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Abstract

We examine the effect of screen-based activities on obesity and mental well-being for children, exploiting exogenous variation in the entry date of the digital television transition in the UK. The digital transition increased the number of available free television channels from 5 to 40, leading to an increase in television viewing time. Our results show that one additional year with access to digital television signal increases BMI z-scores by 0.159 standard deviations and the mental health total difficulties score by 2.13% among children. Underlying the net effects appears to be a decrease in physical activity among children, while neither eating habits nor personal views about self-appearance seem to play a significant role.

Keywords: Television, BMI, Obesity, Mental Health, Well-being

JEL classification: D60, I10, I31, J13.

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1 Introduction

Obesity and mental health problems among children have considerably increased during the last decades in most high-income countries (OECD, 2019a,b).[1] This raises important societal concerns, first, in light of the associated disease burden itself, but also beyond, due to adverse effects on educational performance (Currie and Stabile, 2006; Currie, 2009), future labour market outcomes (Smith, 2009; Fletcher, 2014; Lundborg et al., 2014) and life expectancy (Frijters et al., 2010), among others. Television (TV) viewing, a very popular (in-)activity among children and adolescents in most high-income countries, has been commonly hypothesized to be one underlying driver of poor health during childhood, both in terms of physical health – especially concerning children's weight (Swinburn and Shelly, 2008) – and mental well-being (Dickson et al., 2018). Yet, as plausible as these consequences may be, the literature on the effect of exposure to television on obesity and mental-wellbeing has struggled to identify a meaningful causal relationship (Biddle et al., 2017; Dickson et al., 2018).

As recent data shows, children spend a substantive share of their free time in front of the television. For example, in the UK, 94% of children watched TV for an average of 13.25 hours per week in 2018 (Ofcom, 2019). Given such magnitudes, it is important to understand the causal effect of TV viewing on mental and physical health, an ambition which – for several reasons – is not met easily. First, the (widely) observed correlation between TV viewing and overweight and mental (ill-)health could also be the result of reverse causality: children who are overweight – or that feel mentally low – may be less motivated or able to be physically active and, hence, turn to TV viewing more often. Second, there could be third factors – either unobservable or not accounted for in the empirical work (e.g parental preferences and education styles, socioeconomic background) – that simultaneously affect both sides of the observed relationship (Nakamuro et al., 2015).

[1] Appendix A.1 provides some descriptive background evidence on the international as well as UK-specific obesity and mental health context in children and adolescents.

In the present study, we seek to provide evidence on the causal effects of TV watching on child obesity and mental health, as well as on the underlying mechanisms. We do so by exploiting a natural experiment design offered by the "digital television transition" that occurred in the UK between 2008 and 2012, forcing – in stages – every television transmitter to stop broadcasting analogue signal and start transmitting high power digital signal. Several important changes occurred at the time of transition from analogue to digital signal, including an increase in the number of television channels from 5 to 40, the possibility of watching television in several languages, the introduction of multimedia services, and a higher definition. As a result, the switchover was one of the biggest changes in British television history (DigitalUK, 2012). The digital switchover did not exclusively occur in the UK, but also in many other countries world-wide.

Some previous research has used the digital transition in Italy to explore the effect of television on voting attitudes (Barone et al., 2015) and crime concerns (Mastrorocco and Minale, 2018), and the digital transition in the UK to examine the effect of television on academic outcomes (Nieto, 2019). Besides digital transition reforms, earlier work has exploited variation in the timing of the introduction of TV infrastructure to provide evidence on the impact of childhood TV exposure on educational performance test scores in the US (Gentzkow and Shapiro, 2008).

The digital transition in the UK provides for an adequate natural experiment to study the causal impact of television on health outcomes for two reasons. First, the digital transition was implemented in stages by two independent organizations, based on the physical characteristics of the British television transmitters. These had been constructed in the 1960s and 1970s, hence reducing the likelihood that the switchover is correlated with unobserved determinants of children's health outcomes. Second, we are able to exploit fine-grained geographical variation in the switchover timing across more than 40,000 geographical units.

We merge the switchover information with the first seven waves of the Understanding Society survey. This is a high-quality longitudinal survey dataset representative of the UK population, providing information on the health outcomes and socio-demographic characteristics (among others) of children that have been interviewed annually since 2009. Using this information, we construct a large panel dataset and estimate an empirical setting that compares the health characteristics of children living in areas that received access to the digital signal at different dates.

Our paper adds in at least three main ways to the literature on the effect of screen-based activities on overweight and mental health. First, we provide causal evidence on the effect of exposure to television on child obesity and mental well-being, using the digital television transition in the UK as a natural experiment, combined with a rich longitudinal, nationally representative survey dataset. Second, we examine potential heterogeneity in the effects across relevant sub-groups of children with different socio-demographic characteristics, to examine whether body weight and mental well-being of some groups of children are particularly affected by exposure to television. Third, we explore plausible mechanisms operating behind these effects, including changes in physical activity, eating habits and personal views about appearance.

Our results demonstrate a harmful influence of exposure to television on both the physical and mental health of children. We find an additional year with access to digital television to increase children's BMI z-scores by 0.159 standard deviations, with the effect being largely driven by socio-economically disadvantaged children. As for mental well-being, an additional year with access to digital signal increases children's mental health total difficulties score by 2.13% through a rise in their conduct problems (e.g. easily losing temper, lying, manipulating others, etc.). However, we find no evidence of exposure to television having a negative impact on children's emotional symptoms, hyperactivity, and relational problems. Finally, we show that the digital transition increases overweight and reduces mental well-being through decreasing children's physical activity, but not through a change in their eating habits or in the perceptions about their appearance.

The paper is structured as follows: Section 2 reviews the literature on the effect of television on health, Section 3 explains our natural experiment as well as identification strategy and Section 4 describes the data we use. Section 5 presents and discusses our findings, and Section 6 explores plausible mechanisms. Lastly, Section 7 provides concluding remarks.

2 The Relationship between TV Viewing and Children's Overweight and Mental Health

While there exists a significant – and extensively reviewed – literature that has empirically analysed the relationships between TV viewing and either overweight (Zhang et al., 2016; Biddle et al., 2017; Ghobadi et al., 2018; Tripathi and Mishra, 2020) or mental health (Dennison et al., 2016; Dickson et al., 2018) in children and adolescents, the existing evidence is, as the here-cited reviews underline, dominated by either cross-sectional evidence that is remarkably mixed in terms of the size and significance of the estimated relationship, or based on small-scale, hard-to-generalize experimental intervention studies. Taken together, this leaves the question of a causal, population-level effect of TV viewing still widely open.

Much of the early work focused on either cross-sectional or – in rare cases – a limited longitudinal design. For instance, in what appears to be the first empirical study of its kind, Dietz and Gortmaker (1985) used data from two (mostly) cross-sectional rounds to show a significant, but in the authors' judgement "small" association between TV watching and child obesity.[2] An important advance in the direction of more extensive, yet somewhat regionally constrained, longitudinal analysis was by Hancox et al. (2004), who used longitudinal data from a rich birth cohort of over 1,000 children born in one town in New Zealand in 1972-73, to show that weekday TV viewing was associated with higher future body mass index (BMI).

