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Time-varying Effects of Screen Media Exposure in the Relationship Between Socioeconomic Background and Childhood Obesity

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Background: We investigated to what extent social inequalities in childhood obesity could be reduced by eliminating differences in screen media exposure.

Methods: We used longitudinal data from the UK-wide Millennium Cohort Study (n = 11,413). The study measured mother's educational level at child's age 5. We calculated screen media exposure as a combination of television viewing and computer use at ages 7 and 11. We derived obesity at age 14 from anthropometric measures. We estimated a counterfactual disparity measure of the unmediated association between mother's education and obesity by fitting an inverse probability-weighted marginal structural model, adjusting for mediator–outcome confounders.

Results: Compared with children of mothers with a university degree, children of mothers with education to age 16 were 1.9 (95% confidence interval [CI] = 1.5, 2.3) times as likely to be obese. Those whose mothers had no qualifications were 2.0 (95% CI = 1.5, 2.5) times as likely to be obese. Compared with mothers with university qualifications, the estimated counterfactual disparity in obesity at age 14, if educational differences in screen media exposure at age 7 and 11 were eliminated, was 1.8 (95% CI = 1.4, 2.2) for mothers with education to age 16 and 1.8 (95% CI = 1.4, 2.4) for mothers with no qualifications on the risk ratio scale. Hence, relative inequalities in childhood obesity would reduce by 13% (95% CI = 1%, 26%) and 17% (95% CI = 1%, 33%). Estimated reductions on the risk difference scale (absolute inequalities) were of similar magnitude.

Conclusions: Our findings are consistent with the hypothesis that social inequalities in screen media exposure contribute substantially to social inequalities in childhood obesity.

Keywords: Causal mediation analysis; Childhood obesity; Health inequalities; Marginal structural model; Screen media exposure

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Replication of results: Due to data protection regulations, the data cannot be made available by the authors. Interested researchers may obtain the data via UK Data Archive. Annotated Stata code is provided in the eAppendix.

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The prevalence of excess weight among children has risen dramatically in the last 4 decades.[1,2] Childhood obesity is linked to a range of adverse outcomes across the life course, including greater risk of chronic diseases, more mental health problems, and lower socioeconomic attainment.[3] Especially alarming is the differential distribution of childhood obesity across socioeconomic groups.[4] Socioeconomically disadvantaged children are at a considerably higher risk to develop obesity, and recent evidence from the United Kingdom suggests that these inequalities will keep rising.[4] Given the already disproportionate health disadvantage of children growing up in lower socioeconomic environments, and the need to intervene early in life to prevent obesity before it is established, tackling social inequalities in childhood obesity is listed as a vital public health strategy.[5] Particularly for children, who have little control over the circumstances affecting their health, potentially avoidable health inequalities are considered unjust.[6,7] Reducing these inequalities, however, requires evidence on the effect of intervening on modifiable mechanisms in the relationship between socioeconomic background and childhood obesity.

Screen media exposure is a major risk factor for childhood obesity and an increasingly common leisure activity of children.[8–10] Many children spend hours per day behind television or computer screens, which substantially increases their obesity risk.[11] Screen media exposure may affect body weight by increasing food consumption and exposure to food and beverage advertisements, lowering energy expenditure, and reducing sleep duration.[9,12] Moreover, screen media exposure is substantially higher among children from lower socioeconomic backgrounds than among children from higher socioeconomic backgrounds.[13,14] Limited financial resources to engage in more expensive leisure activities are likely to be associated with increased screen media exposure among lower socioeconomic status families. Moreover, more disadvantageous neighborhood conditions may discourage playing outside.[15] Differences in screen media habits may also result from other social determinants and transmit to children via socialization and social learning practices.[16–19] First, norms in more-educated social environments have shifted to disapproval and stigmatization of sedentary activities, such as television, viewing in favor of a more active lifestyle.[20,21] Second, childrearing practices of more-educated parents are increasingly aimed at improving children's development, resulting in more extracurricular activities and less screen media exposure.[22] Third, greater cognitive abilities may result in a higher awareness of the negative health consequences of screen media exposure and a preference for other activities that require greater information processing capacities.[23]

