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Television, time use and academic achievement: Evidence from a natural experiment

by

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Television, Time Use and Academic Achievement: Evidence from a Natural Experiment*

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Abstract

This article studies the impact of television on academic performance and a plausible mechanism behind this effect: whether television changes time use. I identify a causal effect by using a natural experiment that consists in the staggered introduction of the digital television signal in the British television market. The digital switchover leads to an increase in television viewing time but does not change television contents. I find that the digital switchover increases academic performance, contributing to human capital formation, and that the effect is larger for schools at the bottom of the score distribution, reducing educational inequality. I also show that the digital switchover decreases the probability of children taking part in detrimental activities such as alcohol drinking, and their frequency. I test for alternative mechanisms, but do not find an effect of television on time dedicated to homework neither behaviour. The results point that the true determinant of academic achievement is the relative educational value of out-of-school activities, rather than the absolute one.

Keywords: Academic Performance, Educational Inequality, Time Use, Digital Television Switchover, Natural Experiment

JEL classification: I2, I24, I26.

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1 Introduction

Television viewing is one of the main daily activities for most of children. A large body of empirical research has investigated the impact of television on academic achievement. Most of studies have reported a negative effect (Christakis et al., 2004; Hancox et al., 2005; Zimmerman and Christakis, 2005), but recent research has shown that preschool television raises adolescent test scores (Gentzkow and Shapiro, 2008). Besides the mixed evidence, little is known about the mechanism that operates behind the effect of television on education.[1]

This paper provides two important sets of causal estimates. First, I provide causal evidence on the short-run impact of television on academic performance and educational inequality. The relevance of this set of results lies in the importance of cognitive development for future labour market performance (Angrist and Keueger, 1991). Second, I explore a mechanism behind my baseline estimates on education: the effect of television on the time use of children. Addressing these research questions introduces identification concerns. For example, academic achievement may determine the time that children dedicate to television. Alternatively, television viewing may be correlated with unobserved characteristics, such as preferences, that also determine education and habits. To confront potential endogeneity problems, I use a natural experiment that consists in the digital television switchover that took place in UK between 2008 and 2012. During this period, UK adapted in stages all its television transmitters to stop broadcasting analogue television and strengthen the power of the digital television signal that they provided.

There are two main methodological advantages of using the digital switchover as a natural experiment. First, the decentralized location of the television transmitters induced substantial geographical variation in the timing of the switchover process. Neighbouring postcode units obtained access to digital television at different years, which allows me to exploit exogenous variation in my natural experiment

[1] Additional studies have reported a negative impact of television on reading skills (Beentjes and Van der Voort, 1988), language acquisition (Rice, 1983), and reading achievement (Walberg and Ling Tsai, 1985)

at the postcode level. Second, the government delegated the digital switchover process to Ofcom, which is the official communications regulator in UK, and DigitalUK, which is an independent non-profit organization funded by the public-service broadcasters and operators. The main goal of these two institutions was to implement the switchover process on time attending to the physical characteristics of the television transmitters. These had been built in the 1960s and 1970s. Therefore, it is unlikely that the switchover is correlated with unobserved characteristics that determine education or time use.

The switchover process was an important revolution in the British television market. It increased the number of television channels from 5 to 40 for more than 10 million of television viewers for the first time in their lives. It also introduced the possibility of watching television in different languages. According to data from the Broadcasters Audience Research Board in UK, these changes increased the average television viewing time by 34 minutes per day. As the daily average television viewing time in 2008 was 224.7 minutes, the digital switchover raised this number by 15.1%.[2] The digital switchover also decreased the audience share of the five traditional channels by 12%.[3] However, the television contents that people watch remained unchanged during the period of analysis.

Using web scraping, I extract information on the date when the digital switchover takes place in every postcode unit in UK. Given that there are about 1.7 million of postcode units in UK, I exploit exogenous variation in my natural experiment at a very precise geographical level. I use two additional datasets to conduct the analysis. The first is a panel administrative dataset that contains yearly information on the Key Stage 2 (KS2) test results of each of the 16,000 schools in England during the period 1991-2016. This dataset also contains annual sociodemographic information on schools. I use KS2 exam data as this test is taken when students are

[2]See https://www.barb.co.uk/trendspotting/data/average-weekly-viewing/ I calculate this number by subtracting the average television viewing time in the last week of 2008, which is right before the beginning of the switchover, to the average TV viewing time in the final week of 2012, which is just after the end of the switchover.

[3]See https://www.barb.co.uk/trendspotting/data/channel-viewing-share/.

pre-adolescents, which is when they start spending time with friends and may begin to get involved in detrimental activities (Duncan et al., 2006; Milton et al., 2007). The dataset comes from the UK Department for Education. The use of external assessed exam information avoids sample selection and self-reported biases. My second dataset comes from the youth questionnaire of the Understanding Society Survey in UK. This is a panel survey dataset at the individual level that contains yearly information on the activities at which children get involved.

Regarding my empirical strategy, I use a difference-in-difference approach. This not only compares the academic performance of schools that are affected by the digital switchover at different years, but also the test scores within schools before and after the switchover takes place. I find that the digital switchover increases KS2 test scores by 0.028 standard deviations. This is not a small impact. The digital switchover increases television viewing time by 34 minutes. However, an average individual watches television for 224.7 minutes per day. Subsequently, the average television viewing time raises academic performance by 0.185 standard deviations. This is in line with the estimates provided in recent literature (Gentzkow and Shapiro, 2008), but higher in magnitude. The effect lasts for three years, which substantially contributes to human capital formation. Importantly, the magnitude of the impact depends on the academic performance of schools previous to the introduction of the digital switchover. The effect is positive for schools below the median of the score distribution previous to the switchover process, and negligible for schools above it. This reduces educational inequality. The baseline estimates on education are robust to: (i) checking for pre-trends in grades, (ii) controlling for school individual trends, (iii) performing placebo tests, (iv) using alternative dependent variables, and (v) using the number of students in schools as weights.

My second set of estimates explores a plausible mechanism behind my results on education. I examine whether obtaining access to digital television signal changes the time use of children. I show that the digital switchover reduces the probability and the frequency with which children get involved in detrimental activities, such as alcohol drinking. Importantly, the impact is driven by economically disadvantaged, male and non-white British children. I also study heterogeneity in age, as the KS2 exam is taken at the age 10-11. My findings show that children aged 10-11 get involved in detrimental activities, and that the impact of television on time use is driven by them. I also check for alternative mechanisms, such as whether the digital switchover changes behaviour or the amount of time that children dedicate to homework. My estimates show that this is not the case. Taken together, the results suggest that the effect of out-of-school activities on academic performance does not depend on their absolute educational value, but on their relative one.

This paper primarily contributes to three literatures. First, my paper belongs to the literature that studies the impact of television on cognitive development. A large number of studies have reported a negative effect (Beentjes and Van der Voort, 1988; Christakis et al., 2004; Hancox et al., 2005; Rice, 1983; Timmer et al., 1985; Walberg and Ling Tsai, 1985), but recent research has shown that preschool television raises adolescent test scores (Gentzkow and Shapiro, 2008). My paper contributes to this literature by shedding light on: (i) the mechanism that operates behind the effect of television on academic achievement, (ii) the causal impact of television on education in the short-run, (iii) the effect of television on educational inequality, and (iv) the dynamics of the previous effects. I make these contributions using the staggered introduction of the digital television signal in the British television market as a natural experiment. As the family background is an important determinant of academic achievement (Blanden and Gregg, 2004), I also explore heterogeneity of the previous effects in the proportion of disadvantaged, non-native, and Special Educational Needs students. Second, this paper adds to previous literature on the importance of television on behaviour and habits formation (Wright et al., 2001). Previous evidence has reported that exposure to entertainment and violent content lowers academic achievement (Kirkorian et al., 2008), increases aggressiveness at an adult age (Huesmann et al., 2003) and raises the frequency of harmful habits (Robinson et al., 1998).[4] Yet, the previous effects may be due to the type of TV programs that children watch (Huston et al., 1999), and so, alternative television contents may contribute towards the development of children. For example, prior evidence has shown that age appropriate educational programs have a positive impact on cognitive development (Fisch, 2014; Calvert and Kotler, 2003). I contribute to this literature by providing causal evidence on the impact of television on time use and behaviour. Furthermore, I examine heterogeneity of the previous effects in age, gender and ethnicity. As children from disadvantaged households spend more time in unstructured activities (Rokicki and McGovern, 2017), I also study heterogeneity in income. Finally, my paper belongs to the literature on the importance of television on social attitudes, perceptions and behaviour. Related to perceptions, previous research has shown that a lower exposure to media with strong political covarage reduces voter turnout (Gentzkow, 2006). Furthermore, exposure to the conservative Fox News Channel has been shown to increase the vote share of Republicans (DellaVigna and Kaplan, 2007). More recently, Barone et al. (2015) have used the digital switchover in Italy to show that an increase in the number of television channels with a lower media bias in favour of Berlusconi's coalition decreases his electoral support. Regarding attitudes and behaviour, Mastrorocco and Minale (2018) also use the digital switchover in Italy to show that a reduction in the exposure to channels characterized by reporting high levels of crime decreases crime perceptions. Recent research has also found that novelas, which portray small families, have a negative impact on fertility (La Ferrara et al., 2012), and that the introduction of cable television, which is associated with access to new information about the outside world, improves the status of women in developing countries (Jensen and Oster, 2009). This paper contributes to this literature from a different, but relevant, policy point of view. I study the impact of television on academic achievement and time use. I show that the true determinant of academic achievement is the relative educational value of out-of-school activities, rather than

[4] Watching television has been also associated with causing sleep patterns among children (Johnson et al., 2004)

the absolute one.

The remainder of the paper is organized as follows. Section 2 describes the digital television switchover and its introduction in the British television market. Section 3 presents the data. Section 4 contains the empirical strategy and section 5 presents the results on academic performance. Section 6 explores a mechanism behind the baseline results and presents the estimates on time use. Section 7 concludes.

2 Digital Switchover Process

Digital television has been the first revolution in the television industry since colour television was introduced in the 1950s. Digital television offers several important advantages relative to its analogue predecessor, such as the possibility of watching television in different languages, additional services related to multimedia, a higher definition, and multiplexing, which is the ability of having more than one program on the same channel. However, the crucial feature of digital television is that it increased the number of television channels that could be watched from 5 to 40.

The television signal in UK is provided by 1,235 television transmitters that can be classified in two different groups: 81 principal transmitters and 1,154 relay transmitters which receive television signal from the former and repeat it to the households that are unable to receive television signal from the principal ones. In 2004, the British Government appointed Ofcom and DigitalUK and delegated to them the task of adapting all the television transmitters in UK so that they stopped transmitting analogue television signal and started providing high-power digital signal. Ofcom is the communications regulator in UK, and DigitalUK is an independent non-profit organisation funded by the public-service broadcasters and operators. Ofcom amended the broadcast licences required for the delivery of the analogue switch-off to the different television transmitters according to a specific timetable. DigitalUK organised the timetable of the digital switchover, managed the upgrade of the television transmitters, and ensured that individuals were supported and understood the process.

The digital switchover started at the end of 2008 and ended in 2012. During this process, every television transmitter in UK was adapted to cease broadcasting analogue television signal and to strengthen the power of their digital signal. The digital switchover was done in stages and in a transmitter group basis.[5] Figure 1 presents a mapping of the digital switchover process, and shows that there was a strong geographical variation in its timing.

Figure 2 explains in detail the switchover definition that I use in the analysis. In England, every postcode unit receives television signal from different television transmitters. To see this, I set as example a hypothetical postcode unit that receives television signal from transmitters located in different regions. There are two types of transmitters: the principal transmitters (A, B, C and E), which broadcast television signal, and the relay transmitters (D), which receive television signal from the principal ones and repeat it to other geographical areas. Given that television transmitters have different switchover dates, the postcode unit is affected by the analogue switch-off at the earliest of the switchover dates of its television transmitters.

In summary, I define the digital switchover date of a particular postcode unit as the earliest of the switchover dates of the television transmitters that provide television signal to that postcode. The decentralized location of television transmitters lead to a strong geographical variation in the timing of the digital switchover. Neighbouring postcode units got access to digital television signal at different years. I exploit exogenous variation in my natural experiment at the postcode unit level.

[5]A transmitter group is a bunch of transmitters, one principal transmitter and several relay transmitters, each of which provides television signal. The former broadcasts television signal to individuals and to a number of relay transmitters, which repeat the television signal to many other individuals who cannot receive television signal from the principal transmitters.

2.1 Importance of the Digital Switchover

The digital switchover process made the digital television signal available to more than 10 million of individuals for the first time in their lives. Additionally, there were millions of households who had access to digital signal before the analogue switch-off, but that waited to adapt their television device to be able to watch digital television until they could no longer watch analogue television (at the time when the switchover occurred). Overall, and according to a DigitalUK report, more than 75% of households were only able to watch analogue television signal on at least one television three years before the switchover process start.[6]

Figure 3 presents the weekly average television viewing time in England during the period of analysis. The two red vertical lines respectively represent the start and completion date of the switchover process. As shown, the digital switchover significantly increased the average time that individuals dedicate to watch television. After 2012, the year when the switchover process finished, there was a continuous decrease in the traditional television-set viewing time. Two possible explanations are the growing popularity of non-broadcast services such as Netflix and Amazon Prime Instant Video, and the growth in the adoption of smartphones and tablets.

As shown in Figure 4, the digital switchover also decreased the total audience share of the five traditional channels in UK from 63.5% in 2007 to 51% in 2013.[7] This reduction was compensated by an increase in the audience share of the newly available digital channels. However, the fall in the relative importance of the main traditional channels did not translate into a change in the television contents that people watch. Figure 5 presents the proportion of the total television viewing time by genre during the period of analysis. I classify television contents in eight different groups: entertainment, soap operas, documentaries, current affairs, news, educational television programmes, children contents, and other. The latter category includes television channels such as music or movie channels. As

[6] See "Digital TV switchover 2008-2012 Final Report".

[7] The five traditional channels that could be watch through analogue television signal were BBC One, BBC Two, ITV, Channel 4 and Channel 5.

shown in Figure 5, the digital switchover does not change the television contents that people watch. Appendix A.2 shows a Figure similar to 5, but that uses a more disaggregated classification of television contents.