[2] A similarly influential, early study was by Gortmaker et al. (1996), who established a statistical link between TV viewing hours in adolescents and the probability of being overweight, using (mostly) 1990 data.

Similar results were found for the US by Boone et al. (2007), using nationally representative data from a prospective cohort study of adolescents followed from 1995 to 2001, and more recently by Tahir et al. (2019) who established a dose-response relationship between hours of TV viewing in childhood/adolescence and BMI at age 18 and in adulthood, among females in the US. Other studies contradicted or at least attenuated the Hancox et al. (2004) results, finding a weaker and sometimes insignificant association between TV viewing and BMI (Hammer et al., 1993; DuRant et al., 1994; Katzmarzyk et al., 1998; Nakamuro et al., 2015).

Alongside the observational studies, a set of experimental, generally small-scale intervention studies have been conducted (Buchanan et al., 2016). According to the systematic review by Buchanan et al. (2016), the existing evidence indicates that reductions in screen time may decrease BMI from -0.09 to -0.44, suggesting that limiting television viewing time may help prevent child obesity (Robinson, 1999). It is, however, important to bear in mind that the experimental studies were typically of very small sample size and with only short follow-up post-intervention.

Several potential mechanisms may explain the effect of TV viewing on obesity. First, TV watching is a sedentary activity that might substitute the time children spend being physically active (Jenvey, 2007). For the UK, Sandercock et al. (2012) showed a graded, negative association between higher screen time and lower free-time physical activity in a cross-sectional sample of 10-15 year olds. Similarly, Tammelin et al. (2007) found screen time to be negatively correlated with physical activity for Finnish adolescents. Second, watching TV may reduce the resting metabolic rate, i.e. the amount of calories burnt by the body when at rest (Klesges et al., 1993). Lastly, television viewing may increase energy intake (Crespo et al., 2001; Van den Bulck and Van Mierlo, 2004), through the behavioural influence of TV advertising targeting children and adolescents to increase their fast-food, sugary beverages and alcohol consumption (Hastings et al., 2003; Saffer and Dave, 2006; Chou et al., 2008; Andreyeva et al., 2011; Avery et al., 2017; Powell et al., 2017).

Regarding mental well-being, TV viewing has been commonly associated with aggressive behaviour (Johnson et al., 2002; Huesmann et al., 2003; Nakamuro et al., 2015), irregular sleeping time (Johnson et al., 2004; Thompson and Christakis, 2005), anxiety (Bryant et al., 1981), depression (de Wit et al., 2011) and attentional problems (Christakis et al., 2004). The suggested mechanisms behind the potential adverse mental health outcomes comprise: TV watching increasing physical inactivity and/or sedentary time, which in turn harms mental well-being (Lechner, 2009; Harvey et al., 2010; Lubans et al., 2016); TV viewing contributing to weight gain and unfavourable body composition, provoking weight-based bullying, teasing, stigmatization, and ultimately poor mental health (Russell-Mayhew et al., 2012; Nikolaou, 2017); and the sedentary behaviour associated with TV viewing increasing the intake of unhealthy food and beverages (Chou et al., 2008; Hobbs et al., 2015), which harms children's and adolescents' psychological mood (Jacka and Berk, 2007; van Strien et al., 2013).

3 Natural Experiment and Identification Strategy

3.1 Digital Television Switchover

The digital transition involved the upgrade of every TV transmitter in the UK in order to switch off the transmission of analogue signal and start the provision of high-power digital signal. The digital switchover was one of the biggest revolutions in the history of the British television market, as it gave digital television access to millions of households for the first time in their lives and equipped them with several important improvements. For example, the digital television signal increased the number of television channels from 5 to 40, allowed individuals to watch television in several languages, offered multimedia services, and provided a higher definition. To be able to watch digital television, it is not only necessary to receive digital signal but people also need to install a set-top box in their TV device, which could be bought for approximately 30 pounds and which was subsidized for economically disadvantaged individuals by the UK Government.

Two independent organizations were in charge of the digital television transition implementation: Ofcom and DigitalUK. Ofcom is the media regulator in the UK and DigitalUK is a non-profit organization. They implemented the switchover process based on the physical components of the British television broadcasters, which had been built in the 1960s and 1970s.

The switchover process took place at different dates in the different television transmitters during the period of 2008 and 2012. There are 1,235 television transmitters in the UK and it is common for individuals to receive television signal from more than one television transmitter. This generates a strong geographical variation in the timing of the digital switchover, which we exploit across more than 40,000 Lower Layer Super Output areas. These are small statistical areas with an average population of 1,500.[3] Figure 1 displays the variation we use in the analysis on the switchover process during the period of 2008-2012.

The changes brought about by the digital switchover notably increased television viewing time. Figure 2 shows that television viewing time did not change much in the years prior to the switchover commencement, but that it rapidly increased after the digital transition start. Television viewing time remained higher during the digital transition period and steadily decreased upon its completion, probably due to the increase in use of tablets and the introduction of internet-based streaming services such as Netflix, Youtube and Amazon Prime video (Ofcom, 2019). Not surprisingly, Figure 2 shows that the TV viewing share of the analogue television channels fell during the digital transition period due to the higher supply of digital television channels. The TV viewing shares of the traditional channels also fell prior to the switchover process start because part of the population already had access to

[3]The name of the geographical units we use in Scotland and Northern Ireland are Data Zones and Super Output Areas, respectively. These are equivalent in size and population to LSOAs in England and Wales.

a higher number of TV channels before the switchover start. Lastly, Figure 3 shows that television content did not change considerably during the period of analysis. Here, we classify television content into eight different categories: entertainment, educational programmes, cultural content, novelas, children content, news, documentaries and other.

3.2 Empirical Strategy

We estimate an OLS specification that compares BMI z-scores and mental well-being outcomes of children who live in LSOAs that receive access to digital signal at different dates. Our baseline model is the following:

$$y_{i,r,t} = \alpha + \beta Nyears_{r,t} + \theta X_{i,r,t} + \zeta_r + \lambda_t + \varepsilon_{i,r,t} \tag{1}$$

where $y_{i,r,t}$ is the outcome of interest of child i, who lives in LSOA r, in year t. Our two main outcomes of interest are the BMI z-score and mental health total difficulties score of child i in year t (see section 4 for definitions). $Nyears_{r,t}$ is a continuous variable that provides information on the number of years that have passed at the interview date since the digital transition deadline in LSOA r. $Nyears_{r,t}$ takes a value of 0, if the digital transition has not yet taken place in LSOA r by the interview date. We control for a number of time-varying covariates at the individual level such as gender, a set of age dummies, the logarithm of household income, the number of members, bedrooms and cars in the household, and whether children live in a rural or urban area. We denote this set of socio-demographic controls by $X_{i,r,t}$.[4] We control for LSOA fixed effects, which are denoted by ζ_r, to account for time invariant unobserved determinants of the weight and mental health of children at the LSOA level. λ_t is a set of year dummies that control for non-linear trends in the outcome variables common across children over time.

[4] It is important to control for a set of age dummies as this allows to account for a non-linear relationship between BMI z-scores/mental health outcomes and the age of children.