To examine to what extent screen media exposure contributes to social inequalities in childhood obesity, we used longitudinal data from the Millennium Cohort Study. We aimed to estimate to what extent social inequalities (measured by mother's educational level) in childhood obesity at age 14 would be reduced if differences in screen media exposure (television viewing and computer use) at ages 7 and 11 were eliminated. To do so, we used mediation methods that are able to estimate the effect of time-varying mediators even in the presence of (time-varying) confounders that are also on the causal pathway from exposure to outcome.[24–27]

METHODS

Data

The Millennium Cohort Study (MCS) is a nationally representative, prospective cohort study of UK children born between September 2000 and January 2002.[28] A stratified clustered sampling design was used to adequately represent children from disadvantaged areas, ethnic minority groups, and children living in Wales, Scotland, and Northern Ireland. Families were invited to participate when eligible cohort children were 9 months old (72% response). Interviews were carried out in the home with the main respondent (over 99% were biologic mothers, hereafter referred to as mothers) and, if applicable, the partner. Information was collected on various topics relating to the child and their family. Additional data were collected when cohort members were 3, 5, 7, 11, and 14 years old from parent(s), siblings, teachers, and cohort members. Parents were given the opportunity to opt out, and consent was sought and obtained at each contact. The MCS received ethical approval from the South West and London Multi-Centre Research Ethics Committees of the National Health Service. This study was restricted to singletons (n = 11,564) who participated in the latest wave (age 14; 61% response), but not necessarily in all previous waves, using data from all 6 waves.[29–34] Data were obtained from the UK Data Archive, University of Essex.

Measures

We used maternal education because it is a frequently used and stable measure of socioeconomic position, a strong predictor of children's life chances, and less sensitive to measurement error than, for example, income.[35–37] We used mother's highest attained educational level at child's age 5 as the main exposure to minimize the number of mothers still enrolled in school, while still allowing for temporal ordering of the measures. We excluded mothers who were a student at child's age 5 from the analysis (n = 151; 1%); we categorized mothers who had obtained qualifications overseas as missing and subsequently imputed their education (described below; n = 312; 3%). Educational categories include (1) university (education to age 20+); (2) education to age 18 (A-level equivalent); (3) education to age 16 (O-level equivalent); and (4) no qualifications.

Screen media exposure was measured combining television viewing and computer use. At child's age 7, mothers reported how many hours, on a normal weekday, their child spent (1) watching television, videos, or DVDs and (2) using a computer or playing electronic games outside school lessons. Answer categories were as follows: (1) none; (2) <1 hour; (3) 1 to <3 hours; (4) 3 to <5 hours; (5) 5 to <7 hours; and (6) ≥7 hours. At child's age 11, the same questions were asked with an additional answer category, differentiating between "1 to <2 hours" and "2 to <3 hours." To calculate an overall score for screen media exposure, the answer categories from the 2 variables were first recoded to 0, 0.5, 2 (1.5 and 2.5 for age 11), 4, 6, and 8 hours/day, and subsequently summed. Because of skewness and outliers, the resulting screen media exposure variables (hours/day at age 7 and hours/day at age 11) were recoded into 4 categories: (1) <1 hour, (2) 1 to <3 hours, (3) 3 to <5 hours, and (4) ≥5 hours.

Trained interviewers took anthropometric measures. Body mass index (BMI) was calculated from weight—measured using Tanita BF-522W (Tanita Corporation, Tokyo, Japan) scales and recorded to the nearest 0.1 kg—and height—measured using a Leicester height measure stadiometer. The primary outcome measure was obesity defined by the International Obesity Task Force (IOTF) age- and sex-specific cutoffs for BMI.[38] We identified potential confounders a priori from existing literature. Potential time-fixed confounders included sociodemographic characteristics at baseline: sex, age, ethnicity (white, Indian/Pakistani/Bangladeshi, black or black British, other), country, mother's age at birth, and mother's religion (none, Christian, Muslim, other). In addition, mother's cognitive ability was included as a time-fixed confounder. This was only measured at child's age 14 and included in the analysis assuming that this measure is a valid indicator for cognitive ability in previous waves.[39] Mother's cognitive ability was measured with a word activity assessment (range: 0–20) derived from a shortened version of the Applied Psychology Unit Vocabulary Test.[40] Potential time-varying confounders (all measured at ages 7 and 11) included equivalized household income (log transformed), managing financially (alright, getting by, difficult), housing tenure (own, public renting, private renting, other), area deprivation (in deciles), maternal BMI (<18.5 kg/m^2, 18.5 to <25 kg/m^2, 25 to <30 kg/m^2, ≥30 kg/m^2), maternal psychological distress (a score of ≥13 on the Kessler-6 scale),[41] child attends club outside of school (no, yes), number of parents/carers (1, 2), natural father in household (no, yes), number of siblings (none, 1, 2, ≥3), parent(s) not in work (no, yes), not enough time to spend with child (no, yes), child illness that limits activity (no, yes), child BMI (normal weight, overweight, or obesity), and maternal fair/poor self-rated health (no, yes).