3 Data

3.1 Digital Television Data

Using web-scraping on the DigitalUK organisation's webpage, I collect information on the dates when the digital switchover took place at every postcode unit in England. As there are 1.7 million of postcode units in England, this allows me to exploit exogenous variation in my natural experiment at a very precise geographical level. The dataset also contains information on the name of the transmitter that first provided digital television signal to each postcode, and on their type (whether they are principal or relay transmitters). Finally, this dataset contains information on the quality of the television signal that each postcode unit receives.

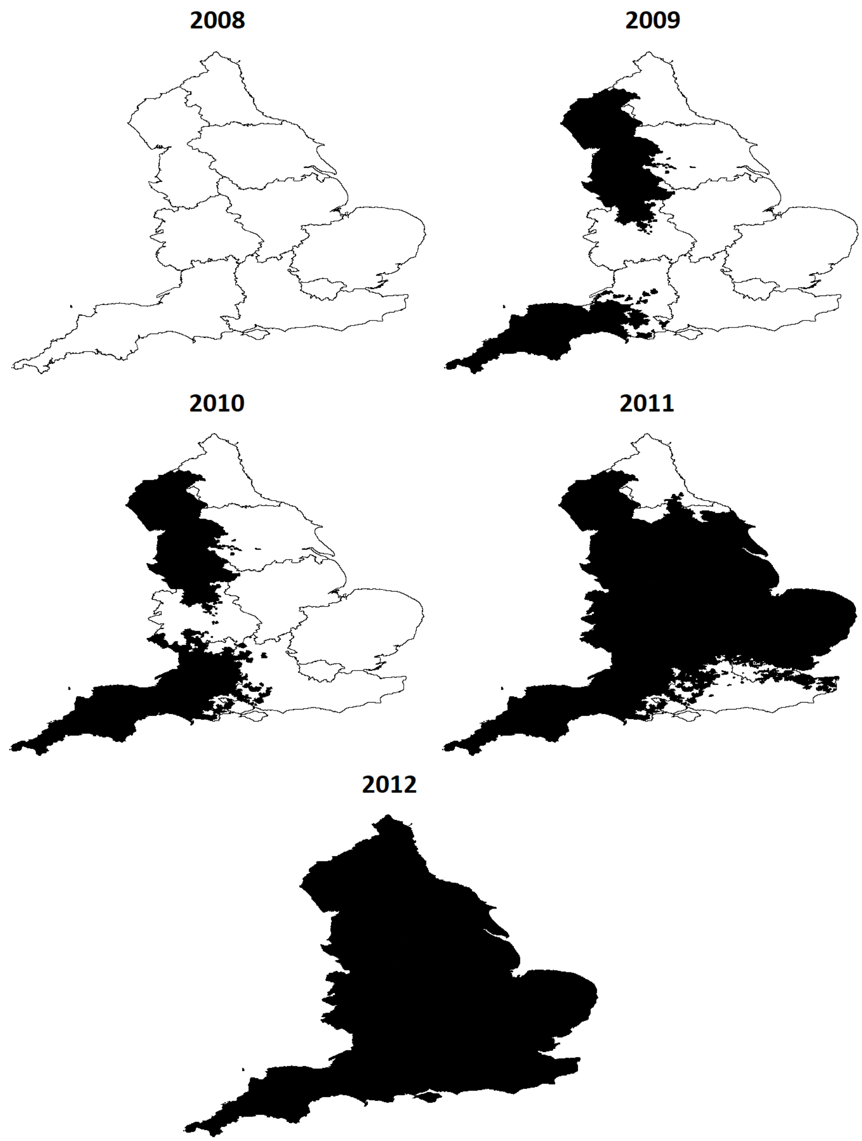
3.2 Schooling Data

I use a panel administrative dataset that contains yearly information on the KS2 test score of each of the 16,000 schools in England during the period 1991-2016. I obtain this data from the UK Department for Education. The KS2 test is an annual external assessed exam taken by students at the later stage of primary education. This is an important stage of life as it coincides with pre-adolescence, when students start to spend time with friends and may begin to get involved in detrimental activities (Duncan et al., 2006; Milton et al., 2007). The KS2 exam consists of several sections respectively on mathematics, English grammar, writing, punctuation and spelling. The KS2 test score ranges from 0 to 33 points, albeit the average grade of most of schools is close to the national average score, which is 27.[8] Figure 6

[8] A mapping of the different test levels and their respective point scores is presented in Appendix A.1.

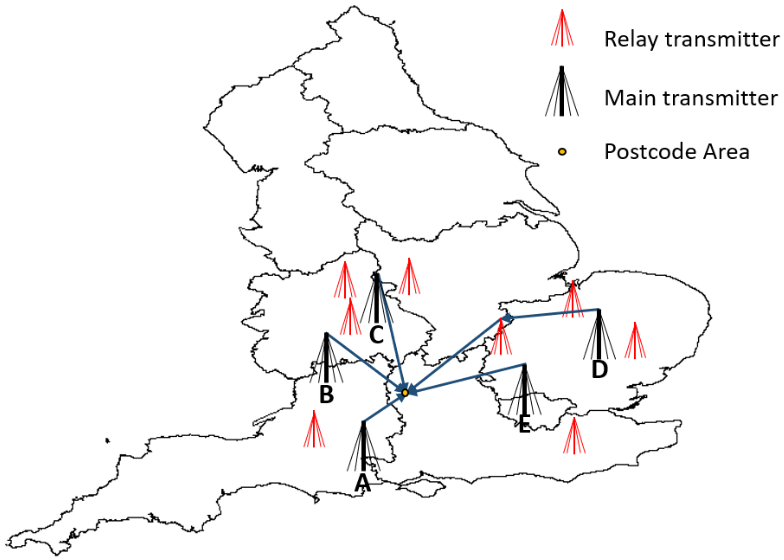
shows the score distribution of schools for each year during the period of analysis. As shown, KS2 scores have increased over time and converged to the mean of the distribution.

Figure 1: Stages of the Digital Switchover in England



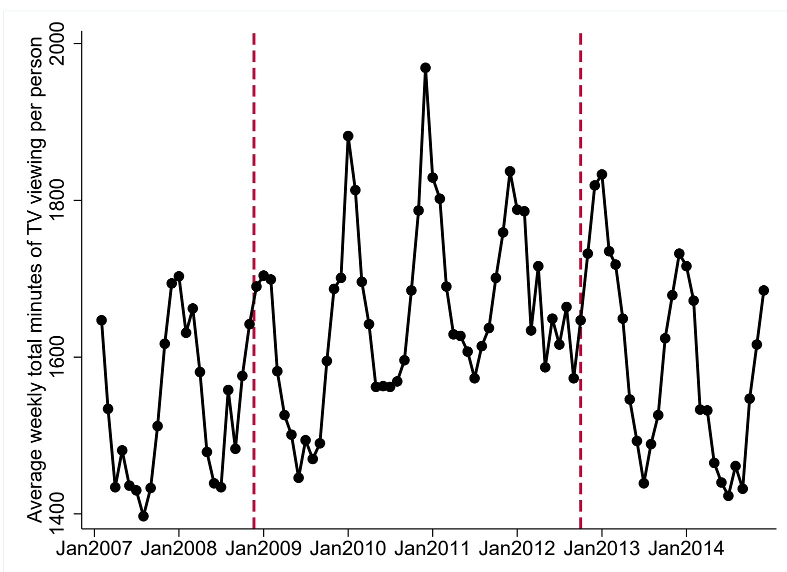
The figure shows a mapping of the digital switchover process in England. Every postcode unit receives television signal from different television transmitters, which have different switchover dates. Therefore, neighbouring postcode units got access to digital signal at different years.

Figure 2: Explanation of Digital Switchover



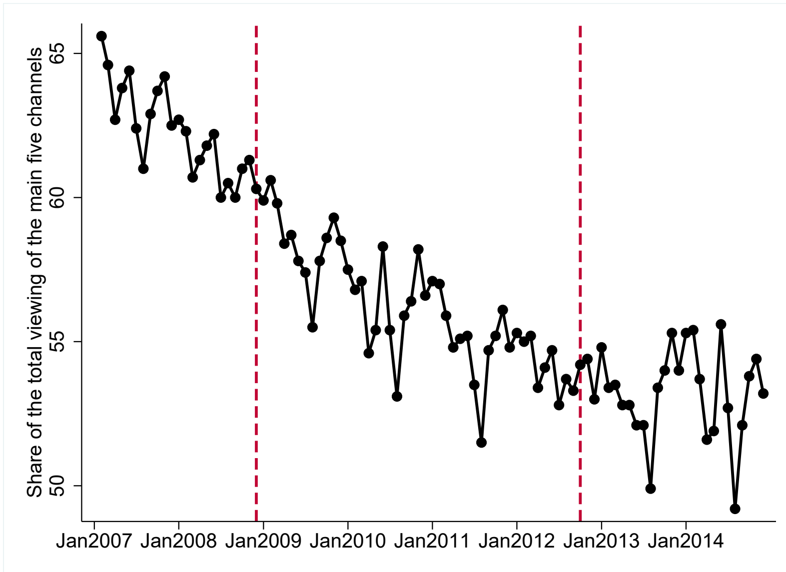
The figure explains the switchover date definition that I use in the analysis. As shown, every postcode unit receives television signal from transmitters located in different regions in UK. As television transmitters had different switchover dates, I define the switchover date for each postcode unit as the earliest of the switchover dates of its television transmitters.

Figure 3: Weekly Average Television Viewing Time



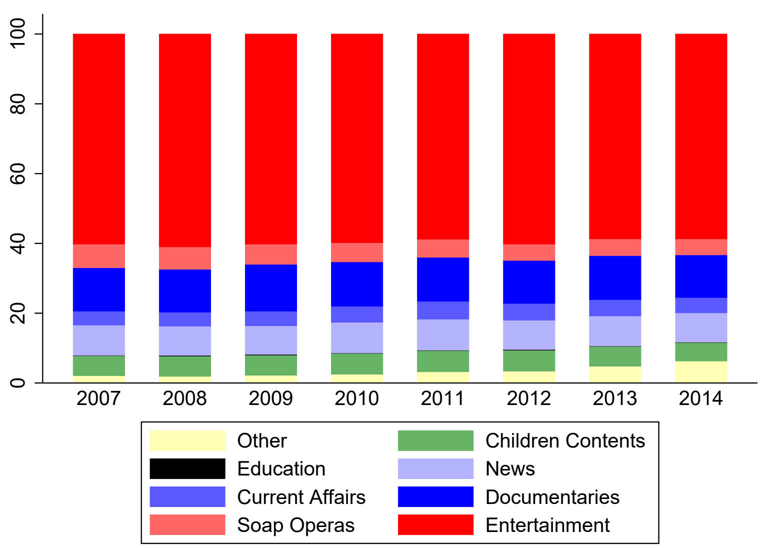
The figure presents the weekly average television viewing time during the period of analysis in UK. The two red vertical lines represent the start date and the completion date of the switchover process.

Figure 4: Total Audience Share of Five Traditional Channels



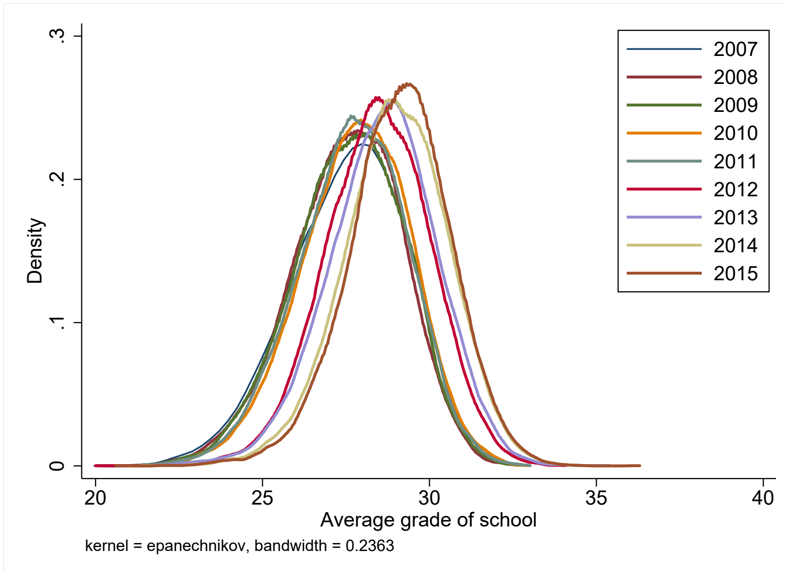
The figure presents the total audience share of the five traditional channels in UK during the period of analysis. The two red vertical lines represent the start date and the completion date of the switchover process.

Figure 5: Proportion of Television Viewing Time by Genre



The figure presents the proportion of television viewing time by genre. I classify television contents in entertainment, soap operas, documentaries, current affairs, news, educative television programmes, children contents, and other.

Figure 6: Yearly Average Grade Distribution



The figure presents the yearly average score distribution of schools during the period 2007 - 2015. As shown, the mean of the score distribution increased during the period of analysis.

This dataset includes information on several academic performance indicators such as the average test score of schools or the percentage of students with a score of 29 or higher. The data also contains annual sociodemographic information at the school level, such as the total number of students, the percentage of pupils whose mother language is not English, and the percentage of economically disadvantaged students.

All the schools included in the dataset are state-funded schools. The reason is that independent schools are not required to ask their pupils to take part in the KS2 test, and so, the UK Department for Education does not publish their KS2 results. Moreover, the UK Department for Education does not publish data on schools where the number of students that participate in the KS2 exam is below 6. Finally, I exclude from my sample Community Special Schools and Foundation Special Schools, as these have only operated since 2010.

Within the sample of schools that I use in the analysis, every student in the final year of primary education is eligible to take the KS2 test. The UK Department for Education includes the score of every pupil eligible for the KS2 test in its calculations of the schools' performance. Students can only be excluded from the schools' performance indicators when they have a limited English and have arrived from a non-English speaking country within the last two years.

I match my datasets on education and television using the postcodes of schools. Students attend a school near where they live due to two main reasons. First, most of schools in UK receive more applications than vacancies available, and one of the main criteria used to select students is the distance from the child's home address to the school. Second, it is unlikely that children attend schools far away from their home due to the high travelling costs they would incur. Subsequently, the digital switchover takes place in the postcode unit where students live at the same time than it occurs at the postcode unit of the school they attend. After merging my television and education datasets, I am left with a panel of 160,776 observations.

It is important to note that there have been two important reforms in the KS2 exam during the last decade. First, the test was initially based on an English, Maths and Science part. However, the Science section ended in 2009 and only the average scores from 2007 until 2009 were recalculated by the UK Department for Education based on the English and Maths sections of the test. I therefore do not include the years before 2007 in the analysis. Second, the highest grade that could be obtained in the KS2 exam increased from 35 to 39 in 2012, and the writing section started to be based on teacher assessment rather than being externally evaluated in the same year. The inclusion of year fixed effects and school trends as controls in the analysis accounts for these changes.