Despite the inclusion of time-varying covariates, LSOA and year dummies in the analysis, we still have enough variation in $Nyears_{r,t}$ as the digital switchover took place in the different LSOAs at different dates. Finally, $\varepsilon_{i,r,t}$ is a time-varying error at the child level. We cluster standard errors at the LSOA level.[5]

4 Data

We use information on the dates when the digital transition occurred at the LSOA level in the UK, which we web-scrape from the DigitalUK website. The dataset on digital transition deadlines also contains information on the transmitters that provide digital television signal to each LSOA, the quality of the signal, and the type of transmitter. There are two types of television transmitter: principal transmitters, which generate television signal, and relay transmitters, which receive television signal from the principal broadcasters and repeat it to areas that cannot receive television signal from the principal transmitters.

We also use data from waves 1-8 of the youth questionnaire of the Understanding Society survey (UKHLS, 2019a), which is a large longitudinal survey representative of the UK population that has followed children aged 10-15 on a yearly basis since 2009. The dataset permits linking children across different waves, allowing us to build a panel dataset containing yearly information on the health outcomes, time use and socio-demographic characteristics of children. Regarding health outcomes, the youth questionnaire of the Understanding Society survey contains information on the height, weight and BMI of children. We link BMI information with the British 1990 growth reference list on BMI to generate BMI z-scores for children during the period of analysis. The Understanding Society survey also contains yearly information on the mental health difficulties of children, providing scores on whether they have: (i) emotional, (ii) relationship, (iii) conduct, and (iv) hyperactivity problems. Each of these components are measured on a scale ranging from 0 to 10 – with higher

[5] Appendix A.2 presents the baseline estimates for BMI z-scores and mental well-being clustering standard errors at alternative levels, such as the household and Government Office region level.

values indicating greater mental discomfort – and can be summed into an overall mental discomfort score, which can range from 0 to 40. We have information about the BMI z-scores of individuals for different survey years than those that we have mental health information for. Throughout the paper, we include all observations we can use for each outcome variable in the analysis to maximize the statistical power we can have.

The Understanding Society survey also provides rich information on the socio-demographic characteristics of children, such as their age, gender, ethnicity, household income and household size, as well as on whether they live in rural or urban areas. Using special licence data from the UK data service (UKHLS, 2019b), we also observe the Lower Layer Super Output Area (LSOA) where children live. Using this information, we match the Understanding Society dataset with the data on digital transition deadlines. Finally, the Understanding Society survey contains information on children's eating habits, as well as on the activities in which they get involved, including schooling, extracurricular, and sports activities.

Table 1 presents the means and standard deviations of some socio-demographic and health characteristics of children, in column 1 for the sample as a whole, and in columns 2 and 3 for boys and girls separately.[6] As shown, boys and girls are very similar in most socio-demographic characteristics, although boys have a higher BMI z-score and lower mental difficulties than girls.

5 Results

5.1 BMI Z-scores

This section assesses the causal impact of the digital television switchover on obesity. To do so, Table 2 presents the estimates of the baseline specification using as dependent variable children's BMI z-scores. The estimate of the impact of the

[6] The paper comprises two analyses, where we study the effect of the digital transition on obesity and mental well-being. Table 1 presents the summary statistics for children who are part of any of the samples we use throughout the paper.

digital transition on BMI z-scores is positive and statistically significant at the 5% confidence level, showing that the digital transition increases obesity. Regarding the magnitude of the effect, one additional year with access to digital television signal increases BMI z-scores by 0.159 standard deviations.

5.2 Mental Well-Being

Having shown that the digital transition increases BMI z-scores, we proceed to test whether the digital switchover also has an impact on children's mental well-being. To do so, column 1 of Table 3 estimates the baseline specification, using as dependent variable a score that measures the overall mental discomfort of children. Columns 2-5 are similar to column 1 but use as dependent variable the following sub-components of the overall mental discomfort score of children: (i) conduct, (ii) emotional, (iii) hyperactivity, and (iv) relationship problems sub-score, respectively. As shown, an additional year with access to digital signal increases the overall mental discomfort score of children by 0.227, which represents an increase of 2.13% relative to the average baseline mental discomfort score. This effect is driven by television negatively affecting the conduct of children, but not through changes in their emotional symptoms, hyperactivity, and relationship abilities. Overall, the estimates suggest that television has a negative impact on the mental well-being of children.

5.3 Robustness Checks

This section estimates multiple robustness checks to support the identification strategy and test whether the estimates are robust to different estimation specifications.

5.3.1 TV Viewing Time

We have previously shown that the digital transition reform increases obesity and deteriorates mental well-being for children. For this to be the case, the digital transition needs to have an effect on children's television habits. Therefore, we next examine the effect of the digital transition on television viewing time. We do so by estimating a specification (similar to the baseline one) but that controls for a dummy taking the value of 1, if the digital transition has already occurred in LSOA r by the date of the interview and 0 otherwise, rather than controlling for the number of years that have passed since the digital transition introduction.[7] This allows to examine the effect of the reform as a whole on television viewing time. Given that television viewing time is cyclical within years, we also control for a set of month-year dummies to account for this seasonality. Figure 4 presents the average marginal effects of the digital transition on TV viewing time, indicating that the digital switchover increased TV viewing time by up to 16.5 minutes per day, and mostly so in the sub-group of socio-economically disadvantaged children. The latter result may be due to socio-economically more privileged children having access to other forms of television such as cable or satellite TV, hence not being as much incentivized to change their TV habits in response to an increase in free television channels.

5.3.2 Balancing Tests

We next provide evidence supporting our empirical strategy by examining whether the digital transition is correlated with a set of pre-determined characteristics that may be determinants of health outcomes. Panel A of Figure 5 presents the unconditional estimates of a set of regressions that study the impact of the number of years that have passed at the time of the interview since the switchover deadline on multiple pre-determined characteristics. Panel B of Figure 5 presents the estimates of a set of regressions similar to the ones we estimate in panel A but that control for LSOA and year dummies. The digital transition is unconditionally correlated with some pre-determined characteristics, but all the estimates become

[7] Although this specification facilitates the interpretation of the results, the functionality form does not allow to distinguish for how long individuals have had access to a digital signal. We therefore estimate the specification using the sample of individuals for whom we have TV viewing information both before and after the reform, so that the estimates are not subject to selection bias.

small and not statistically significant after controlling for LSOA and year dummies.

5.3.3 Placebo Tests

We also examine whether the digital switchover has an impact on health outcomes when we use an incorrect timing of the digital transition. Columns 1 and 2 of table 4 present the estimates of a specification similar to the baseline one but that uses as explanatory variable of interest the number of years that have passed one and two years after the interview date since the digital switchover deadline in LSOA r, respectively. We use as dependent variable children's BMI z-scores. Columns 3–4 are similar to columns 1–2, but the former use as dependent variable children's total mental health difficulties scores. The future occurrence of the digital transition should have no impact on current health outcomes. As shown, we do not find statistically significant estimates of the digital transition neither on BMI z-scores nor on mental well-being when implementing an incorrect timing of the digital transition.

5.3.4 Alternative Specifications

We next account for the fact that children receiving television signal from different transmitters may differ in unobserved characteristics that determine BMI z-scores and mental health. To do so, column 1 of Table 5 presents the estimates of a specification similar to the baseline one but that also controls for a set of transmitter dummies. We use as dependent variable children's BMI z-scores. Column 2 is similar to column 1, but instead uses as dependent variable children's total mental health difficulties scores. As shown, the estimate of the digital transition is robust to controlling for transmitter fixed effects.