Statistical Analysis

First, we calculated descriptive statistics of the participants stratified by mother's educational level to describe group differences in the prevalence of the outcome and mediator.[42] Second, we fitted generalized linear models on both the risk ratio and the risk difference scale (described below).[26] We used multiple imputation by chained equations to impute missing data (M = 20). eAppendix 1 (http://links.lww.com/EDE/B673) lists the percentage of missings (ranging from 0% for age, sex, and country to 13% for maternal psychological distress). We used survey weights (age 14, whole UK analyses) provided by the Millennium Cohort Study to correct for sampling design and attrition.[43] We conducted analyses using Stata 15 (StataCorp, College Station, TX).

To assess to what extent social inequalities in childhood obesity could be reduced by intervening on screen media exposure, we estimated a counterfactual disparity measure.[44,45] The counterfactual disparity measure in this study comparing exposure level a^* to level a is defined on the risk difference scale in equation 1 and on the risk ratio scale in equation 2:

$$E[Y(\bar{m}(t)) \mid A = a] - E[Y(\bar{m}(t)) \mid A = a^*] \tag{1}$$

$$E[Y(\bar{m}(t)) \mid A = a] \; / \; E[Y(\bar{m}(t)) \mid A = a^*] \tag{2}$$

where $\bar{m}(t)$ denotes the mediator trajectory (i.e., screen media exposure at ages 7 and 11). This measure can be interpreted as the magnitude of the association between mother's education and childhood obesity that would remain if a particular trajectory of screen media exposure was fixed at a specific value uniformly in the population. A main advantage of the counterfactual disparity measure is that it can still be identified even if there are confounders of the mediator–outcome relationship that are also on the causal pathway from exposure to outcome.[24,26,27,46] Because the effect of screen media exposure on obesity may be confounded by factors that are itself affected by mother's education (e.g., income, neighborhood deprivation), we estimated the counterfactual disparity measure to adjust for these factors. In this regard, the counterfactual disparity measure is similar to the more widely known controlled direct effect (CDE). However, whereas a CDE also assumes no unmeasured exposure–outcome confounding, identification of a counterfactual disparity measure requires only one exchangeability assumption: no unmeasured mediator–outcome confounding.[44,47] To fulfill this assumption, we adjusted for a comprehensive set of potential confounders of the relationship between screen media exposure and obesity (described previously).

Counterfactual disparity measures (similar to CDEs) can be estimated for each level of the mediator. In the presence of an interaction effect between exposure and mediator on the outcome, these separate counterfactual disparity measures may differ depending on the magnitude of the interaction effect. However, in the absence of an interaction effect, all counterfactual disparity measures will be equal. We examined the presence of interaction effects by including cross-product terms between mother's education and screen media exposure (eAppendix 2; http://links.lww.com/EDE/B673), but due to a lack of precision in the estimated models, we were unable to observe interaction on either the risk ratio or risk difference scale (although at least one must be present if both exposure and mediator have an effect on the outcome).[48,49] Because testing the null hypotheses of no interaction resulted in P values of >0.9 on both the risk ratio and the risk difference scale, including the interaction terms would likely limit precision in our models even more and hinder inference. We, therefore, decided to omit the cross-product terms from the final analysis and estimated only one counterfactual disparity measure (similar to, e.g., Nandi et al[50]). As a result, our analysis assumes that intervening to eliminate differences in screen media exposure between children from different socioeconomic backgrounds has the same effect regardless of the amount of screen media exposure that is imposed by the hypothetical intervention.