It is also possible to use to use the National Pupil Dataset to perform the analysis. This individual-level data provides information on the academic performance and sociodemographic characteristics of all the students in England. However, the KS2 exam is only taken by students once in life and my natural experiment varies at the postcode level. Therefore, individual data only allows me to compare the average scores of postcodes that were affected by the switchover at different years, and the average scores within postcodes before and after the switchover takes place. To simplify the differences-in-differences approach, and to have a panel-setting dataset, I use the UK Department for Education dataset on the yearly academic performance of every school in England. As this is a large panel dataset that contains yearly academic and sociodemographic information of every school in England, I obtain very precise estimates in the analysis.

3.3 Understanding Society Survey Data

The third dataset I use in the analysis contains yearly information on the time use of children, and it is based on the youth questionnaire of the Understanding Society Survey (UKHLS, 2017). The Understanding Society Survey is a longitudinal survey that has followed the members of 40,000 households in the United Kingdom every year since 2009. Among these individuals, there are approximately 3,000 children aged 10-15 that annually respond to the youth questionnaire of the Understanding Society Survey. This section contains self-completion questions about their lives, experiences, habits, and the social activities in which they get involved. For example, the youth questionnaire contains queries on how happy children are at school, the frequency with which they do homework, sport, use computer, attend extracurricular activities, play video games, go out at night, smoke, or drink alcohol, among others. The youth questionnaire also provides sociodemographic information on children such as their age, gender and family income. It also allows me to identify children over the years. Using this information, I construct an unbalanced panel of 15,069 observations. On average, children are present in 2.92 years during the period of analysis. Importantly, the Understanding Society Survey provides information on the Lower Layer Super Output Area (LSOA) where individuals live. These are very precise geographical units designed with a minimum population of 1,000 and a mean population of 1,500. The total number of LSOAs in England is 32,844, and each of them consists of a grouping of Output Areas, typically five. The Office for National Statistics in UK provides data on the postcode units that pertain to each of the

LSOAs in England. Using this information, I match the Understanding Society Survey dataset with the data on when did the digital switchover occur at each of the postcode units in England.

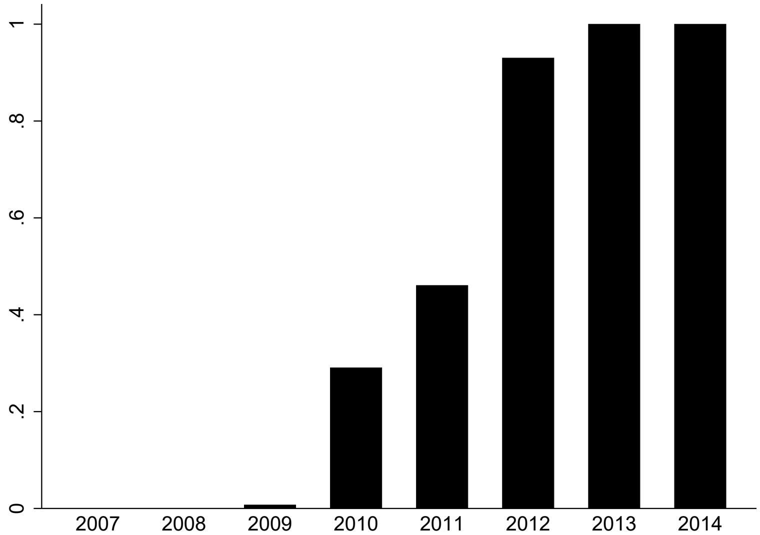
4 Empirical Framework

4.1 Summary Statistics

As the digital switchover was implemented in stages in England, it took place at different dates for the different postcode units of schools. Figure 7 displays the percentage of schools that had already received access to digital television in the different years during the period of analysis. As shown, the percentage of schools with access to digital television gradually increased from 2009 to 2013, and the conversion rate was the highest in 2012.

I next present some descriptive statistics of my sample, and study whether schools that are affected by the digital switchover at different years are different in observed characteristics that may explain discrepancies in their academic performance. Column 1 of Table 1 presents unweighted summary statistics of my sample. As shown, the average KS2 grade previous to the start of the switchover process is 27.66 points. This score remains almost unchanged in 2009, and increases after it. Columns 2-5 respectively assign schools into four different groups attending to the year when they are affected by the digital switchover. For example, column 2 presents the summary statistics of the schools that receive access to digital signal in 2009. As shown, schools with late access to digital television have more students, and these are slightly more likely to be socioeconomically disadvantaged or to have special needs. Importantly, schools with different switchover dates have similar average grades in the years before the start of the switchover process, and their average scores evolve in a parallel manner during the period of analysis.

Figure 7: Percentage of the Territory Affected by the Digital Switchover



The figure presents the percentage of schools that had already received access to digital television in the different years of the period of analysis. No school had received access to digital television by 2008, and all of them had done so by 2013.

4.2 Empirical Strategy

This paper identifies the causal impact of television on education by exploiting exogenous variation in the timing of the digital switchover in England at the postcode level. This allows me to implement a difference-in-difference approach that not only compares the average scores of schools that receive access to digital television at different years, but also the average scores within schools before and after the switchover process takes place. More formally, I estimate the following specification:

$$y_{s,t} = \alpha + \beta DigitalSwitch_{s,t} + \phi DigitalTenure_{s,t} + \gamma X_{s,t} + \delta_s + \lambda_t + \delta_s t + \varepsilon_{s,t} \quad (1)$$

where $y_{s,t}$ is the average KS2 test score of school s at year t. $DigitalSwitch_{s,t}$ is a dummy variable that takes value 1 if the postcode unit of school s has already been affected by the digital switchover by year t, and 0 otherwise. Using information on my natural experiment at the postcode unit allows me to exploit strong exogenous

Table 1: Descriptive Statistics

	Total	2009	2010	2011	2012
	(1)	(2)	(3)	(4)	(5)
N of students	269.99	237.66	231.10	263.43	315.70
	(147.56)	(121.45)	(132.70)	(144.40)	(163.51)
N of students with SEN	3.55	3.03	2.71	3.48	4.28
	(3.37)	(2.91)	(2.94)	(3.33)	(3.72)
% of students free meals	0.27	0.27	0.20	0.25	0.30
	(0.21)	(0.21)	(0.18)	(0.20)	(0.22)
Average grade in 2007	27.66	27.69	27.77	27.62	27.67
	(1.75)	(1.72)	(1.72)	(1.74)	(1.80)
Average grade in 2008	27.62	27.68	27.70	27.58	27.62
	(1.66)	(1.61)	(1.72)	(1.67)	(1.65)
Average grade in 2009	27.65	27.70	27.67	27.58	27.71
	(1.68)	(1.63)	(1.63)	(1.70)	(1.70)
Average grade in 2010	27.78	27.88	27.84	27.66	27.89
	(1.62)	(1.57)	(1.62)	(1.66)	(1.59)
Average grade in 2011	27.82	27.89	27.90	27.71	27.93
	(1.61)	(1.59)	(1.63)	(1.62)	(1.59)
Average grade in 2012	28.56	28.57	28.56	28.46	28.70
	(1.56)	(1.52)	(1.56)	(1.59)	(1.54)
Average grade in 2013	28.69	28.70	28.71	28.57	28.88
	(1.61)	(1.55)	(1.69)	(1.65)	(1.57)
N	118,729	27,617	6,120	52,681	32,311

The table presents the means of a number of observable variables, and their standard deviations in parenthesis.

variation at a very precise geographical level.

The impact of the digital switchover on education may be temporary or persist in time. I therefore control for $DigitalTenure_{s,t}$, which is the number of years that have passed since digital television was introduced in the postcode unit of school s at year t. More precisely, $DigitalTenure_{s,t}$ takes value 0 if the switchover process has not yet occurred in the postcode unit of school s by year t, 1 if it took place within the last 12 months, 2 if it occurred between 12 and 24 months earlier, and so on. δ_s are school fixed effects that capture school time-invariant characteristics that might be correlated with the timing of the digital switchover and the academic performance of students. λ_t are year fixed effects that allow for flexible trends in the average KS2 test score of schools over time. $\delta_s t$ are a set of variables that control for linear trends in the scores of the different schools over time. $X_{s,t}$ is a vector of time-varying covariates at the school level. This includes the total number of students and the number of students with special needs. $\varepsilon_{s,t}$ is a school and time specific level error term. Throughout the empirical analysis, I cluster standard errors at the regional level, which allows for an arbitrary correlation of residuals within postcodes. My identifying assumption is that the timing of the switchover process is not correlated with unobserved determinants of education, after having controlled for time-varying observable covariates, school and year fixed effects, and school individual trends.

5 Empirical Results

Column 1 of table 2 presents the estimates of specification (1) without controlling for time-varying covariates, $DigitalTenure_{s,t}$ and school trends. The estimates show that the digital switchover increases KS2 test scores by 0.036 standard deviations, and so, that an increase in television viewing time has a positive impact on educational performance. It is important to comment on the magnitude of the estimate. The digital switchover raises television viewing time by 15.1%. Therefore, the estimate points that total television viewing time increases academic performance by 0.238 standard deviations. This finding is in line with the estimates provided by recent research (Gentzkow and Shapiro, 2008), but higher in size. The estimate is statistically significant at the 1% confidence level. Column 2 includes time-varying controls at the school level and column 3 adds a set of linear school trends as additional covariates. As shown, their inclusion in the empirical specification lowers the magnitude of the estimate of the effect of television on education, but does not change its sign neither significance. Column 4 controls for the number of years that have passed since the introduction of the digital switchover in a particular postcode unit. I find that the estimate of the digital switchover is still positive and significant at the 5% confidence level, and that the impact of an additional year with access to digital television signal is negligible. This suggests that the positive impact of television on education persists in time. It is also important to comment on the estimates of the rest of the covariates. An increase in the number of students of a school or in the number of pupils with special needs have a negative impact on test scores.

Previous literature has pointed that television may be most beneficial for children who are relatively disadvantaged (Gentzkow and Shapiro, 2008). I next explore whether the impact of television on education depends on the academic background of students. To do so, columns 5-8 split my sample in quartiles attending to the position of schools in the score distribution of 2008, which is the year before the switchover process started. This allows me to study whether the digital television transition has an impact on educational inequality. I find that the digital switchover has a positive effect on the average educational outcomes of schools at the bottom of the score distribution, but no effect on schools at the top of it. This reduces educational inequality. A possible explanation is that television changes the time use of children differently depending on their socioeconomic background. If television viewing time displaces activities with relatively lower educational value for bad students, an increase in television exposure may improve their academic performance. I test for this hypothesis later in the paper. The estimates in columns 5-8 also show that the positive impact of television on education is persistent in time for schools at the bottom of the score distribution in 2008, but temporary for schools at the second quartile of the distribution. I next study in more detail the timing of the impact of the digital switchover on education.

5.1 Timing of the Effect of Television on Education

The previous section shows that an increase in television viewing time has a positive impact on academic achievement and educational inequality. I next study the dynamics of the previous effect and test whether the digital switchover is correlated with previous trends in grades. To do so, I estimate the following event approach

Table 2: Effect of Digital Switchover on KS2 Test Scores

					Quartiles			
					Q1	Q2	Q3	Q4
Depvar: KS2 Standardized average score	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DigitalSwitch	0.0363***	0.0284***	0.0260**	0.0283**	0.0662**	0.0857***	-0.0120	-0.0270
	(0.0082)	(0.0080)	(0.0085)	(0.0102)	(0.0231)	(0.0204)	(0.0199)	(0.0188)
DigitalTenure				-0.0041	-0.0139	-0.0495**	0.0307	0.0204
				(0.0108)	(0.0244)	(0.0223)	(0.0216)	(0.0199)
% students SEN		-0.0245***	-0.0243***	-0.0243***	-0.0212***	-0.0234***	-0.0272***	-0.0271***
		(0.0004)	(0.0004)	(0.0004)	(0.0007)	(0.0008)	(0.0009)	(0.0008)
log N students		0.1366***	-0.6232***	-0.6233***	-0.5879***	-0.3983***	-0.3853***	-0.3874***
		(0.0287)	(0.0451)	(0.0450)	(0.0761)	(0.0913)	(0.0945)	(0.1052)
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School Trends	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	118,729	117,899	117,899	117,899	27,287	27,703	26,419	27,354

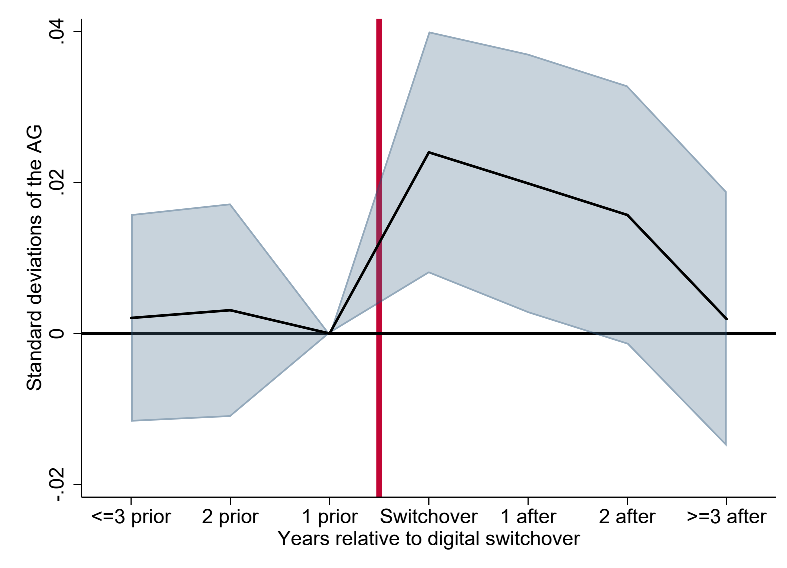
* p<0.10, ** p<0.05, *** p<0.01
standard errors in parenthesis. I allow for an arbitrary correlation of standard errors at the regional level. The dependent variable is standardized to have a mean of zero and a standard deviation of unity.

specification:

$$y_{s,t} = \alpha + \beta \sum_{r=-3}^{3} YearsinceSwitch_{s,t+r} + \gamma X_{s,t} + \delta_s + \lambda_t + \delta_s t + \varepsilon_{s,t} \tag{2}$$

where the second term on the right-hand side is a set of dummies that indicate the years that are left or have passed at year t relative to the introduction of the digital switchover in the postcode unit of school s. For instance, the dummy with $r = 0$ takes value 1 the year when the postcode unit of school s is affected by the digital switchover, and 0 otherwise. Albeit I include year fixed effects in the analysis, I still have enough variation in the previous set of dummies as different postcode units obtained access to digital television at different years. The event time r ranges from -3 to 3. Including event dummies with $r = -1$, $r = -2$ and $r = -3$ allows me to study whether the digital switchover was correlated with previous trends in grades. Were this the case, my empirical strategy would be flawed. As in my baseline specification, I control for school time-varying characteristics, year fixed effects, school fixed effects, and school trends. The results are displayed in Figure 8. As shown, the estimates of the effect of the years previous to the digital switchover on test scores are negligible and not statistically significant. However, the estimates become positive and significant for the years after the introduction of the digital television signal. The impact of television on education lasts for three years and then vanishes. A possible explanation is that children may get used to the availability of a higher number of channels over time. As the positive effect of television on education persists during three years, the introduction of the digital television signal notably increases human capital formation. Appendix A.3 shows the dynamics of the effect of television on education for each of the subsamples that I constructed attending to the position of schools in the score distribution of 2008.