5.4 Heterogeneity

We next study whether the impacts of the digital transition on BMI z-scores and mental well-being are heterogeneous in socio-demographic characteristics of children. Columns 1 and 2 of Table 6 present the estimates of a specification similar to the baseline model but that controls for the deciles of the gross household income distribution and for their interaction with the variable of interest ($Nyears_{r,t}$). Columns 1 and 2 use as dependent variable children's BMI z-score and overall mental discomfort index, respectively. As shown in Table 6, the effect of exposure to television on obesity is driven by socio-economically disadvantaged children. The estimate of the effect of the digital transition on BMI z-scores for the first decile of the income distribution is highly significant and almost doubles the estimates obtained for the rest of deciles in terms of magnitude. In contrast, as shown in column 2 of Table 6, there is no obvious signal that the effect of television on mental well-being is heterogeneous across children's socio-economic status. This may be due to a lack of statistical power in the estimated specification, which has a more complex functional form than our baseline model.

We next estimate three specifications similar to the baseline one but that control for an interaction term between $Nyears_{r,t}$ and children's (i) gender, (ii) age and (iii) nationality (whether the child is British), respectively. Table 7 and 8 present the estimates when using children's BMI z-scores and total mental difficulties scores as dependent variable, respectively. As shown in Table 7, the point estimates of an additional year with access to digital signal are not statistically different across the various socio-demographic groups, suggesting that the effect of the digital transition on BMI z-scores does not depend on children's age, gender or nationality. As shown in Table 8, the effect of the digital transition on mental health is higher for females and white British children. Lastly, previous studies have found that the labour status of parents matters for the probability of children being overweight (Li et al., 2019). Appendix A.3 explores whether parents' labour status also plays a role in our context, and shows that the effects of exposure to television on obesity and mental health do not depend on parents' employment situation.

6 Mechanisms

This section explores several potential mechanisms behind the impact of television on BMI z-scores and mental well-being. First, we explore whether exposure to television changes the eating habits of children by estimating the baseline specification using as dependent variable the frequency with which children eat (i) fast food, (ii) crisps, sweets or fizzy drinks, and (iii) fruit per day, respectively. Figure 6 presents the estimates and shows that the digital transition does not change the eating habits of children.[8]

Second, we explore whether television changes children's physical activity by estimating the baseline specification and using as dependent variable indicators for whether children mention doing the following exercises: (i) walking, (ii) swimming, (iii) cycling, (iv) running/jogging, (v) tennis/squash, (vi) aerobics, (vii) football, (viii) rugby, (ix) basketball/netball, (x) cricket, (xi) athletics, (xii) martial arts, (xiii) horse riding, (xiv) gymnastics, (xv) dancing, and (xvi) other sport. We also test whether the digital transition changes the frequency with which children get involved in sports. Figure 6 presents the estimates and shows that the digital transition reduces the probability of children getting involved in some sports (e.g. running, aerobics, gym training, and dancing).

Finally, we examine whether the digital transition increases obesity and worsens mental well-being through a change in children's personal views about their weight and appearance. We do so by estimating the baseline specification using as dependent variable (i) children's personal view about their weight, (ii) children's feelings about their appearance and (iii) a variable that provides information on whether children have ever tried doing diet or losing weight. Figure 6 presents the estimates, showing that an additional year with access to digital signal does not change children's perceptions about their weight and neither their likelihood of trying to lose weight. Overall, these results suggest that television had an effect on

[8]Figure 6 presents estimates of regressions that use standardized dependent variables to make the estimates more comparable. Appendix 6 presents tables containing information on the estimates presented in Figure 6 as well as on their standard errors.

obesity and mental well-being through a displacement of physical activities but not through changes in children's eating habits or personal views about appearance.

7 Conclusions

This paper has contributed evidence on the causal impact of exposure to television on children's BMI z-scores and mental well-being, using the digital television transition in the UK as a natural experiment. The digital switchover consisted in the transformation of every television transmitter in the UK to cease the broadcast of analogue television signal and start the provision of high power digital signal. The reform gave access to digital television signal to millions of households, increasing the number of television channels they could watch from 5 to 40. The digital transition took place during the period of 2008-2012 in stages across the different areas of the UK, and we exploit variation in the switchover dates across more than 40,000 geographical units.

Using a panel dataset covering the years 2009 to 2018 with annual information on the health characteristics of children and a model that compares the health outcomes of children living in areas where the digital transition occurs at different dates, we provide causal evidence on the effect of television on BMI z-scores and mental well-being. First, we find that an additional year with access to digital television signal increases BMI z-scores and that the effect is driven by socio-economically disadvantaged children. Second, we show that the digital transition worsens the mental well-being of children, and that the impact is driven by an increase in their conduct problems (e.g. easily losing temper, lying, manipulating others, etc.). However, we find no effect of exposure to television on children's propensity to suffer from hyperactivity, emotional symptoms, and relational problems. We test for potential channels behind the effects of the digital transition on BMI z-scores and mental well-being. We show that the switchover reduces children's physical activity, but that it does not change children's eating habits neither personal views about appearance.

As this paper focuses on the effects of television, one might question the true relevance of the findings, given that the time that children dedicate to television viewing has decreased during the last years. First, while we acknowledge that television watching has indeed recently decreased, it is also true that this reduction has been slow, and that the time that children spend in front of the TV remains substantial. Following a report from Ofcom, children aged 12-15 dedicated on average 13.25 hours per week to watch television in the UK in 2018. Second, the decrease in television viewing time through a television set has been compensated by a rise in the time that children dedicate to watch internet-based streaming services, such as Youtube, Netflix or Amazon Prime video, which is an activity very similar if not identical to television watching. Thus, the estimates provided in this paper are also relevant to evaluate the effect of other types of screen watching activities that have recently become very popular on children's health.

Based on our results, policymakers should seriously consider policies that reduce children's access to television (and likely similar media) as potentially promising means of improving children's physical and mental health.