Subsequently, we calculated a "percentage reduction" by dividing the difference between the total disparity (TD) in childhood obesity and the counterfactual disparity measure (CDM) by the total disparity (i.e., $[TD - CDM]/[TD - 1]$ on the risk ratio scale and $[TD - CDM]/TD$ on the risk difference scale).[51] This percentage reduction indicates how much the disparity in childhood obesity would be reduced if differences in screen media exposure were eliminated. We bootstrapped the percentage reduction parameter (1,000 repetitions) to obtain 95% bias-corrected confidence intervals (CIs).[52]

To estimate the counterfactual disparity measure, we fitted a marginal structural model (MSM) using inverse probability of treatment weighting.[24,25,27] This method uses weighting to adjust for (time-varying) confounding, which bypasses the need to condition on confounders in the outcome model as is traditionally done in mediation analysis. To do so, we first calculated stabilized inverse probability weights (IPWs) of the probability that each participant received the level of screen media exposure that he/she actually received, given exposure, mediator, and confounder history. For each individual i in the sample, the mediator weight at time t is calculated by:

$$w^{M}{}_{i}(t) = \frac{P[M(t) = m_i(t) | a_i, m_i(t-1)]}{P[M(t) = m_i(t) | a_i, m_i(t-1), l_i(t-1), v_i]}$$

where a_i, $m_i(t)$, $l_i(t)$, and v_i are the actual values of the exposure, the mediator, the time-varying confounders, and the baseline confounders, respectively, for individual i.[26] Second, we fitted generalized linear regression models with robust standard errors as shown in equations 3 and 4, weighted by the product of the inverse probability and survey weights[53]:

$$E[Y \mid A = a, \bar{M}(t)=\bar{m}(t)] = \gamma_0 + \gamma_1 a + \gamma_2 m(t=\text{age7}) + \gamma_3 m(t=\text{age11}) \quad (3)$$

$$\text{Log}(P[Y=1 \mid A=a, \bar{M}(t)=\bar{m}(t)]) = \theta_0 + \theta_1 a + \theta_2 m(t=\text{age7}) + \theta_3 m(t=\text{age11}) \quad (4)$$

The parameters of this weighted regression give valid estimates of the counterfactual disparity measure (assuming no model misspecification, selection bias, or measurement error).[25,27] eAppendix 3 (http://links.lww.com/EDE/B673) provides more information and annotated Stata code. By applying weights in the final regression model, a pseudopopulation is created where the distribution of measured confounders is unrelated to the effect of interest (as illustrated in the causal diagram in the Figure). In other words, to the extent that mother's education is related to obesity of the child via the (time-varying) confounders (e.g., income, neighborhood deprivation), but not via screen media exposure, this effect is still captured in the estimated disparity measure. However, to the extent that the effect of screen media exposure on obesity is confounded by the measured covariates, this confounding is removed by applying the weights.

Several effective interventions to reduce screen media exposure among children exist, with some replacing screen time with other activities (e.g., sports or extracurricular activities) and others targeted at decreasing screen time without encouraging replacement activities (e.g., by educational programs or automatic time locks).[54] The hypothetical intervention considered in our study is best envisioned by putting an automatic time lock on the television and computer, limiting screen time uniformly for all children. As previously discussed, by omitting interaction terms, we assume that this hypothetical intervention will have the same effect on social inequalities in childhood obesity regardless of the amount of screen time set by the automatic lock. Furthermore, it is important to note that by not specifying replacement activities, our models assume that these activities do not differ between children from different socioeconomic backgrounds (at least with regard to their effect on obesity).[55,56] If, for example, children from more-educated mothers