Figure 8: Dynamic Impact of Television on Education



The figure estimates the event approach specification (2), and shows the dynamics of the effect that television has on education. More specifically, the figure presents the estimates of the set of dummies $\sum_{r=-3}^{3} YearsinceSwitch_{s,t+r}$.

5.2 Robustness Checks

This section implements a number of robustness tests that support the validity of my identification strategy and explore whether the baseline estimates are robust to the use of different specifications. Columns 1 and 2 of Table 3 estimate my benchmark specification but respectively using as dependent variable the percentage of students that obtain a score of 25 or higher in the Maths and English section of the KS2 test. This robustness test is important because of two reasons. First, it allows me to study whether the positive effect of television on academic performance is due to an enhancement in the verbal or mathematical skills of students. Second, it serves to examine whether the baseline estimates are robust to the use of alternative dependent variables. As shown, the estimates of the digital switchover are positive and significant in both sections of the test, albeit higher in magnitude for Maths. The estimates of an additional year with access to digital television are negative, but only significant in the English section of the test. As previously explained, a possible explanation is that the digital switchover allowed for the possibility of watching television in languages other than English. Non-native students may opt for watching television in their own language rather than English, and this may have a negative impact on their English language skills. Column 3 estimates the benchmark specification using the contextual value added (CVA) score as dependent variable. The CVA score is a statistical measure of the students and schools academic progress. It is calculated by the UK Department for Education using a statistical model that calculates the prediction of the national average score for each category of students, and then compares the score of each student against that prediction. As shown, the estimate of the impact of an increase in television viewing time on education is positive and significant at the 1% significance level.

Column 4 uses the number of students in each school as weights in my regression. The estimate of the digital switchover is positive, significant at the 1% confidence level, and similar in magnitude than my baseline estimate. Finally, columns 5-6 adopt a placebo test to evaluate whether television has an impact on education when I use an incorrect timing of the digital switchover as a natural experiment. More specifically, columns 5 and 6 respectively estimate whether obtaining access to digital television signal at year $t+1$ and $t+2$ has an impact on academic performance at year t. As shown, the estimates do not support the presence of an effect of television on educational outcomes when I use an incorrect timing of the digital switchover. Overall, the estimates are robust across the different specifications.

5.3 Heterogeneity

This section explores whether the effect of television on education varies in the sociodemographic characteristics of schools. Figure 9 estimates a specification similar to the baseline model but includes an interaction between the digital switchover variable and a set of dummies indicating the quartile of school s in the distribution of the proportion of students eligible for free school meals. As shown, the estimate of the impact of the digital switchover on test scores is driven by schools at the

Table 3: Robustness Checks

	Different Dependent Variables			Weights	Placebo Tests	
	Maths	English	CVA		Switch_{t+1}	Switch_{t+2}
	(1)	(2)	(3)	(4)	(5)	(6)
DigitalSwitch	0.0032**	0.0027*	0.0709***	0.0352***		
	(0.0016)	(0.0015)	(0.0147)	(0.0100)		
DigitalTenure	-0.0021	-0.0038**	-0.0377**	-0.0105		
	(0.0016)	(0.0015)	(0.0158)	(0.0106)		
$\text{DigitalSwitch}_{t+1}$					0.0031	
					(0.0087)	
$\text{DigitalSwitch}_{t+2}$						-0.0025
						(0.0090)
Time-varying covariates	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
School Trends	Yes	Yes	Yes	Yes	Yes	Yes
Weights	No	No	No	Yes	No	No
Observations	118,079	118,022	117,460	117,899	103,824	89,444

* p<0.10, ** p<0.05, *** p<0.01
standard errors in parenthesis. Standard errors clustered at the regional level. All dependent variables are standardized to have a mean of zero and a standard deviation of unity. I include (not shown in the table) as controls the logarithm of the number of students and the number of students with special needs.

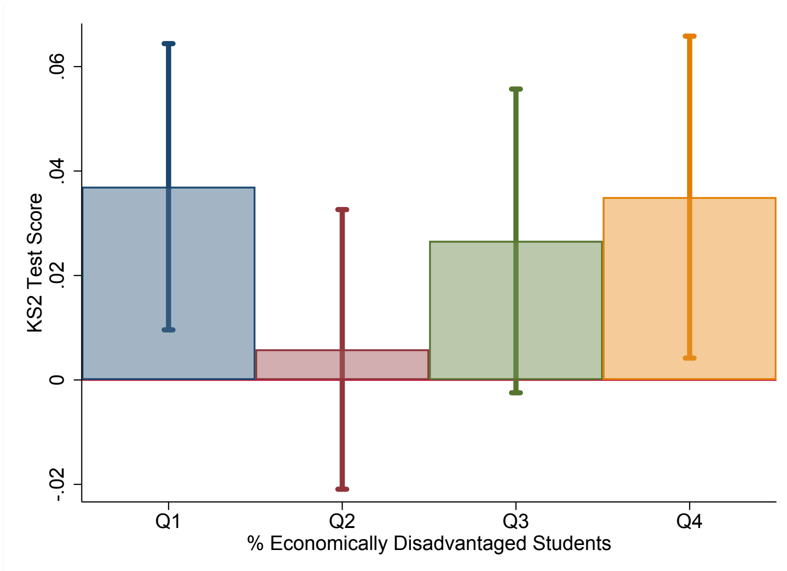
top and bottom of the distribution. This points that students who benefited from television are not only economically disadvantaged students. Figure 10 is similar to Figure 9, but instead studies heterogeneity in the proportion of students who are not English native speakers. As shown, the impact of the digital switchover is positive and statistically significant when schools have a low and a high proportion of non-native students. The impact is higher in magnitude when the proportion of non-native students is low. A possible explanation is that the digital switchover allowed for the possibility of watching television in languages other than English. Non-native students may opt for watching television in their own language rather than English, and this may have a negative impact on their English language skills.

Figure 11 tests whether the effect of television on education depends on the proportion of students with Special Educational Needs in schools. Students are defined to have Special Educational Needs when they have a low educational attainment or any kind of behavioural or physical problem. As shown, the estimates of the digital switchover become higher as the number of students with Special Educational Needs increases.Finally, Figure 12 studies the effect of television on education attending to the number of students of schools. The estimates of the impact of television on academic achievement are only positive and statistically significant for schools below the median size of schools.

The evidence provided up until now suggests that students who benefit the most from an increase in television viewing time are: (i) low achievers, (ii) economically disadvantaged or with a very high income, and (iii) Special Educational Needs students.[9] Low-achieving students are more likely to get involved in out-of-school activities that may lower their academic achievement. Subsequently, television may increase test scores of children if it reduces the frequency with which they get involved in detrimental activites. The following section tests for this hypothesis and so explores the underlying mechanism behind the baseline estimates.

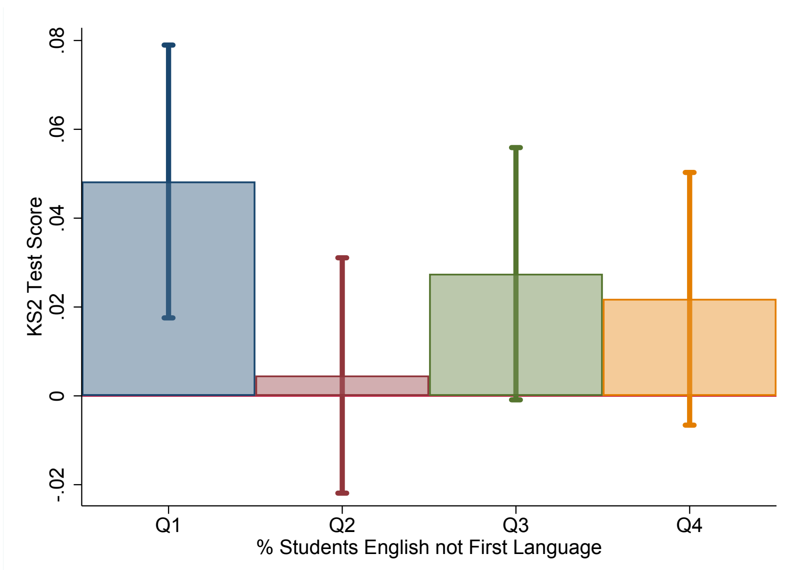
[9] Table A.2 of Appendix A.4 presents the proportion of disadvantaged, native and SEN students for each of the subsamples that I assigned attending to the position of schools in the score distribution of 2008. The Table also presents the average number of students and the proportion of religious schools for each of the quartiles.

Figure 9: Heterogeneity in % of Economically Disadvantaged Students



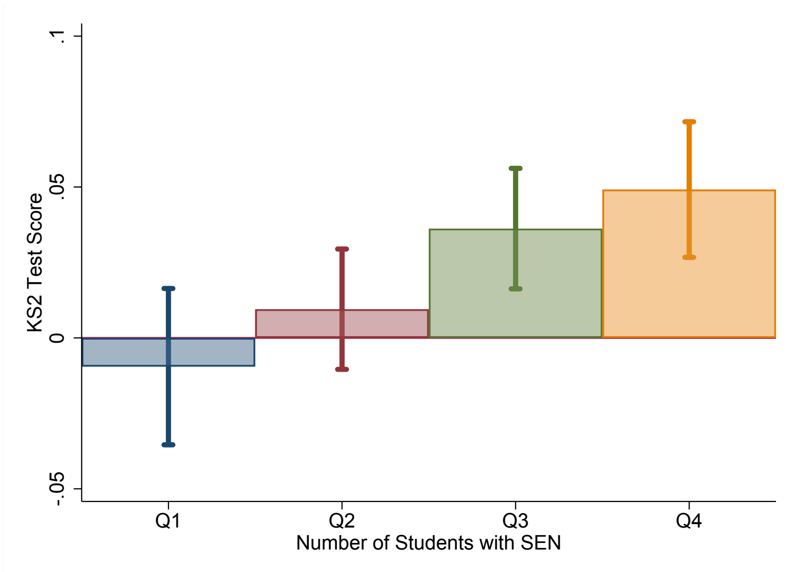
The figure estimates a specification similar to the baseline one but controls for an interaction between the digital switchover and a set of dummies indicating the quartile of school s in the distribution of the proportion of students eligible for free school meals.

Figure 10: Heterogeneity in % of Students who are not English Native Speakers



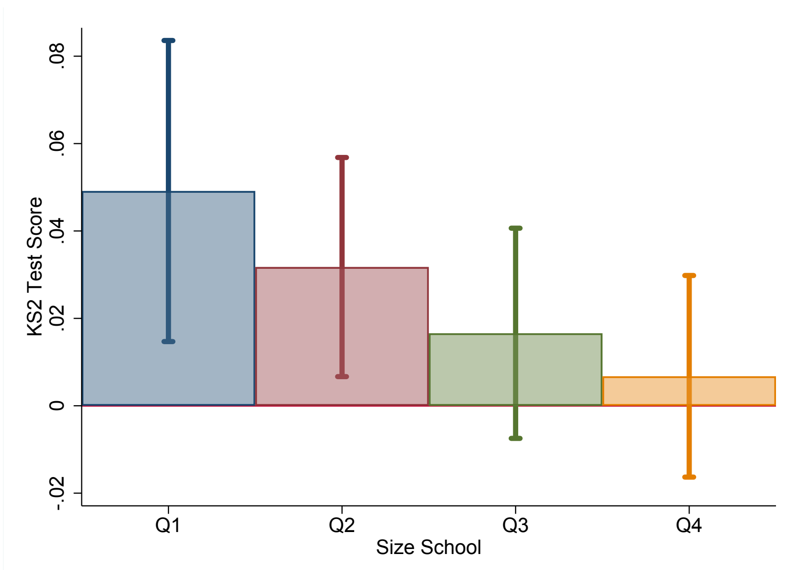
The figure estimates a specification similar to the baseline one but controls for an interaction between the digital switchover and a set of dummies indicating the quartile of school s in the distribution of the proportion of students who are not English Native Speakers.

Figure 11: Heterogeneity in % of Students with SEN



The figure estimates a specification similar to the baseline one but controls for an interaction between the digital switchover and a set of dummies indicating the quartile of school s in the distribution of the proportion of students with special educational needs.

Figure 12: Heterogeneity in the Number of Students



The figure estimates a specification similar to the baseline one but controls for an interaction between the digital switchover and a set of dummies indicating the quartile of school s in the distribution of the total number of students.

6 Impact of Digital Television on Habits

I previously showed that television has a positive impact on test scores and reduces educational inequality. I next explore a plausible mechanism behind the baseline estimates, which is whether television changes the amount of time that children dedicate to activities that may harm their academic performance. I do so by estimating the impact of the digital switchover on the time use of children, and on the frequency with which they get involved in detrimental activities.

6.1 Data and Summary Statistics

In this part of the analysis, I use a panel survey dataset at the individual level that contains yearly information on the time use of children. I have previously described this dataset, which comes from the youth questionnaire of the Understanding Society Survey in UK. The panel is unbalanced and contains 15,069 observations on approximately 5,000 children. I next present some descriptive statistics of the sample that I use in the analysis. Column 1 of Table 4 displays the unweighted summary statistics of the whole sample, and columns 2-5 assign individuals into four different groups attending to the year when they got access to digital television for the first time. As shown, children have a similar age, and are equally likely to be female or native independently of the year when they were affected by the digital switchover. Households also have a similar number of members and children across the different subsamples. Regarding socioeconomic characteristics, the number of bedrooms, cars, and the gross income of households are approximately the same across the different subsamples, with the exception of households that got access to digital television in 2009, who have a lower income. Finally, children affected by the digital switchover at the beginning or at the end of the process are more likely to live in urban areas. I control for these observable characteristics in the analysis.