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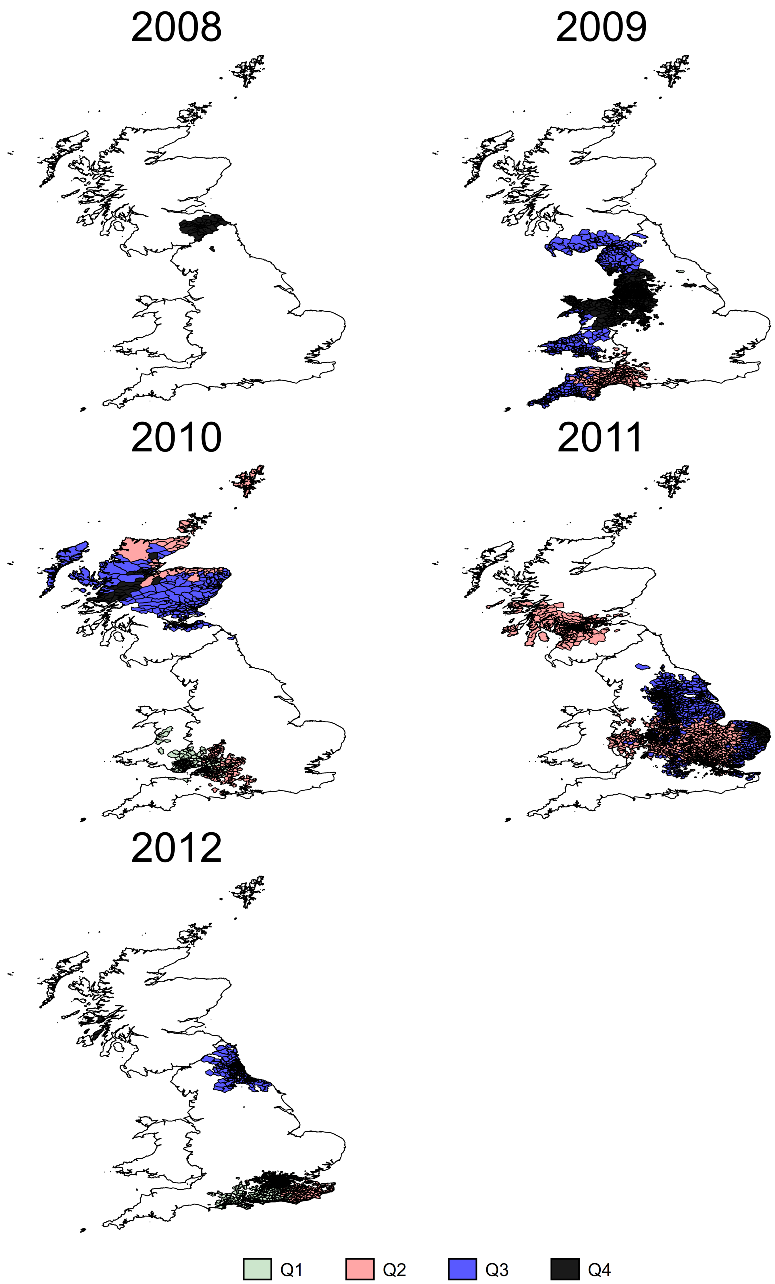
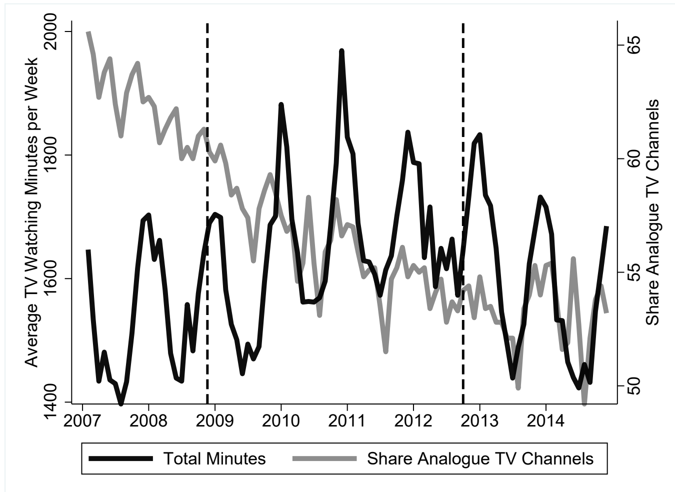
8 Figures

Figure 1: Switchover Process



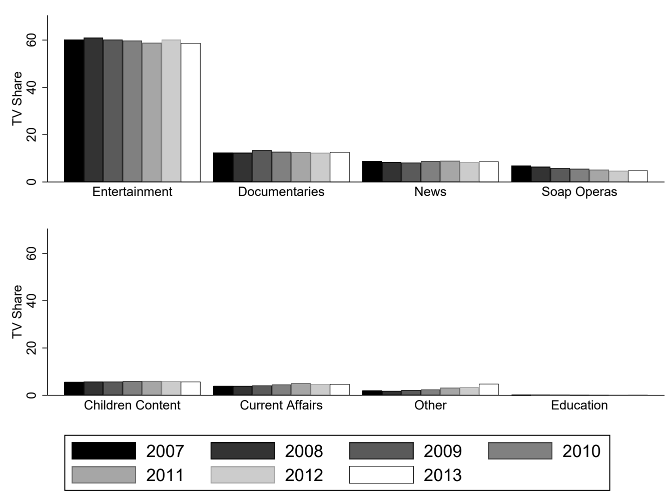
The figure shows the staggered introduction of the digital switchover in the UK. By 2012, all regions in the UK had obtained access to digital television signal. Albeit not shown, the digital television transition also occurred in Northern Ireland during the period of 2008-2012.

Figure 2: TV Viewing Time and TV Shares



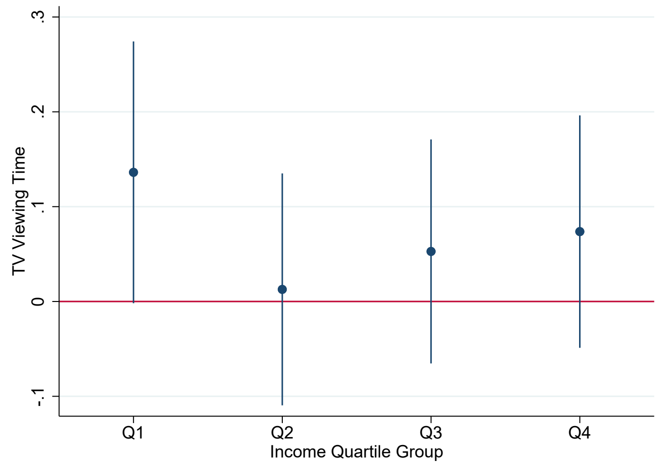
The figure uses data from the Broadcasters Audience Research Board to present the average television viewing time of the UK population per week and the share of the channels that could be watched via analogue television signal during the period of analysis.

Figure 3: TV Content



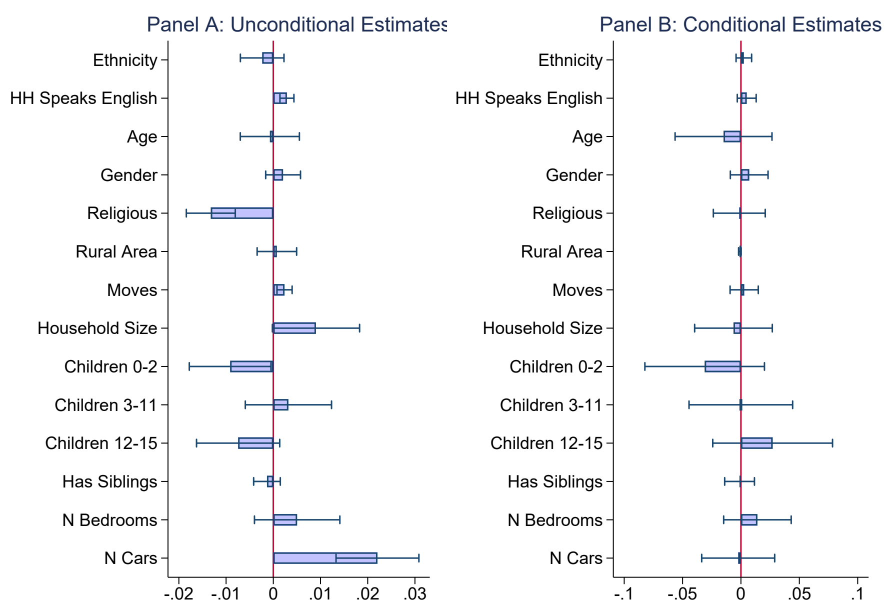
The figure uses data from Ofcom to present the share of each television content during the period of analysis. In particular, we show the proportion of television viewing time that individuals dedicate to the entertainment, documentaries, news, soap operas, children content, current affairs, education content and other genres.