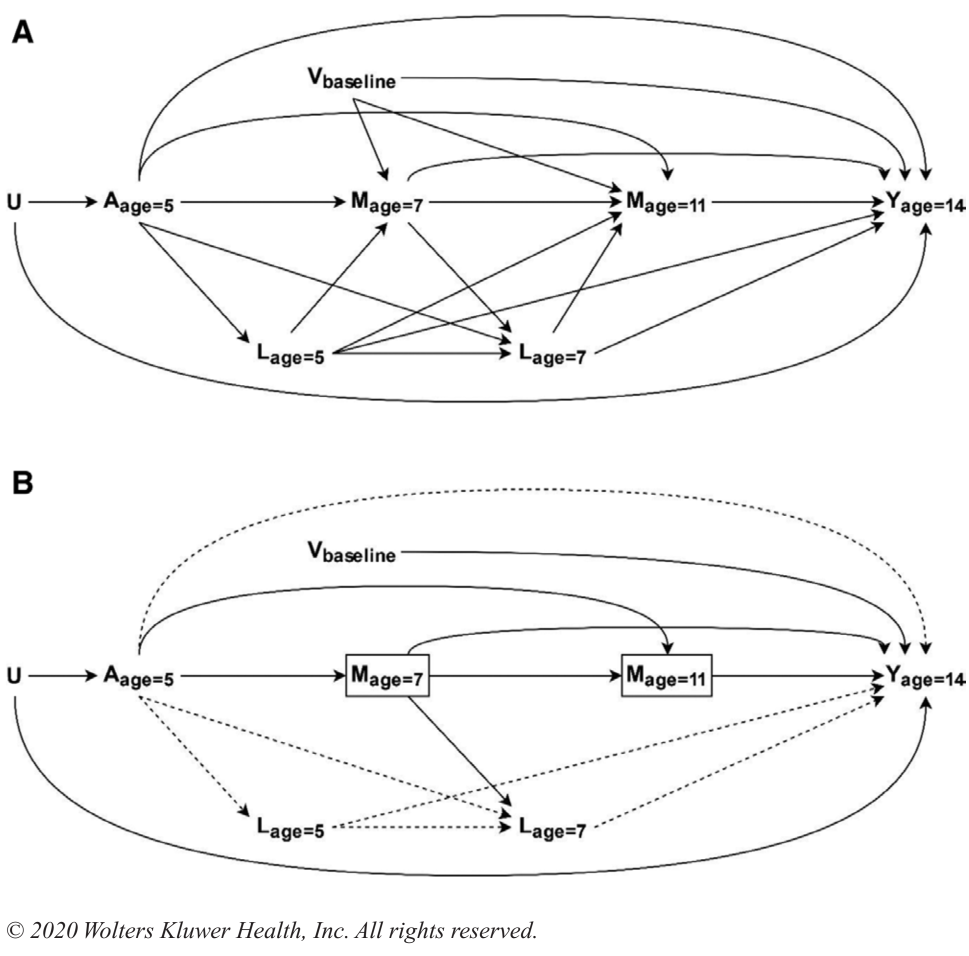

FIGURE. Causal diagrams (directed acyclic graphs) of the proposed mediation analyses before and after applying the inverse probability weights. A, Causal diagram of the proposed mediation analysis: A = mother's education (in this diagram shown as if it were effectively randomized), M_t = screen media exposure, V = time-fixed (baseline) confounders, L_t = time-varying confounders, Y = childhood obesity, U = unmeasured confounders. L_t is on the causal pathway $A \rightarrow Y$, but also a confounder in the relationship $M_t \rightarrow Y$, which prohibits conventional adjustment for L_t. B, Causal diagram of the scenario encountered after applying the inverse probability weights: A = parental education, M_t = screen media exposure (depicted with a box to indicate that they are conditioned on in the regression model), V = time-fixed (baseline) confounders, L_t = time-varying confounders, Y = childhood obesity, U = unmeasured confounders. The dashed lines depict the counterfactual disparity measure. By applying the weights, several arrows are "erased" (i.e., the effect of V and L_t on M_t) and it becomes possible to estimate the combined magnitude of the dashed lines.

TABLE 1. Descriptive Statistics of the Millennium Cohort Study Participants Stratified by Mother's Educational Level (Percentages)