Table 4: Descriptive Statistics

	Sample	2009	2010	2011	2012
	(1)	(2)	(3)	(4)	(5)
Age	12.51	12.51	12.43	12.53	12.50
	(1.69)	(1.67)	(1.70)	(1.70)	(1.68)
Female	0.50	0.47	0.52	0.51	0.49
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Native	0.96	0.96	0.98	0.97	0.95
	(0.20)	(0.20)	(0.13)	(0.18)	(0.22)
N members	4.42	4.37	4.37	4.38	4.50
	(1.37)	(1.29)	(1.23)	(1.36)	(1.43)
N children	1.90	1.92	1.89	1.88	1.91
	(1.15)	(1.15)	(1.10)	(1.16)	(1.14)
Gross Income	4158.1	3805.0	4491.2	4114.7	4376.6
	(2767.8)	(2291.4)	(3223.0)	(2584.6)	(3123.1)
Rural Area	0.19	0.18	0.26	0.26	0.10
	(0.39)	(0.39)	(0.44)	(0.44)	(0.30)
N bedrooms	3.40	3.40	3.57	3.47	3.29
	(0.94)	(0.91)	(0.98)	(0.93)	(0.95)
N cars	1.39	1.42	1.71	1.46	1.25
	(0.88)	(0.83)	(0.86)	(0.85)	(0.92)
N	15,053	3,131	706	6,037	5,179

The table presents the means of a number of observable variables, and their standard deviations in parenthesis. I divide individuals in groups attending to the year when they were first affected by the digital switchover. This allows me to compare the summary statistics of the different groups.

6.2 Empirical Model

Similarly to the baseline specification, I follow a difference-in-difference approach that uses exogenous variation in the timing of the digital switchover as a natural experiment. More formally, I estimate the following specification:

$$a_{i,t} = \alpha + \beta DigitalSwitch_{s,t} + \gamma X_{i,t} + \delta_i + \lambda_t + \varepsilon_{i,t} \tag{3}$$

where $a_{i,t}$ is the frequency/probability with which child i gets involved in activity a at year t. $DigitalSwitch_{i,t}$ is a dummy that takes value 1 if the LSOA where child i

lives has already been affected by the digital switchover by year t, and 0 otherwise.[10] As previously explained, the reason for using exogenous variation at the LSOA level is that this is the smallest geographical unit at which the Understanding Society Survey provides information. The total number of LSOAs in England is 32,844, and they have a mean population of 1,500. $X_{i,t}$ is a set of time-varying characteristics at the child level such as age, or whether the child lives in an urban area. $X_{i,t}$ also includes time-varying household characteristics such as the number of members, children, cars and bedrooms in the house. Finally, $X_{i,t}$ controls for the gross income of the household where child i lives at year t. δ_i are child fixed effects that control for unobserved time-invariant characteristics at the individual level, such as preferences. λ_t are year fixed effects, and $\varepsilon_{i,t}$ is a time-varying error term at the individual level. I allow for an arbitrary correlation of standard errors at the regional and child level.[11]

6.3 Results

Column 1 of Table 5 tests whether the digital switchover increases motivation of children towards school. This serves as a second set of evidence on the causal impact of television on education by using a different dataset than the one I adopted to estimate the baseline results. More specifically, column 1 estimates specification (3) using as dependent variable a categorical variable that measures how happy children are with their school work in a scale that ranges from 1 (not happy at all) to 7 (very happy). I find that digital switchover has a positive impact on the degree of happiness of children towards school work, and the estimate is significant at the 10% confidence level. This is in line with the baseline estimates of this paper.

Columns 2-7 study the causal impact of television on the probability and

[10] In this part of the analysis, I do not control for $DigitalTenure_{i,t}$, which is the number of years that have passed by year t since child i got access to digital television. The reason is that the main purpose of this section is to explore the mechanism behind the baseline estimates, but not its dynamics. Moreover, $DigitalTenure_{i,t}$ is highly correlated with age, which generates an important multicollinearity problem when I include $DigitalTenure_{i,t}$ in the regression. Yet, the inclusion of $DigitalTenure_{i,t}$ as a covariate does not change the estimates presented in this part of the analysis.

[11] The reason why I use a two-way cluster is that some children move across regions during the period of analysis.

frequency with which children: (i) drink alcohol, (ii) smoke, and (iii) arrive late at home. I measure all the frequencies in a scale that ranges from 1 (never) to 5 (most days). These columns allow me to test whether the positive impact of television on education is due to television reducing the time that children dedicate to out-of-school activities that may harm their academic achievement. More specifically, column 2 of Table 5 estimates specification (3) using as dependent variable a dummy that takes value 1 if child i has ever drunk alcohol by year t, and 0 otherwise. As shown, the digital switchover reduces the probability of children having ever drunk alcohol by 2.8 percentage points. Given that the digital switchover raises television viewing time by 15.1%, the average television viewing time reduces the probability of children drinking alcohol by 18.5%. The estimate is significant at the 5% confidence level. Column 3 is similar to column 2, but uses as dependent variable the frequency with which child i drinks alcohol per week at year t. As shown, an increase in television viewing time reduces the frequency with which children drink alcohol. The estimate is significant at the 1% confidence level. Column 4 studies the impact of television on a binary variable that takes value 1 if child i has ever smoked by year t, and 0 otherwise. Column 5 is similar to column 4, but uses the frequency with which children smoke per week as dependent variable. As shown, the digital switchover reduces the probability of having ever smoked and the frequency of smoking, albeit the estimates are not statistically significant. Finally, columns 6-7 respectively use as dependent variable the probability and frequency with which children have arrived late at home in the last month. I define arriving late as reaching home after 9:00 pm. The estimates of the digital switchover are negligible and not statistically significant. Overall, the results suggest that the positive impact of television on academic performance is at least partially due to television reducing the probability/frequency with which children get involved in detrimental activities.[12,13,14]

Another plausible explanation as to why television has an impact on education is that television may change the importance that children give to school grades, the time they dedicate to homework, or their interest in extra-curricular activities. As shown in Appendices A.5-A.6, this is not the case. It is also important to note that my baseline estimates on education are based on a sample of children aged 10-11, whereas the set of results of this section is based on children aged 10-15. Therefore, it is important to explore whether children aged 10-11 are likely to drink alcohol, smoke or arrive late at home. If they do not get involved in this type of activities, then the digital switchover cannot reduce the probability or frequency with which children aged 10-11 take part in them. As shown in Appendix A.9, it is not rare for children aged 10-11 to drink alcohol, smoke and arrive late at home. I next explore heterogeneity in the impact of television on time use by age, income, gender and ethnicity.

6.4 Heterogeneity in Age

I have so far studied the average effect of television on the probability and frequency with which children get involved in detrimental activities. I next examine whether this impact is heterogeneous in the age of children. This is relevant as my analysis on education is based on a sample of children whose age is 10-11, whereas my analysis on time use on children aged 10-15. This part of the analysis also allows me to evaluate

[12] Appendix A.7 also tests whether the digital switchover changes the probability and frequency with which children use social media and play video games. As shown, the digital switchover only reduces the time that children spend on social media.

[13] Appendix A.8 combines bad activities (drinking alcohol, smoking and arriving late at home) into one variable. It also studies the impact of the digital switchover on this variable.

[14] It is also possible to test whether the digital switchover has an effect on television viewing time. However, the data on television viewing time available in the Understanding Society Survey is subject to three important limitations. First, the variables that contain this information only take five possible values: no television viewing time, less than one hour, 1-3 hours, 4-6 hours, 7 hours or more. Second, 85% of observations fall in the second and third categories. Third, there only exists information on television viewing time during weekends in two waves. These limitations markedly reduce the variability in the information available on television viewing time. It is therefore not surprising that I find no effect of the digital switchover on television viewing time.

Table 5: Harmful Activities and Practices

	Happ school (1)	Prob drunk alcohol (2)	Freq drinks alcohol (3)	Prob smoked (4)	Freq smokes (5)	Prob arrives late (6)	Freq arrives late (7)
Digital Switch	0.056*	-0.031**	-0.058***	-0.004	-0.003	0.001	0.002
	(0.034)	(0.014)	(0.021)	(0.009)	(0.017)	(0.012)	(0.019)
Age	0.048	0.019	0.001	0.020	0.036	-0.032**	-0.033
	(0.047)	(0.020)	(0.032)	(0.012)	(0.023)	(0.016)	(0.026)
Gross Income	-0.006	-0.014	-0.019	-0.003	-0.005	0.012	0.016
	(0.023)	(0.011)	(0.016)	(0.006)	(0.011)	(0.008)	(0.012)
Rural Area	-0.061	0.022	-0.111	0.033	-0.022	-0.095**	-0.168**
	(0.165)	(0.054)	(0.108)	(0.044)	(0.112)	(0.047)	(0.076)
N bedrooms	-0.033	-0.016	-0.049*	-0.006	-0.018	-0.011	-0.003
	(0.049)	(0.016)	(0.026)	(0.011)	(0.018)	(0.012)	(0.020)
N members	-0.014	-0.004	0.021	-0.002	0.002	0.030***	0.023
	(0.034)	(0.014)	(0.020)	(0.009)	(0.020)	(0.012)	(0.019)
N children	0.02	-0.03**	-0.13***	-0.03***	-0.07***	-0.03***	-0.05***
	(0.025)	(0.011)	(0.017)	(0.007)	(0.016)	(0.009)	(0.014)
Children FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,182	12,200	12,153	12,237	11,989	12,252	12,252

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

Standard Errors in parenthesis. I allow for an arbitrary correlation of standard errors at the regional and child level. The number of observations vary depending on the specification because sometimes information is missing depending on the dependent variable.

whether children of different ages re-distribute their time allocation differently as a response of the digital switchover process. I study heterogeneity in age by estimating a specification similar than 3, but that includes an interaction between the digital switchover dummy and age.[15] Figures 13-15 present the average marginal effects of television for the different ages, respectively using as dependent variable the probability of having ever drunk alcohol, smoked or arrived late at home in the last month. As shown, the digital switchover decreases the probability of children

[15]To simplify the analysis, I do not control for $DigitalTenure_{i,t}$, which is the number of years that have passed by year t since child i got access to digital television. However, its inclusion would lead to similar estimates than the ones presented in this section.

getting involved in any of these detrimental activities when they are younger, and the estimates are significant at the 5% confidence level. However, television increases these habits when children are older, albeit the estimates are only significant for the probability of smoking or arriving late at home. A possible explanation is that teenagers watch television contents that induce them to get involved in harmful activities. Appendix A.10 estimates an analysis similar to the one presented in this section, but uses as dependent variables the frequency of children drinking alcohol, smoking or arriving late at home. As shown, I obtain similar estimates than the ones presented in this section.

6.5 Heterogeneity in Income

This subsection studies heterogeneity in the impact of television on habits attending to the income of the household where children live. This is important because I previously found that the effect of television on education varies in the socioeconomic background of students. If children with poorer socioeconomic conditions are more likely to get involved in detrimental activities, an increase in television viewing time may benefit them more. I therefore explore whether the effect of the digital switchover on habits varies in the household income of children. I do so by estimating a model analogous to 3, but that includes an interaction between the digital switchover indicator and income quartiles.[16] Figure 16 presents the average marginal effects of the digital switchover when I use as dependent variable the probability of having ever had an alcoholic drink. As shown, the impact of the digital switchover on this habit is negative for every income quartile. However, the estimates are higher for children at the bottom of the income distribution, and only statistically significant at the 5% confidence level for the first income quartile. Figure 17 shows the estimates when I use the probability of having ever smoked as dependent variable. Interestingly, the estimate of the digital switchover is only neg-

[16] Similarly than in the analysis where I study heterogeneity in age, I do not include $DigitalTenure_{i,t}$ in the model of this section to simplify the analysis. However, including it as a covariate gives similar estimates than the ones I show in this section.

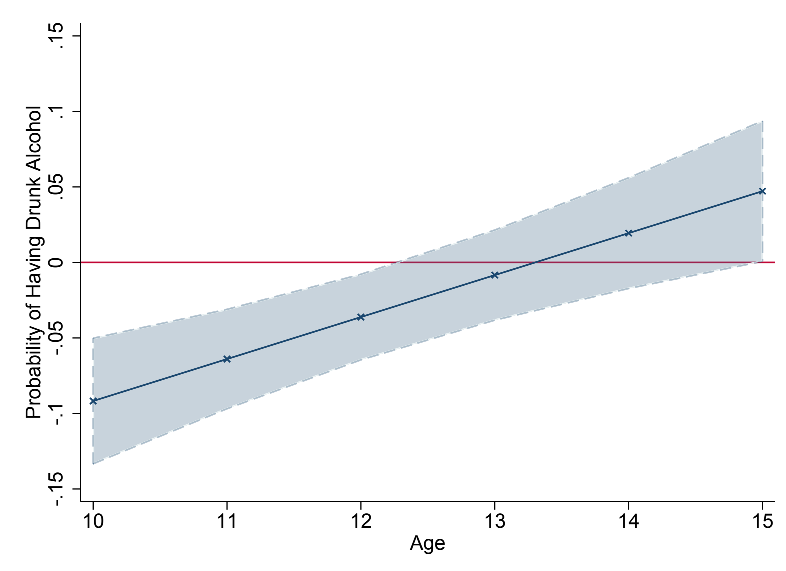
ative and significant at the 5% confidence level for children at the top of the income distribution. This provides further evidence on television reducing the probability of children getting involved in detrimental activities. This set of estimates also indicates that children who benefit from television are not only those with worse socioeconomic background. Finally, Figure 18 presents the estimates when I use the probability of arriving late at home in the last month as dependent variable. As shown, all the estimates are small and not statistically significant. In Appendix A.11, I perform an analysis similar to the one of this section, but respectively adopting as dependent variables the frequency of children drinking alcohol, smoking, or arriving late at home. As shown, I find analogous results to the ones presented in this section.