Figure 4: TV Viewing Time



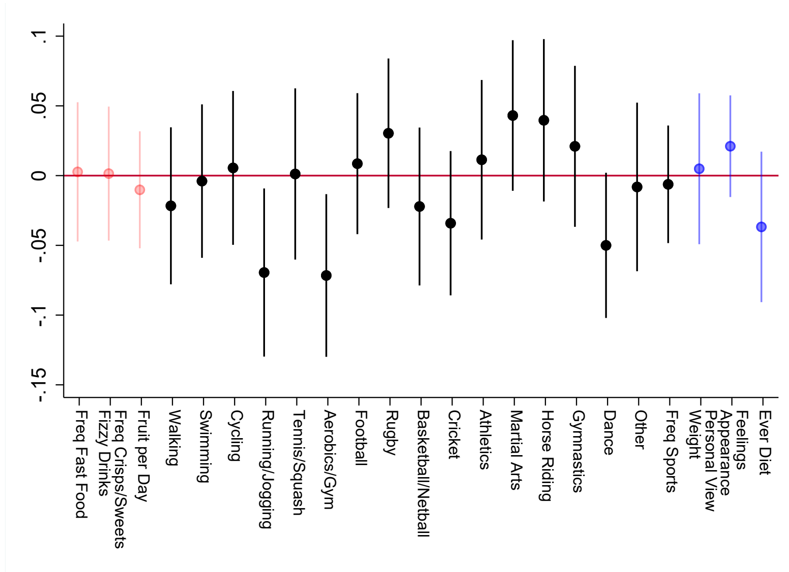
The figure presents the estimates of a specification similar to the baseline one that studies the effect of the digital transition reform on TV viewing time while exploring heterogeneity by household income quartiles.

Figure 5: Balancing Tests



The figure presents the estimates of a set of regressions that study the effect of a set of pre-determined characteristics on the timing of the digital television transition in the UK. Panel A presents the unconditional estimates whereas panel B shows the estimates after having controlled for LSOA and year dummies.

Figure 6: Mechanisms



The figure presents the estimates of the baseline specification using as dependent variable several measures on the eating habits, physical activity and personal views about appearance of children.

9 Tables

Table 1: Descriptive Statistics

	Sample	Boys	Girls
Age	12.57	12.57	12.58
	(1.68)	(1.68)	(1.68)
Non-British	0.23	0.22	0.23
	(0.42)	(0.41)	(0.42)
HH Speaks English	0.96	0.96	0.96
	(0.19)	(0.19)	(0.19)
Gross HH Income	4164.73	4200.85	4127.53
	(2745.08)	(2864.88)	(2615.62)
Rural Area	0.24	0.25	0.23
	(0.43)	(0.43)	(0.42)
N bedrooms	3.47	3.48	3.45
	(0.92)	(0.93)	(0.91)
N cars	1.47	1.48	1.47
	(0.86)	(0.85)	(0.88)
Has siblings	0.91	0.92	0.90
	(0.29)	(0.28)	(0.30)
Household Size	4.51	4.53	4.49
	(1.36)	(1.35)	(1.36)
N Children	2.21	2.22	2.21
	(1.06)	(1.05)	(1.08)
BMI z-score	0.29	0.42	0.15
	(1.61)	(1.68)	(1.52)
Mental Difficulties Score	10.62	10.59	10.66
	(5.71)	(5.71)	(5.71)
Observations	18,905	9,591	9,314

* p<0.10, ** p<0.05, *** p<0.01
Standard errors in parentheses. The table presents the mean and standard deviation of some socio-demographic characteristics of children. The table presents summary statistics for the whole sample as well as for boys and girls separately.

Table 2: BMI Z-scores

	BMI Z-scores
N Years	0.159**
	(0.068)
Individual Covariates	Yes
Age Dummies	Yes
LSOA Dummies	Yes
Year Dummies	Yes
Observations	5,030

* p<0.10, ** p<0.05, *** p<0.01
Standard errors in parentheses. We control for children's gender, logarithm of household income, household number of members, bedrooms, cars and probability of living in a rural area as individual covariates. We cluster standard errors at the LSOA level.

Table 3: Mental Health Outcomes

	Total Difficulties Score	Conduct Problems	Emotional Symptoms	Hyper-activity	Rel Problems
N Years	0.227*	0.094**	0.017	0.081	0.032
	(0.134)	(0.043)	(0.053)	(0.055)	(0.039)
Individual Cov	Yes	Yes	Yes	Yes	Yes
Age Dummies	Yes	Yes	Yes	Yes	Yes
LSOA Dummies	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Observations	13,833	13,854	13,853	13,845	13,856

* p<0.10, ** p<0.05, *** p<0.01
Standard errors in parentheses. We control for children's gender, logarithm of household income, household number of members, bedrooms, cars and probability of living in a rural area as individual covariates. We cluster standard errors at the LSOA level.

Table 4: Placebo Tests

	BMI z-score	BMI z-score	TDS	TDS
N Years_{t+1}	0.163*		0.243	
	(0.094)		(0.171)	
N Years_{t+2}		-0.010		0.199
		(0.139)		(0.245)
Individual Covariates	Yes	Yes	Yes	Yes
Age Dummies	Yes	Yes	Yes	Yes
LSOA Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observations	5,030	5,030	13,833	13,833

* p<0.10, ** p<0.05, *** p<0.01
Standard errors in parentheses. We control for children's gender, logarithm of household income, household number of members, bedrooms, cars and probability of living in a rural area as individual covariates. We cluster standard errors at the LSOA level.

Table 5: Alternative Specifications

	BMI z-score	TDS
N Years	0.159**	0.227*
	(0.069)	(0.135)
Individual Covariates	Yes	Yes
Age Dummies	Yes	Yes
LSOA Dummies	Yes	Yes
Year Dummies	Yes	Yes
Transmitter Dummies	Yes	Yes
Observations	5,030	13,833

* p<0.10, ** p<0.05, *** p<0.01
Standard errors in parentheses. We control for children's gender, logarithm of household income, household number of members, bedrooms, cars and probability of living in a rural area as individual covariates. We cluster standard errors at the LSOA level.