	Mother's Educational Level[a]			
	University (n = 4,050)	Education to Age 18 (n = 1,554)	Education to Age 16 (n = 3,571)	No Qualifications (n = 1,223)
Female, %[b]	48	46	47	49
Ethnicity, %[b]				
White	87	88	91	69
Indian/Pakistani/Bangladeshi	4	5	4	16
Black or British black	4	2	2	8
Other	5	5	3	7
Country, %[b]				
England	82	78	84	84
Wales	5	6	5	4
Scotland	9	12	7	7
Northern Ireland	4	5	4	5
Mother's religion, %[b]				
None	37	47	55	53
Christian	57	46	40	24
Muslim	3	4	4	19
Other	3	3	2	4
Mother's age at birth,[b] mean (SD)	31 (5.5)	27 (5.9)	27 (5.7)	26 (5.7)
Mother's cognitive ability,[c] mean (SD)	13 (4.5)	11 (3.9)	9.7 (3.2)	7.1 (2.9)
Area deprivation decile,[a] mean (SD)	6.7 (3.1)	5.4 (2.8)	4.7 (2.6)	3.1 (2.1)
Household equivalized income,[a] mean (SD)	490 (272)	348 (193)	285 (158)	196 (101)
Managing financially, %[a]				
Alright	73	60	55	40
Getting by	20	30	33	41
Difficult	7	9	12	19
Housing tenure, %[a]				
Own	83	67	49	26
Public renting	8	21	35	58
Private renting	6	8	12	13
Other	3	5	4	3
Maternal BMI (kg/m^2), %[a]				
18.5 to <25	53	44	43	35
<18.5	16	19	21	29
25 to <30	20	23	21	20
≥30	10	14	14	16
Maternal psychological distress, %[a]	1	3	5	8
Child attends club outside of school, %[a]	16	11	8	5
One parent/carer, %[a]	12	19	28	34
Natural father not in household, %[a]	14	25	34	41
No. siblings, %[a]				
None	15	20	17	13
1	54	50	46	32
2	24	21	24	25
≥3	7	9	13	31
Parent(s) in work, %[a]	73	62	50	21
Not enough time to spend with child, %[a]	38	32	28	15
Child illness that limits activity, %[a]	5	6	6	8
Maternal fair/poor self-rated health, %[a]	2	4	5	7
Screen media exposure (hours) (per day; age 7), %				
<1	23	15	12	10
1 to <3	48	47	44	42
3 to <5	21	27	31	29
≥5	8	12	13	18
Screen media exposure (hour) (per day; age 11), %				
<1	16	9	7	7
1 to <3	59	58	54	50
3 to <5	16	19	21	22
≥5	10	13	18	20
Obesity (age 14), %[c,d]	5	6	10	10

Descriptive statistics calculated on nonimputed data weighted by the survey weights. Descriptive statistics of the confounders only shown for the earliest measurement.
[a]Derived at age 5.
[b]Derived at baseline.
[c]Derived at age 14.
[d]Defined by the International Obesity Task Force age- and sex-specific cut-offs for BMI.

spend this time on physical activity, while children from less-educated mothers do not, this assumption would be violated and the estimated counterfactual disparity measure may be biased.

We conducted several sensitivity analyses to investigate the robustness of the results (eAppendix 4; http://links.lww.com/EDE/B673). First, analyses were repeated using the UK 1990 growth reference (UK90) BMI cut-offs.[57] Whereas the IOTF cut-off defines obesity as an age- and sex-specific cut-off extrapolated from the adult BMI cut-off of 30 kg/m^2, the UK90 cut-off defines obesity as those at or above the 95th percentile based on age- and sex-specific reference charts. Using the UK90 cut-off, the prevalence of childhood obesity ranges from 15% for children from mothers with a university degree to 25% for children from mothers with no qualifications. Second, we repeated analyses using the highest attained educational level in the household (either from the mother or partner) and household income quartiles as the exposure (while controlling for education). Third, we repeated analyses using only television viewing and using only leisure-time computer use as a mediator, instead of a combined measure (while including the other measure as a confounder). Fourth, we repeated analyses without using imputed data for exposure and outcome (n = 9,749).

RESULTS

Among the children's mothers included in the study, 39% had a university degree, 15% had education to age 18, 34% had education to age 16, and 12% had no educational qualifications. Table 1 shows that 8% of 7-year-old children and 10% of 11-year-old children from mothers with a university degree were exposed to ≥5 hours of screen media per weekday. This percentage increased steadily among children from mothers with a lower educational level to 18% of 7-year-old children and 20% of 11-year-old children from mothers with no educational qualifications.

Children from mothers with no educational qualifications were 2.0 (confidence interval = 1.5, 2.5) times as likely to be obese and had a 5.6 (3.1, 8.1) percentage-point higher risk of obesity than children from mothers with a university degree (Table 2). Children from mothers with education to age 16 were 1.9 (1.5, 2.3) times as likely to be obese and had a 5.1 (3.4, 6.7) percentage-point higher risk of obesity. Children from mothers with education to age 18 were 1.3 (1.0, 1.7) times as likely to be obese and had a 1.6 (−0.4, 3.6) percentage-point higher risk of obesity. Because of the relatively small inequality in obesity between children from mothers with education to age 18 and mothers with university qualifications, we refrain from making inferences for this contrast.