6.6 Heterogeneity in Gender and Ethnicity

It is also important to test whether the impact of television on time use is heterogeneous in gender and ethnicity. To do so, I first estimate specification 3, but controlling for an interaction between the digital switchover dummy and gender. I respectively use as dependent variables the probability of having ever had an alcoholic drink, smoked, or arrived late at home in the previous month. Figure 19 presents the average marginal effects of television for boys and girls. As shown, the impact of television on time use is driven by boys. Figure 20 is similar to figure 19, but instead explores heterogeneity in the ethnicity of children. I classify children into two different groups: white British and non-white British. As shown, the switchover reduces the time that non-white British children dedicate to detrimental activities, but has a negligible impact for white British children.[17]

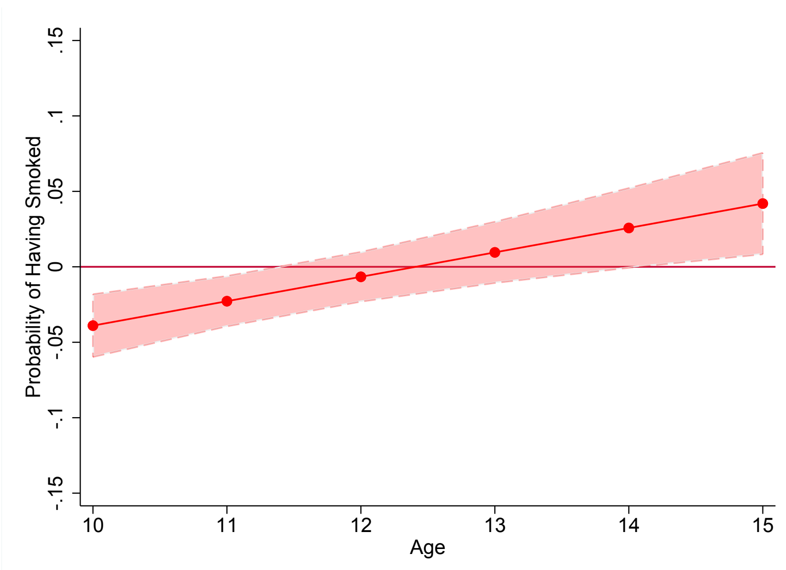
[17] Appendix A.12 studies whether the impact of the digital switchover on detrimental activities is heterogeneous in ethnicity, and uses a more disaggregated classification of race.

Figure 13: Impact on Probability of Having Ever Drunk Alcohol



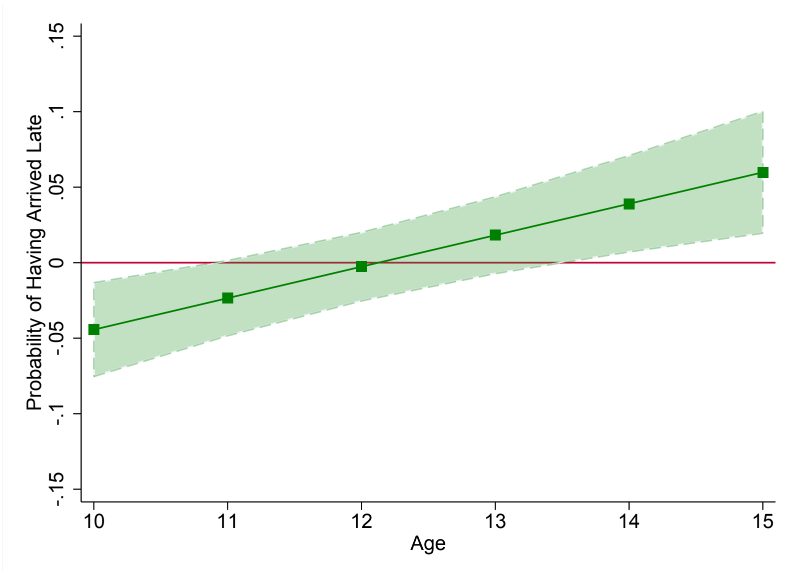
The figure estimates equation (3), including as control an interaction between the switchover dummy and age. I use as dependent variable the probability of having ever had an alcoholic drink. I show the average marginal effects of television for the different ages of children.

Figure 14: Impact on Probability of Having Ever Smoked



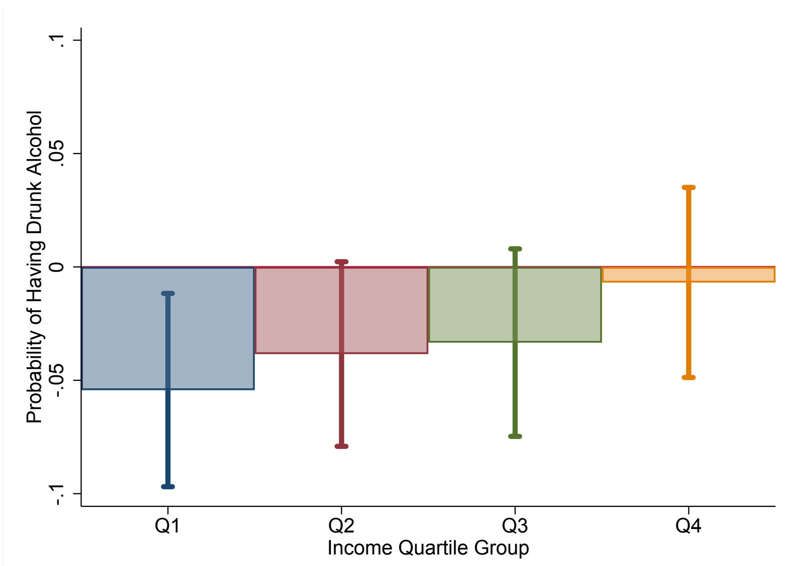
The figure estimates equation (3), including as control an interaction between the switchover dummy and age, and using as dependent variable the probability of having ever smoked. I show the average marginal effects of television for the different ages of children.

Figure 15: Impact on Probability of Having Arrived Home after 9pm



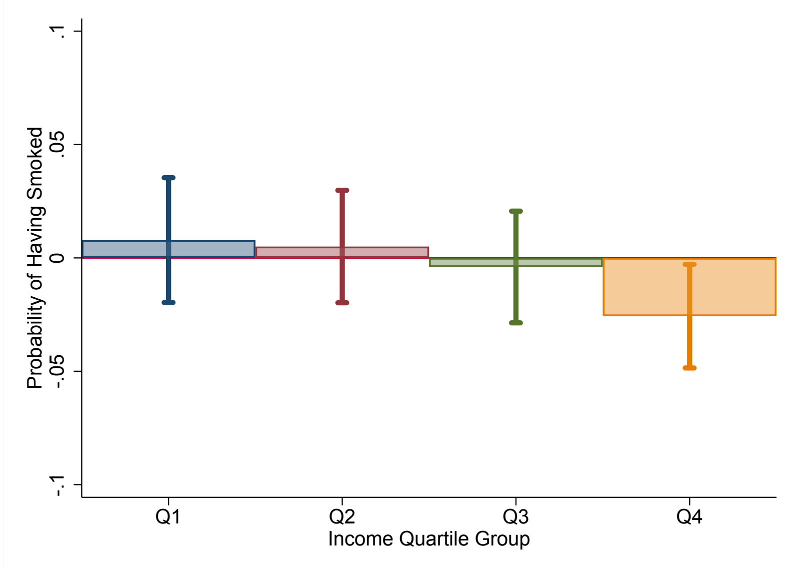
The figure estimates equation (3), including as control an interaction between the switchover dummy and age, and using as dependent variable the probability of having arrived late at home in the past month. I show the average marginal effects of television for the different ages of children.

Figure 16: Impact on Probability of Having Ever Drunk Alcohol



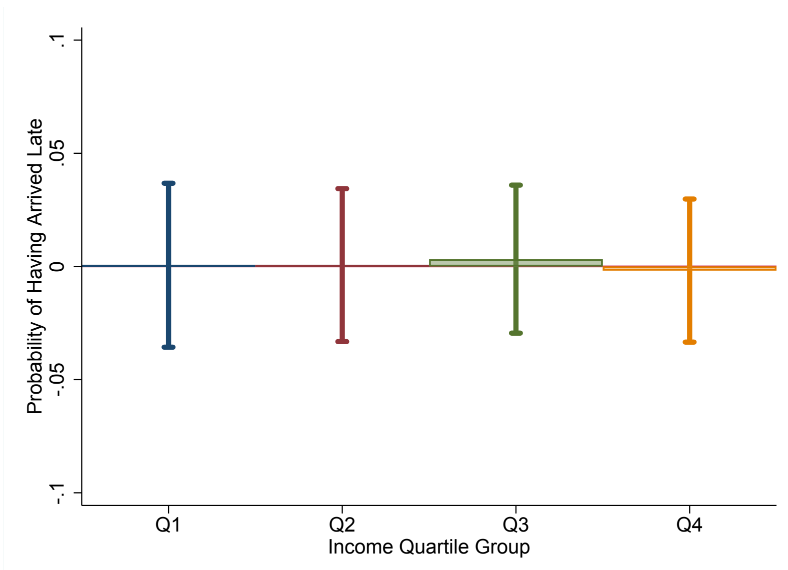
The figure estimates equation (3), but including as control an interaction between the digital switchover indicator and income quartiles, and using as dependent variable the probability of having ever drunk an alcoholic drink. I show the average marginal effects of television for the different income quartiles of the households where children live.

Figure 17: Impact on Probability of Having Ever Smoked



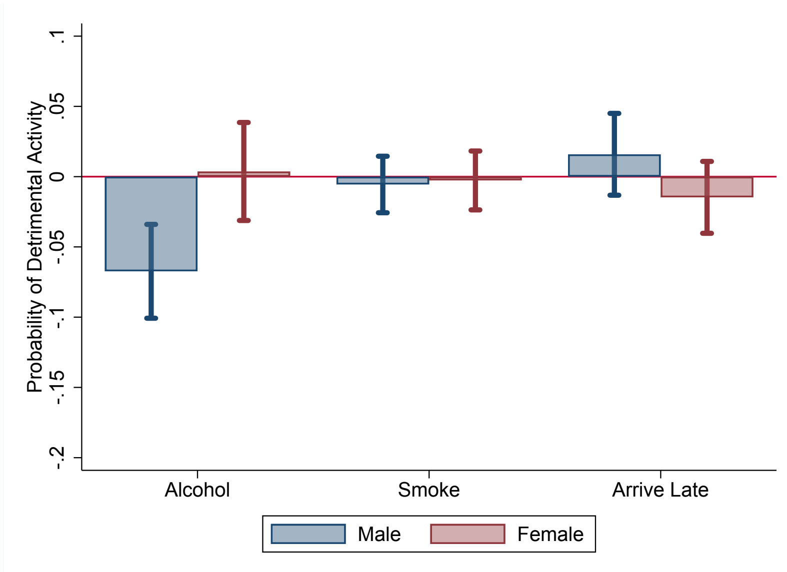
The figure estimates equation (3), but including as control an interaction between the digital switchover indicator and income quartiles, and using as dependent variable the probability of having ever smoked. I show the average marginal effects of television for the different income quartiles of the households where children live.

Figure 18: Impact on Probability of Having Arrived Home after 9pm



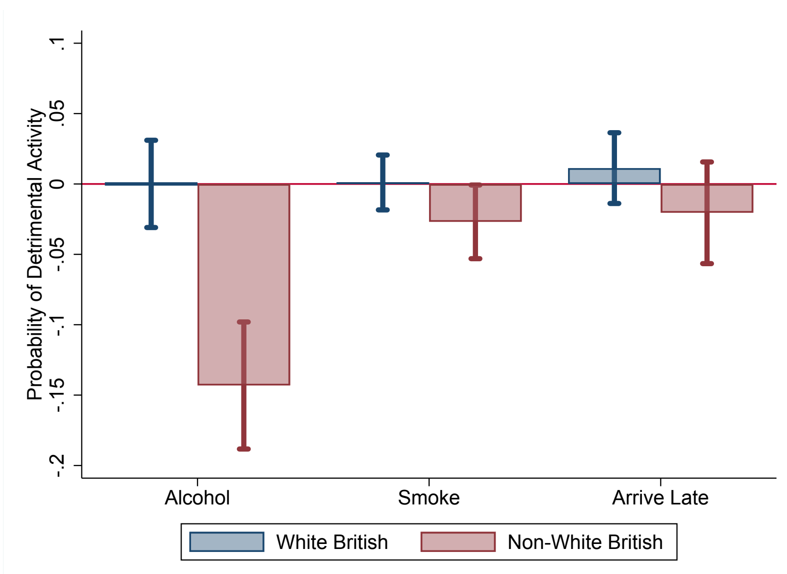
The figure estimates equation (3), but including as control an interaction between the digital switchover indicator and income quartiles, and using as dependent variable the probability of having arrived home after 9pm in the past month. I show the average marginal effects of television for the different income quartiles of the households where children live.

Figure 19: Impact on Probability of Detrimental Activity



The figure estimates equation (3), but including as control an interaction between the digital switchover dummy and gender. I respectively use as dependent variables the probability of having ever drunk an alcoholic drink, smoked, or arrived late at home in the last month. I show the average marginal effects of television for boys and girls.

Figure 20: Impact on Probability of Detrimental Activity



The figure estimates equation (3), but including as control an interaction between the digital switchover dummy and ethnicity. I respectively use as dependent variables the probability of having ever drunk an alcoholic drink, smoked, or arrived late at home in the last month. I show the average marginal effects of television for white British and non-white British children.

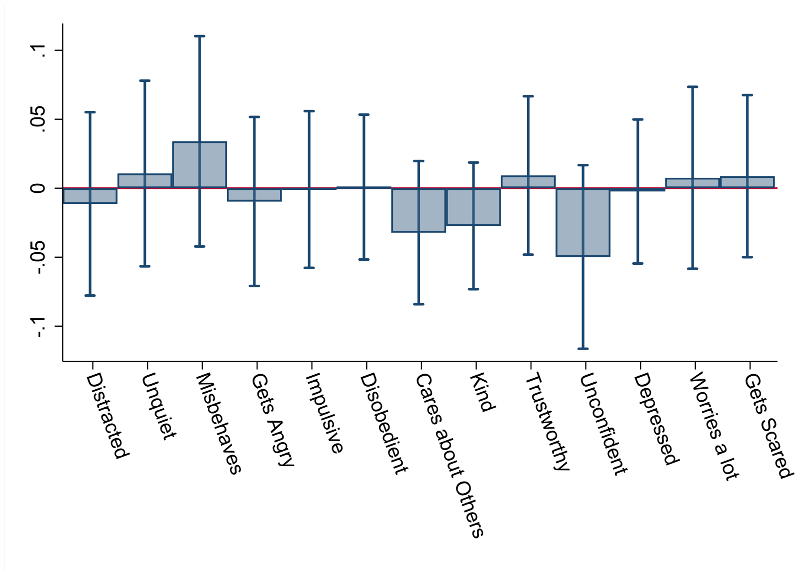
6.7 Exploring further Outcomes: Behaviour

This paper has shown that television has a positive impact on academic achievement and educational inequality. Moreover, I have found that television reduces the probability and frequency with which children get involved in detrimental out-of-school activities. I next explore whether the digital switchover also has an effect on the behaviour of children. To do so, I estimate specification (3), but using as dependent variable different measures of the behaviour and feelings of children. To simplify the analysis, I do not control for $DigitalTenure_{i,t}$. More specifically, I use as dependent variables the frequency with which, over the previous six months, a child: (i) got distracted, (ii) felt unquiet, (iii) misbehaved, (iv) got angry, (v) made decisions impulsively, (vi) was disobedient, (vii) cared about others, (viii) was kind, (ix) trustworthy, (x) unconfident, (xi) felt depressed, (xii) worried a lot, and (xiii) got scared. All these variables are measured with categorical scales that take three possible values: not true (0), somewhat true (1) and certainly true (2). As shown in Figure 21, no estimate is statistically significant at the 5% confidence level, indicating that the digital switchover has no impact on the behaviour of children.