Table 6: Heterogeneity in Household Income

	BMI z-score	BMI z-score
N Years	0.275***	0.196
	(0.085)	(0.186)
HH Income D2 × N Years	-0.129**	0.014
	(0.065)	(0.160)
HH Income D3 × N Years	-0.148**	-0.035
	(0.071)	(0.158)
HH Income D4 × N Years	-0.147*	-0.056
	(0.078)	(0.162)
HH Income D5 × N Years	-0.095	-0.040
	(0.076)	(0.169)
HH Income D6 × N Years	-0.114*	-0.034
	(0.068)	(0.162)
HH Income D7 × N Years	-0.148**	0.192
	(0.064)	(0.157)
HH Income D8 × N Years	-0.100	0.154
	(0.062)	(0.161)
HH Income D9 × N Years	-0.134**	0.050
	(0.062)	(0.178)
HH Income D10 × N Years	-0.115*	-0.010
	(0.062)	(0.161)
Individual Covariates	Yes	Yes
Age Dummies	Yes	Yes
LSOA Dummies	Yes	Yes
Year Dummies	Yes	Yes
Observations	5,033	13,889

* p<0.10, ** p<0.05, *** p<0.01
Standard errors in parentheses. We control for children's gender, logarithm of household income, household number of members, bedrooms, cars and probability of living in a rural area as individual covariates. We cluster standard errors at the LSOA level.

Table 7: Further Heterogeneity – Obesity

	BMI z-score	BMI z-score	BMI z-score
N Years	0.154**	0.196**	0.143**
	(0.070)	(0.078)	(0.071)
Female × N Years	0.011		
	(0.029)		
Age 11 × N Years		0.006	
		(0.050)	
Age 12 × N Years		-0.035	
		(0.042)	
Age 13 × N Years		-0.044	
		(0.046)	
Age 14 × N Years		-0.040	
		(0.045)	
Age 15 × N Years		-0.049	
		(0.048)	
Non-white British × N Years			-0.054
			(0.052)
Individual covariates	Yes	Yes	Yes
LSOA Dummies	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Observations	5,030	5,030	4,027

* p<0.10, ** p<0.05, *** p<0.01

Standard errors in parentheses. We control for children's gender, logarithm of household income, household number of members, bedrooms, cars and probability of living in a rural area as individual covariates. We cluster standard errors at the LSOA level.

Table 8: Further Heterogeneity – Mental Health

	TDS	TDS	TDS
N Years	0.149	0.076	0.265*
	(0.137)	(0.157)	(0.141)
Female × N Years	0.161***		
	(0.061)		
Age 11 × N Years		0.211**	
		(0.103)	
Age 12 × N Years		0.081	
		(0.088)	
Age 13 × N Years		0.234**	
		(0.103)	
Age 14 × N Years		0.156	
		(0.100)	
Age 15 × N Years		0.185*	
		(0.103)	
Non-white British × N Years			-0.186*
			(0.095)
Individual covariates	Yes	Yes	Yes
LSOA Dummies	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Observations	13,833	13,833	12,422

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Standard errors in parentheses. We control for children's gender, logarithm of household income, household number of members, bedrooms, cars and probability of living in a rural area as individual covariates. We cluster standard errors at the LSOA level.

A Appendix

A.1 The Obesity and Mental Health Context

Obesity and mental ill-health have received growing attention from governments in high-income countries, in response to the high and growing magnitude of the problems. Panels A—B of Figure A.1 show the percentage of young people suffering from obesity and mental disorders in high-income countries.[9] As shown, both obesity and mental disorders are highly prevalent in most European societies, if with considerable variation across countries. The situation in the UK appears to be particularly challenging, in that it has one of the highest obesity and mental health disorder rates in Europe.

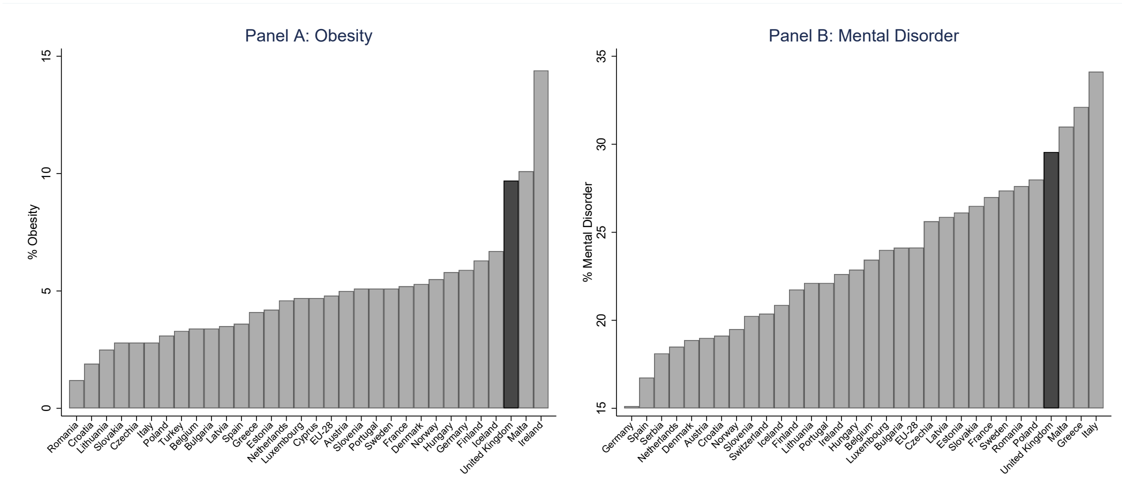
Figure A.2 explores whether obesity and mental health disorders have increased or fallen over time within the UK child and adolescent population. Using NHS data,[10] panels A—B show the percentage of boys and girls aged 11-15 who have suffered from obesity and mental health disorders within the UK over the last decades.[11] As shown, both obesity and mental health disorders appear to have increased over the last decades in the UK, underlining the associated policy urgency.

[9] We focus on young people because the present study evaluates the effect of television on obesity and mental well-being for children. Panel A of Figure A.1 presents statistics about obesity for people aged 15-24 in 2014 using Eurostat data, as this is the youngest age group available. Panel B uses WHO data on the mental well-being of children aged 13 in 2018.

[10] See NHS (2017) for obesity and NHS (2018) for mental disorders.

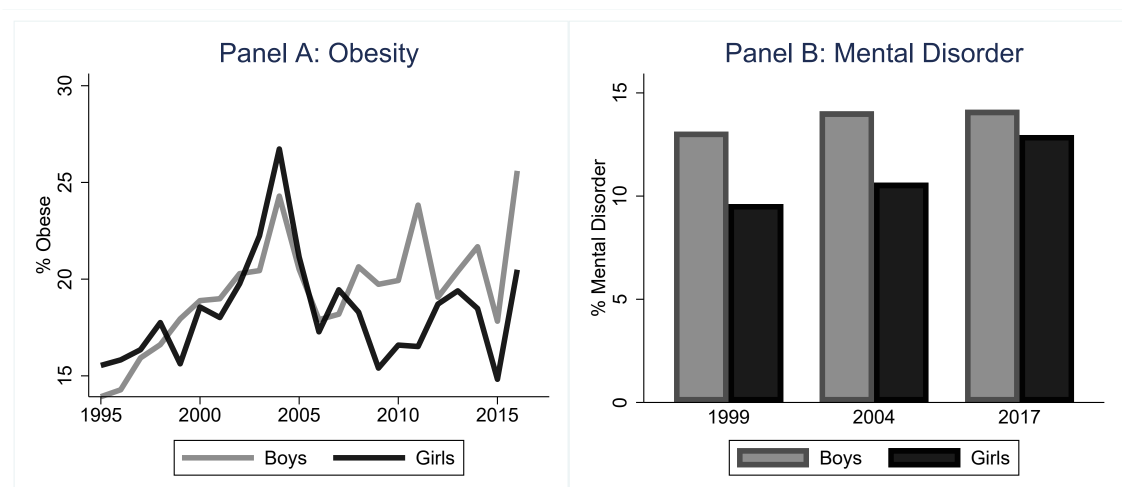
[11] We present statistics for boys and girls aged 11-15 because the sample used in this study is based on children aged 10-15. Figures A.1 and A.2 present different scales for obesity and mental disorders because these two variables are measured differently by Eurostat, WHO and NHS. Regarding obesity, Eurostat defines obesity as having a BMI equal or greater than 30, whereas NHS defines obesity as being at or above the 95th UK National BMI percentile. The definition of 'mental disorders' used in the WHO data displayed in Figure A.1 comprises children suffering from irritability, nerves, sleeping difficulties and feeling low. For the NHS data used in Figure A.2, the percentage of children with a mental disorder includes those suffering from any form of anxiety, depressive symptoms, behavioural, hyperactivity or other less common disorders.