Results from the inverse probability-weighted regression model showed that longer exposure to screen media is associated with a higher risk of childhood obesity (Table 3). Five hours or more of screen media per day at age 11 was associated with 1.7-fold (1.0, 2.8) increased risk of obesity or 3.9 (0.4, 7.4) percentage-points, compared with <1 hour/day.

Compared with mothers with university qualifications, the estimated counterfactual disparity in obesity at age 14, if educational differences in screen media exposure at ages 7 and 11 were eliminated, was 1.8 (1.4, 2.2) for mothers with education to age 16 and 1.8 (1.4, 2.4) for mothers with no qualifications on the risk ratio scale. On the risk difference scale, the same comparison was 4.3 (2.5, 6.1) for mothers with education to age 16 and 4.6 (2.0, 7.2) for mothers with no qualifications (Table 3). This corresponds to an estimated reduction in relative inequalities in childhood obesity of 13% (1%, 26%) for mothers with education to age 16 and 17% (1%, 33%) for those with no qualifications (Table 4), and an estimated reduction in absolute inequalities of 15% (2%, 28%) for mothers with education to age 16 and 18% (−1%, 37%) for those with no qualifications (Table 5).

Sensitivity analyses (eAppendix 4; http://links.lww.com/EDE/B673) showed (again respectively contrasting children from mothers with education to age 16 and no qualifications against children from mothers with university qualifications)

TABLE 2. Total Disparity in Childhood Obesity

	RR (95% CI)	RD 95% CI)
Mother's educational level		
University	1	0
Education to age 18	1.3 (1.0, 1.7)	1.6 (−0.4, 3.6)
Education to age 16	1.9 (1.5, 2.3)	5.1 (3.4, 6.7)
No qualifications	2.0 (1.5, 2.5)	5.6 (3.1, 8.1)

RD indicates risk difference (in percentage-points); RR, risk ratio.

TABLE 3. Results From the Inverse Probability-weighted Regression Model Regressing Obesity on Mother's Educational Level and Screen Media Exposure

	RR (95% CI)	RD (95% CI)
Mother's educational level		
University	1	0
Education to age 18	1.2 (0.9, 1.7)	1.1 (−1.1, 3.3)
Education to age 16	1.8 (1.4, 2.2)	4.3 (2.5, 6.1)
No qualifications	1.8 (1.4, 2.4)	4.6 (2.0, 7.2)
Screen media exposure per day (hour) (age 7)		
<1	1	0
1 to <3	1.3 (0.9, 1.9)	1.3 (−1.1, 3.7)
3 to <5	1.3 (0.9, 1.9)	1.5 (−1.1, 4.0)
≥5	1.2 (0.7, 1.8)	1.0 (−2.1, 4.1)
Screen media exposure per day (hour) (age 11)		
<1	1	0
1 to <3	1.3 (0.8, 2.1)	1.8 (−0.8, 4.4)
3 to <5	1.6 (1.0, 2.7)	3.4 (0.1, 6.7)
≥5	1.7 (1.0, 2.8)	3.9 (0.4, 7.4)

RD indicates risk difference (in percentage-points); RR, risk ratio.

TABLE 4. Reduction in Relative Inequalities in Childhood Obesity if Educational Differences in Screen Media Exposure Were Eliminated

	Total Disparity	Counterfactual Disparity	Percentage Attenuated
	RR (95% CI)	RR (95% CI)	Estimate (95% CI)
Mother's educational level			
University	1	1	
Education to age 18	1.3 (1.0, 1.7)	1.2 (0.9, 1.7)	29% (−18%, 174%)
Education to age 16	1.9 (1.5, 2.3)	1.8 (1.4, 2.2)	13% (1%, 26%)
No qualifications	2.0 (1.5, 2.5)	1.8 (1.4, 2.4)	17% (1%, 33%)

RR indicates risk ratio.