7 Conclusions

This paper studies the effect of television on academic performance and time use. I provide causal estimates by using the British digital television switchover as a natural experiment. This process occurred during the period 2008-2012, and at different years for each of the TV transmitters. These are located in different regions in UK. Consequently, the timing of the switchover varied at the postcode unit level. The switchover was delegated to Ofcom and DigitalUK, whose goal was to implement the process on time attending to the physical characteristics of the TV transmitters. Therefore, it is unlikely that the switchover is correlated with unobserved characteristics that determine education or habits. Using a difference-in-difference approach, I firstly estimate whether television has an impact on academic performance. I then

Figure 21: Impact on Behaviour of Children



The figure estimates equation (3), but using as dependent variable different measures of the behaviour and feelings of children.

explore a plausible mechanism behind the estimates on education: whether television changes the time use of children.

I find that the digital switchover increases KS2 test scores by 0.028 standard deviations. However, it is important to bear in mind that the digital switchover raises television viewing time by 15.1%. Subsequently, the average television viewing time increases scores by 0.185 standard deviations. This contributes to human capital formation. Moreover, the effect is driven by schools at the bottom of the test score distribution, which reduces educational inequality. The estimates are robust across different samples and specifications.

My second set of resuts explore a plausible mechanism behind my estimates on education: the impact of television on time use. I show that television reduces the probability and the frequency with which children get involved in detrimental activities, such as alcohol drinking. Taken together, the results suggest that the effect of out-of-school activities on academic performance does not depend on their absolute educational value, but on their relative one.

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A Appendix

A.1 Mapping of Point Scores to Levels

Table A.1 presents a mapping between the point scores that students achieve at the Key Stage 2 exam and the levels to which these grades correspond. I collect this information from the UK Department of Education. Regarding the levels, letter "c" means that a child has scored at the lower end of the level, "b" means that the child is working comfortably at that level, and "a" means that the child's score is at the top end of the level. Column 3 of the Table describes what achieving a particular level means in terms of academic performance according to the UK Department of Education. As shown, having a point score of 23 or lower indicates a poor educational performance, and achieving a score of 37 or above reflects outstanding academic attainment.

Table A.1: Scores KS2 Test

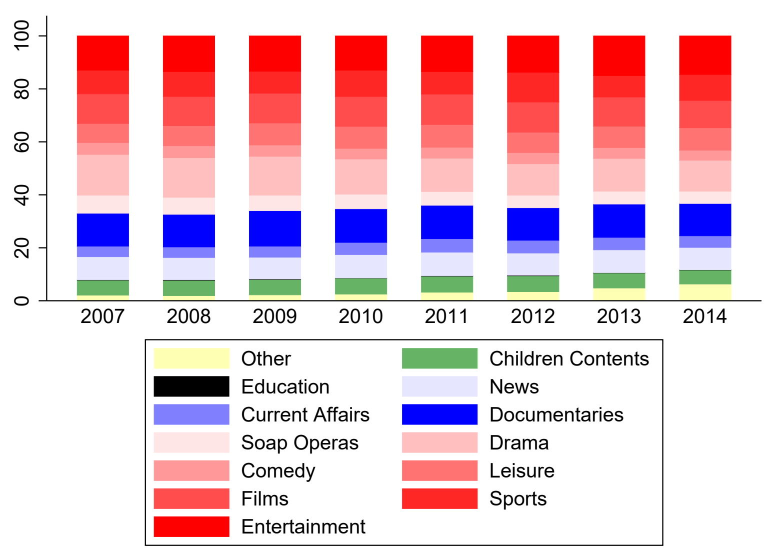
Level (1)	Point Score (2)	Description (3)
3a	23	Below Average
4c	25	About Average
4b	27	About Average
4a	29	Above National Average
5c	31	Above National Average
5b	33	Well Above National Average
5a	35	Well Above National Average
6c	37	Exceptional
6b	39	Exceptional

The Table maps the point scores of the Key Stage 2 exam with their respective academic levels, and with a brief description of what achieving these levels means.

A.2 Proportion of Television Viewing Time by Genre

Figure A.1 presents the proportion of the total television viewing time by genre. This Figure is similar than Figure 5, but presents a more disaggregated classification of the different television contents that are available. More specifically, I classify television contents in thirteen different groups: entertainment, sports, films, leisure, comedy, drama, soap operas, documentaries, current affairs, news, educational television programmes, children contents, and other. Similar to the main analysis, the latter category includes television channels such as music programmes. This classification allows me to further explore whether television contents changed as a response to the digital switchover process. The Figure suggests that this was not the case.

Figure A.1: Proportion of Television Viewing Time by Genre

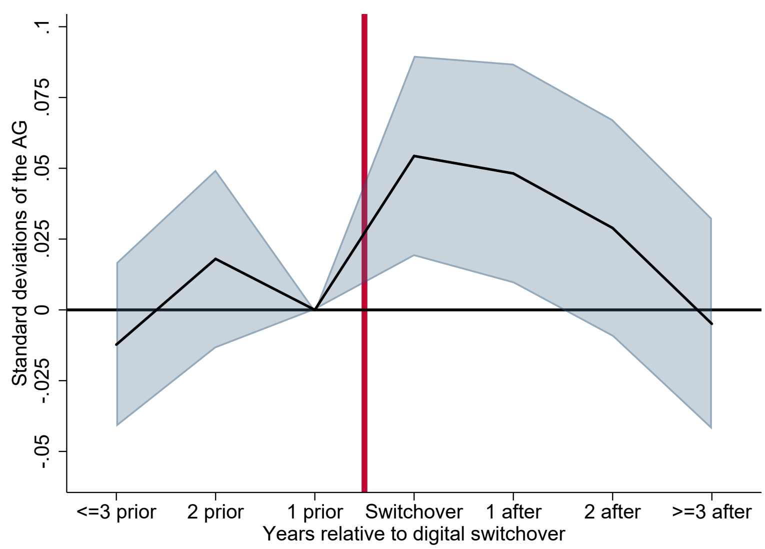


The figure presents the proportion of television viewing time by genre. I classify television contents in entertainment, sports, films, leisure, comedy, drama, soap operas, documentaries, current affairs, news, educational television programmes, children contents, and other.

A.3 Timing of the Effect of Television on Education

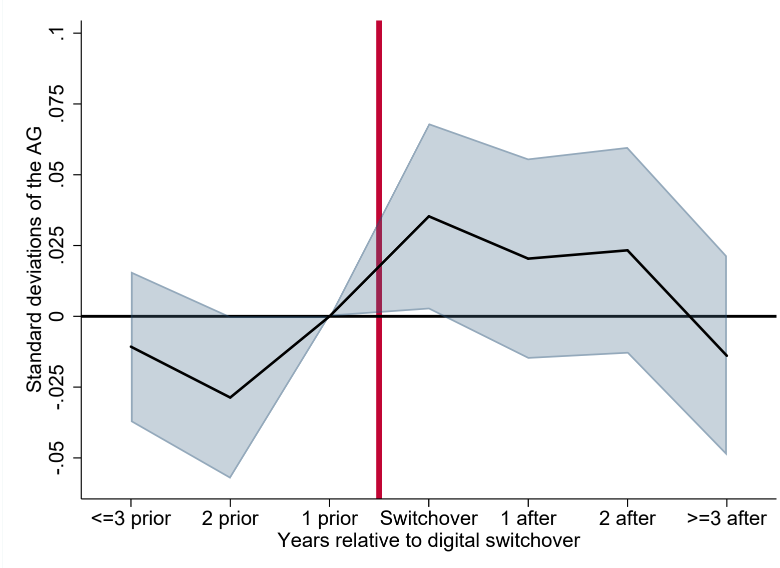
Figures A.2 - A.5 estimate the event approach specification (3) for each of the subsamples that I assigned attending to the position of schools in the score distribution of 2008. As previously explained, I select the grade distribution in 2008 because this is the year before the switchover process started. This subsection allows me to study whether there are differences in the dynamics of the impact of television on education depending on the performance of schools previous to the switchover. As shown, the estimates of the effect of the years previous to the digital switchover on academic scores are not statistically significant. The estimates become positive and significant in the years after the introduction of the digital television signal, and only for the schools that pertain to the first and second quartile of the score distribution in 2008. The switchover process has no impact on the academic scores of schools performing at the top of the score distribution in 2008. Similar to my baseline results, the estimates suggest that the impact of television on education is temporary.

Figure A.2: Dynamic Impact of Television on Education for the First Quartile



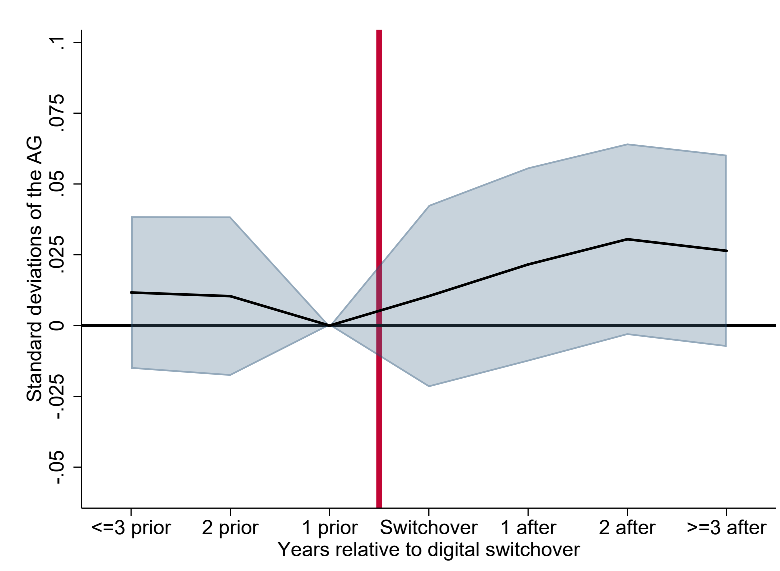
The figure estimates the event approach specification (2) for the first quartile of the score distribution in 2008, showing the dynamics of the effect of television on education.

Figure A.3: Dynamic Impact of Television on Education for the Second Quartile



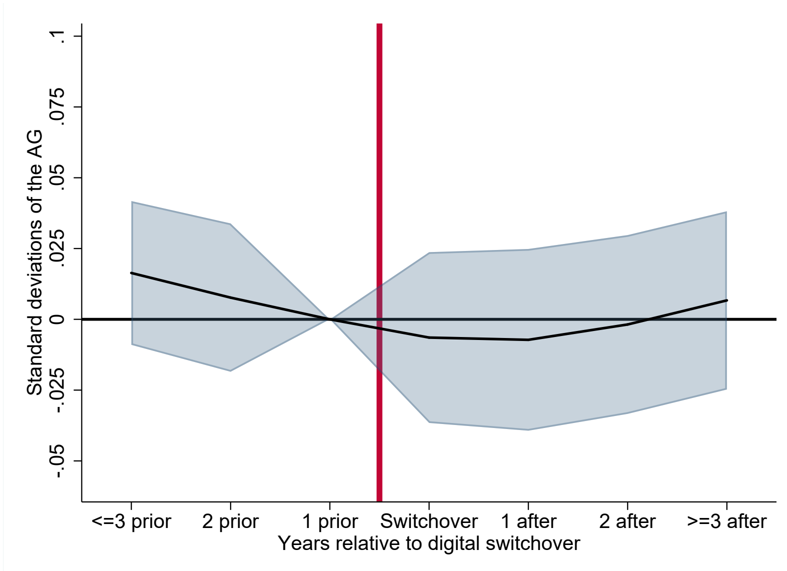
The figure estimates the event approach specification (2) for the second quartile of the score distribution in 2008, showing the dynamics of the effect of television on education.

Figure A.4: Dynamic Impact of Television on Education for the Third Quartile



The figure estimates the event approach specification (2) for the third quartile of the score distribution in 2008, showing the dynamics of the effect of television on education.

Figure A.5: Dynamic Impact of Television on Education for the Fourth Quartile



The figure estimates the event approach specification (2) for the fourth quartile of the score distribution in 2008, showing the dynamics of the effect of television on education.

A.4 Relationship between Predetermined Scores and Observable Characteristics

Table A.2 shows the summary statistics of the variables that I use in the heterogeneity analysis. I show their descriptive statistics for the whole sample and for each of the subsamples that I assigned attending to the position of schools in the score distribution of 2008. This helps to understand the similarity between the baseline estimates on educational inequality and the results obtained in the heterogeneity analysis. As shown in the Table, schools at the top of the score distribution have fewer economically disadvantaged students and are smaller in size. They also have a higher proportion of native students and are more likely to be religious. The proportion of students with special educational needs is independent of the position of schools in the score distribution of 2008.

Table A.2: Descriptive Statistics for Each Quartile

	Sample	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)	(5)
% disadvantaged students	0.27	0.45	0.30	0.20	0.13
	(0.21)	(0.20)	(0.19)	(0.16)	(0.12)
% native students	0.87	0.77	0.85	0.91	0.93
	(0.22)	(0.28)	(0.23)	(0.17)	(0.13)
% SEN students	0.02	0.03	0.02	0.02	0.02
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
N students	269.99	288.07	278.97	269.82	260.60
	(147.56)	(141.64)	(137.38)	(141.62)	(133.85)
% religious schools	0.38	0.22	0.34	0.41	0.52
	(0.48)	(0.41)	(0.48)	(0.49)	(0.50)
N	118,729	27,515	27,849	26,566	27,464

The Table displays the proportion of economically disadvantaged, native and SEN students for each of the subsamples that I assigned attending to the position of schools in the score distribution of 2008. The Table also shows the average number of students and the proportion of religious schools for each of the quartiles.

