating of safety of school: middle	0.28 (0.45)	1039
Mother's rating of school communicating with parents: middle	0.31 (0.46)	1041
Mother's rating of parents participating with school: middle	0.38 (0.48)	1039
Mother's rating of school teaching right and wrong: middle	0.35 (0.48)	1042
Mother's rating of school maintaining order: middle	0.33 (0.47)	1042

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