TABLE 5. Reduction in Absolute Inequalities in Childhood Obesity if Educational Differences in Screen Media Exposure Were Eliminated

	Total Disparity	Counterfactual Disparity	Percentage Attenuated
	RD (95% CI)	RD (95% CI)	Estimate (95% CI)
Mother's educational level			
University	0	0	
Education to age 18	1.6 (−0.4, 3.6)	1.1 (−1.1, 3.3)	30% (−27%, 206%)
Education to age 16	5.1 (3.4, 6.7)	4.3 (2.5, 6.1)	15% (2%, 28%)
No qualifications	5.6 (3.1, 8.1)	4.6 (2.0, 7.2)	18% (−1%, 37%)

RD indicates risk difference (in percentage-points).

that using the UK90 obesity cut-offs resulted an estimated reduction in social inequalities in childhood obesity of 11% and 11% for relative inequalities and 9% and 9% for absolute inequalities. Using highest parental educational level, the estimated reduction was 8% and 9% for relative inequalities and 10% and 11% for absolute inequalities. Using household income quartiles, the estimated reduction was 19% and 17% for relative inequalities and 19% and 16% for absolute inequalities. Both television viewing and leisure-time computer use contributed independently to the estimated reduction in inequalities in childhood obesity, although including only television viewing as a mediator resulted in a slightly higher estimated reduction in inequalities in obesity (15% and 17% reduction in relative inequalities and 11% and 12% reduction in absolute inequalities) than including only leisure-time computer use (16% and 13% for relative inequalities and 9% and 6% for absolute inequalities). Last, not imputing exposure and outcome resulted in an estimated reduction in inequalities in obesity of 16% and 21% for relative inequalities and 16% and 22% for absolute inequalities, respectively.

DISCUSSION

Children of the least-educated mothers were almost twice as likely to be obese at age 14 than children of the most-educated mothers. Similarly, children of the least-educated mothers had greater levels of screen media exposure (19% at age 7 and 20% at age 11) than children of the most-educated mothers (8% at age 7 and 10% at age 11). We estimated that up to 17% of relative and 18% of absolute inequalities in childhood obesity would be reduced if differences in screen media exposure were eliminated.

This study has several limitations. First, even though the sample consisted of 11,413 UK children, our estimates have limited precision. Most notably, this obstructed inclusion of interaction terms in the models. Second, although obesity was derived from anthropometric measures, covariates were self-reported, which risks higher measurement error. Third, although great care was given to adjust for potential confounding, the observational nature of the data implies that there is no guarantee that we were able to fulfill the exchangeability assumption. Specifically, the assumption of no unmeasured mediator–outcome confounding implies that we have to presume that the risk of obesity among children who were exposed to, for example, ≥5 hours of screen media per day would be comparable—given the measured confounders—to the risk of children who were exposed to <1 hour of screen media, if, counter to the fact, they were exposed to <1 hour of screen media per day themselves (and vice versa). In other words, we assume that if we were able to reduce screen media exposure, these children would replace watching television or playing on computers with (healthier) activities comparable to those of the children in our cohort who have less screen media exposure (instead of substituting screen media exposure for an activity with a similar or even higher risk of obesity). Violation of this assumption is perhaps most likely for factors that affect screen media exposure and other lifestyle-related factors that may lead to a higher probability of obesity among children, such as habits and preferences related to food consumption and physical activity. In an attempt to block these pathways, we adjusted for mother's BMI because the same factors would likely also lead to a higher BMI of the mothers. However, mother's BMI may not fully account for these confounding effects. Fourth, in addition to differences in the quantity of screen media exposure, children from different socioeconomic backgrounds may be exposed to different screen media content (e.g., children from more-educated mothers may more often consume media with less exposure to food advertisements). Because we had no data on screen media content, we could not adjust for these differences. Fifth, whereas extensive data were collected from mothers, less data were available from their partners. Moreover, because a substantial number of mothers had no partner, partner information could not be included in the models. To the extent that the level of screen media exposure of children and their risk of obesity was affected by partner's factors independently of maternal factors, this may have affected our results. Sixth, mother's cognitive ability was measured as knowledge of vocabulary, which may not reflect the full spectrum of cognitive abilities.

Previous studies have found indications that television viewing tracks from childhood to adulthood, suggesting that intervening on screen media exposure in childhood may also affect screen media exposure in later life.[58] Moreover, because childhood obesity is a strong predictor of adult obesity and other adverse health outcomes, intervening on the causes of childhood obesity will positively affect health chances throughout the life course. Future research that examines how screen media exposure can be effectively reduced in socioeconomically disadvantaged families is, therefore, warranted. Furthermore, given the fact that new forms of screen media emerge rapidly (e.g., smartphones, tablets, virtual reality media) and are increasingly used by (young) children, screen media exposure may become an increasingly relevant determinant of childhood obesity in the next decade. To prevent a further surge of (social inequalities in) obesity, we need to carefully monitor how these technologic innovations affect our youth's health across different social groups.

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