Figure A.1: Obesity and Mental Health



Panel A uses data from Eurostat to show the proportion of people aged 15–24 who have a BMI equal or greater than 30 in each European country (see http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=hlth_ehis_bm1e&lang=en (accessed October 7, 2020)). Panel B uses data from the World Health Organization to show the proportion of children aged 13 suffering from irritability, nerves, sleeping difficulties and feeling low in each European country (data comes from WHO (2020)).

Figure A.2: Obesity and Mental Health in the UK



Panel A uses data from the National Health Service in the UK to show the percentage of boys and girls aged 11-15 above the 95th UK National BMI percentile (data comes from NHS (2017)). Panel B also uses data from the National Health Service in the UK to show the percentage of children aged 11-15 suffering from any form of anxiety, depressive symptoms, behavioural, hyperactivity and other less common disorders (data comes from NHS (2018)).

A.2 Alternative Specifications

Table A.1: Alternative Clustering of Standard Errors

	BMI z-score	BMI z-score	TDS	TDS
N Years	0.159**	0.159**	0.227*	0.227*
	(0.070)	(0.058)	(0.129)	(0.105)
Individual covariates	Yes	Yes	Yes	Yes
LSOA dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Observations	5,030	5,030	13,833	13,833

* p<0.10, ** p<0.05, *** p<0.01
Standard errors in parentheses. We control for children's gender, logarithm of household income, household number of members, bedrooms, cars and probability of living in a rural area as individual covariates. We cluster standard errors at the household level in columns 1–3 and at the Government Office Region level in columns 2–4.

A.3 Parental Labour Characteristics

We next explore whether the impacts of the digital transition on BMI z-scores and mental well-being are heterogeneous in parents' labour market participation and employment probabilities. To do so, panels A–D present the estimates of a specification similar to the baseline model but that also controls for (i) mothers' probability of labour market participation, (ii) fathers' probability of labour market participation, (iii) mothers' employment probabilities, and (iv) fathers' employment probabilities, respectively. In panels A–D, we also control for the interaction between the previous four variables and $Nyears_{r,t}$, respectively. As shown, the effects of television on obesity and mental well-being do not depend on parents' labour status.

Table A.2: Heterogeneity in Parents' Labour Outcomes – Obesity

	BMI z-score	BMI z-score	BMI z-score	BMI z-score
N years	0.185**	0.102	0.176**	0.137
	(0.081)	(0.109)	(0.079)	(0.105)
Mother participates × N years	-0.014			
	(0.041)			
Father participates × N years		0.045		
		(0.073)		
Mother has job × N years			-0.005	
			(0.039)	
Father has job × N years				0.012
				(0.063)
Individual covariates	Yes	Yes	Yes	Yes
LSOA dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Observations	4,676	3,236	4,676	3,236

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Standard errors in parentheses. We control for children's gender, logarithm of household income, household number of members, bedrooms, cars and probability of living in a rural area as individual covariates. We cluster standard errors at the LSOA level.

Table A.3: Heterogeneity in Parents' Labour Outcomes – Mental Health

	TDS	TDS	TDS	TDS
N years	0.118	-0.019	0.076	0.151
	(0.153)	(0.254)	(0.153)	(0.216)
Mother participates × N years	0.059			
	(0.082)			
Father participates × N years		0.220		
		(0.197)		
Mother has job × N years			0.116	
			(0.079)	
Father has job × N years				0.055
				(0.143)
Individual covariates	Yes	Yes	Yes	Yes
LSOA dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Observations	12,688	8,214	12,688	8,214

* p<0.10, ** p<0.05, *** p<0.01

Standard errors in parentheses. We control for children's gender, logarithm of household income, household number of members, bedrooms, cars and probability of living in a rural area as individual covariates. We cluster standard errors at the LSOA level.

A.4 Tables Mechanisms

Table A.4: Eating Habits

	Fast Food	Fruit	Crisps
N Years	0.003	-0.010	0.001
	(0.025)	(0.021)	(0.025)
Individual covariates	Yes	Yes	Yes
LSOA dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	13,854	18,034	13,810

* p<0.10, ** p<0.05, *** p<0.01
Standard errors in parentheses. We control for children's gender, logarithm of household income, household number of members, bedrooms, cars and probability of living in a rural area as individual covariates. We cluster standard errors at the LSOA level.

Table A.5: Personal Views

	Personal View of Weight	Feelings about Appearance	Ever Diet
N Years	0.005	0.021	-0.037
	(0.028)	(0.019)	(0.028)
Individual covariates	Yes	Yes	Yes
LSOA dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	12,389	29,921	13,222

* p<0.10, ** p<0.05, *** p<0.01
Standard errors in parentheses. We control for children's gender, logarithm of household income, household number of members, bedrooms, cars and probability of living in a rural area as individual covariates. We cluster standard errors at the LSOA level.

Table A.6: Physical Activity

	Walk	Swim	Cycle	Run	Tennis	Aerobics /Gym	Foot-ball	Rugby	Basket
N Years	-0.022	-0.004	0.006	-0.069**	0.001	-0.072**	0.009	0.030	-0.022
	(0.029)	(0.028)	(0.028)	(0.031)	(0.031)	(0.030)	(0.026)	(0.027)	(0.029)
Individual covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LSOA dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,202	13,202	13,202	13,202	13,202	13,202	13,202	13,202	13,202

* p<0.10, ** p<0.05, *** p<0.01
Standard errors in parentheses. We control for children's gender, logarithm of household income, household number of members, bedrooms, cars and probability of living in a rural area as individual covariates. We cluster standard errors at the LSOA level.

Table A.7: Physical Activity (Continued)

	Cricket	Athletics	Martial Arts	Horse Riding	Gymnastics	Dance	Other	Sports Frequency
N Years	-0.034	0.011	0.043	0.040	0.021	-0.050*	-0.008	-0.006
	(0.026)	(0.029)	(0.028)	(0.030)	(0.029)	(0.027)	(0.031)	(0.021)
Individual covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LSOA dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,202	13,202	13,202	13,202	13,202	13,202	13,202	18,053

* p<0.10, ** p<0.05, *** p<0.01
Standard errors in parentheses. We control for children's gender, logarithm of household income, household number of members, bedrooms, cars and probability of living in a rural area as individual covariates. We cluster standard errors at the LSOA level.

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