A.5 Impact on Dedication to School

This section tests an alternative mechanism behind my estimates on education, which is whether television increases the importance that children give to school, or the time they dedicate to homework. To do so, columns 1-6 of Table A.3 estimate my baseline specification respectively using as dependent variable: (i) a dummy that takes value 1 if the child wants to study after school and 0 otherwise, (ii) a dummy that takes value 1 if the child wants to go to University after school and 0 otherwise, (iii) a categorical variable that takes 4 possible values, where higher values indicate that child i gives more importance to grades, (iv) the number of evenings that child i does homework per week, (v) the number of hours that students dedicate to homework per week, and (vi) a categorical variable that contains information on the frequency with which child i uses computer for homework. As shown in Table A.3, the digital switchover has no effect on any of these variables, as the estimates are not statistically significant.

Table A.3: Impact on Dedication to School

	Study After School	University	GCSE Matters	Evenings Homework	Hours Homework	Freq PC Homework
Digital Switch	0.002	0.008	-0.010	0.116	-0.891	-0.002
	(0.014)	(0.008)	(0.016)	(0.113)	(1.166)	(0.056)
Time-varying covariates	Yes	Yes	Yes	Yes	Yes	Yes
Children FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,665	8,108	11,917	2,570	2,608	4,700

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

Standard Errors in parenthesis. I allow for an arbitrary correlation of standard errors at the regional and child level, as children may move across regions. The number of observations vary depending on the specification because sometimes information is missing depending on the dependent variable. I control for the following time-varying covariates: age, household income, whether the individual lives in a rural area, and the number of bedrooms, members, and children in the household.

A.6 Impact on Extra-curricular Activities

I next test whether the digital switchover has an impact on the time that children dedicate to extra-curricular activities. To do so, columns 1-4 of Table A.4 estimate my baseline specification respectively using as dependent variable: a dummy that indicates whether child i gets involved in (i) music, (ii) art, (iii) dancing or (iv) tutorials for school subjects, when s/he is not at school. Columns 5-7 respectively use as dependent variable the number of books that child i reads per week, and the frequency with which the child gets involved in sports and youth clubs. As shown, the digital switchover has no impact on the time that children dedicate to extra-curricular activities, as no estimate is statistically significant at the 5% confidence level.

Table A.4: Impact on Extra-curricular Activities

	Music	Art	Dance	Tutorial School	Read	Sport	Youth Club
Digital Switch	-0.039*	-0.007	-0.010	0.007	0.415	-0.023	0.179
	(0.024)	(0.020)	(0.023)	(0.018)	(0.550)	(0.056)	(0.129)
Time-varying covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Children FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,514	2,514	2,514	2,514	2,660	6,302	2,792

* p<0.10, ** p<0.05, *** p<0.01
Standard Errors in parenthesis. I allow for an arbitrary correlation of standard errors at the regional and child level, as children may move across regions. The number of observations vary depending on the specification because sometimes information is missing depending on the dependent variable. I control for the following time-varying covariates: age, household income, whether the individual lives in a rural area, and the number of bedrooms, members, and children in the household.

A.7 Impact on Social Media and Videogames

This section tests whether the digital switchover reduces the time that children dedicate to alternative leisure activities at home. More specifically, columns 1-6 of Table A.5 estimate my baseline specification respectively using as dependent variable: (i) a dummy that takes value 1 if child i belongs to a social website, (ii) the hours that child i spends chatting on social media, (iii) the probability of child i having played multiplayer games online, (iv) the frequency with which child i uses computer for videogames, (v) whether the child has a video game console at home, and (vi) the hours that the child spends playing video games per day. As shown in Table A.5, the digital switchover reduces the probability of children belonging to a social website and the time they spend chatting with friends on social media.

Table A.5: Impact on Extra-curricular Activities

	Belongs Social Website	Hours Chatting	Has Played Multiplayer Games	Frequency Use PC Games	Has Game Console	Hours Video-games
Digital Switch	-0.025*	-0.093***	0.009	-0.049	-0.006	0.017
	(0.014)	(0.034)	(0.030)	(0.047)	(0.011)	(0.044)
Time-varying covariates	Yes	Yes	Yes	Yes	Yes	Yes
Children FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,172	8,389	2,706	4,698	4,976	4,497

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

Standard Errors in parenthesis. I allow for an arbitrary correlation of standard errors at the regional and child level, as children may move across regions. The number of observations vary depending on the specification because sometimes information is missing depending on the dependent variable. I control for the following time-varying covariates: age, household income, whether the individual lives in a rural area, and the number of bedrooms, members, and children in the household.

A.8 Combined Bad Activities as Dependent Variable

This section studies whether the digital switchover has an impact on the probability and frequency with which children get involved in detrimental activities, after combining all the bad activities into a unique variable. Column 1 uses as dependent variable a dummy that takes value 1 if child i has ever drunk alcohol, smoked or arrived late at home in the last month. Column 2 uses as dependent variable the sum of the frequencies with which child i has drunk alcohol, smoked or arrived late at home in the past month. As shown, the estimates of the digital switchover are negative but not statistically significant. Albeit the digital switchover reduced the probability and the frequency with which children drink alcohol, it might be difficult for the model to find this effect after I combine this activity with other detrimental habits for which television has no effect. Another possibility is that different children get involved in distinct detrimental activities.

Table A.6: Combined Bad Activities as Dependent Variable

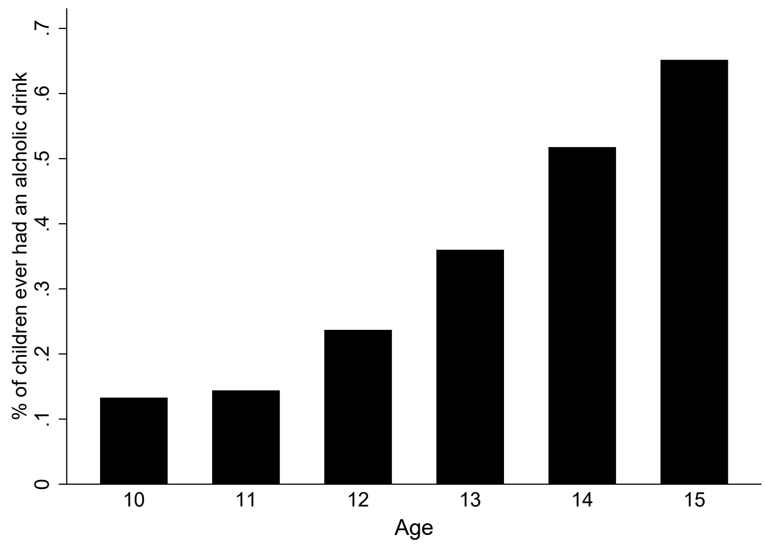
	Prob Bad Activity	Freq Bad Activity
Digital Switch	-0.036	-0.055
	(0.022)	(0.037)
Time-varying covariates	Yes	Yes
Children FE	Yes	Yes
Observations	12,030	11,725

* p<0.10, ** p<0.05, *** p<0.01
Standard Errors in parenthesis. I allow for an arbitrary correlation of standard errors at the regional and child level, as children may move across regions. The number of observations vary depending on the specification because sometimes information is missing depending on the dependent variable. I control for the following time-varying covariates: age, household income, whether the individual lives in a rural area, and the number of bedrooms, members, and children in the household.

A.9 Children and Harmful Activities at Age 10-11

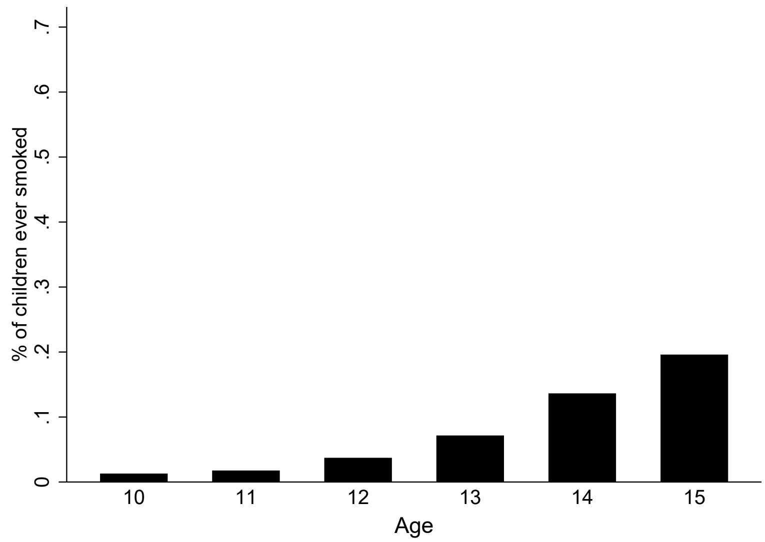
As shown in Figures A.6-A.8, children aged 10-11 are likely to have ever drunk alcohol, smoked, or arrived late at home in the past month. The probability of getting involved in this type of activities increases as children get older.

Figure A.6: Probability of Having Ever Drunk Alcohol



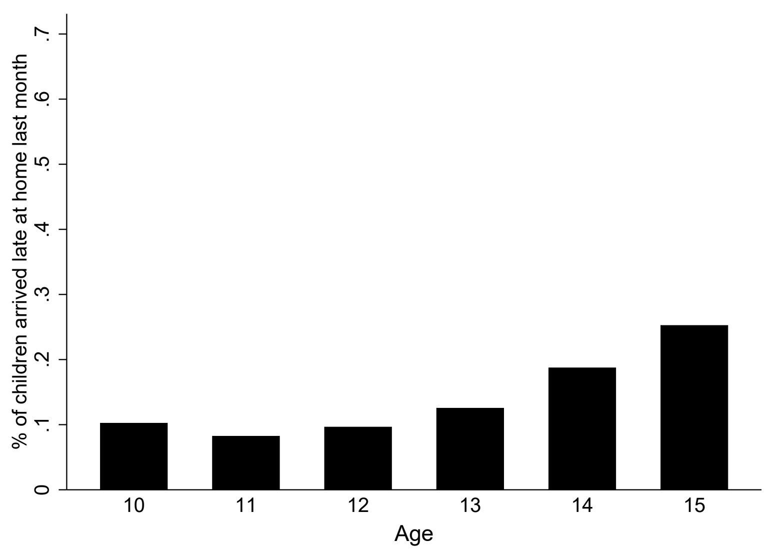
The figure shows the probability of children having ever drunk alcohol at different ages. I select the age range 10-15 as this is the age range of my sample.

Figure A.7: Probability of Having Ever Smoked



The figure shows the probability of children having ever smoked at different ages. I select the age range 10-15 as this is the age range of my sample.

Figure A.8: Probability of Having Arrived Late Last Month

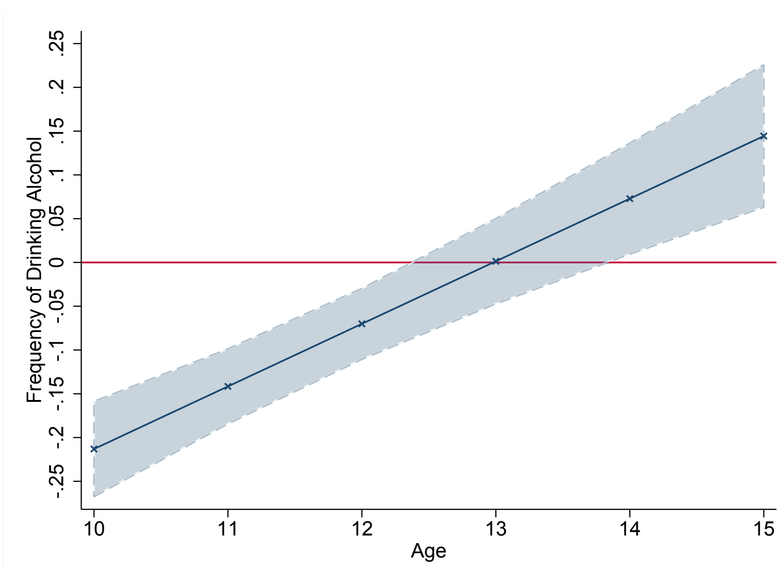


The figure shows the probability of children having arrived after 9pm at home in the past month at different ages. I select the age range 10-15 as this is the age range of my sample.

A.10 Heterogeneity in Age Using Frequencies as Dependent Variables

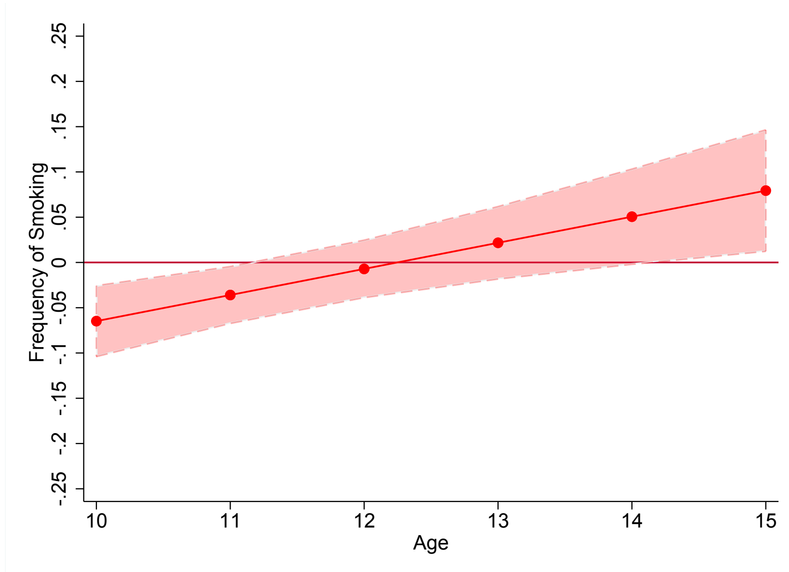
This section studies whether the impact of television on the frequency with which children get involved in detrimental activities is heterogenous in age. To do so, I estimate a model similar to (3), but controlling for an interaction between the switchover covariate and age. Figures A.9 - A.11 present the average marginal effects of the switchover process for the different ages of children, respectively using as dependent variable the frequency with which children drink alcohol, smoke, or arrive late at home. As shown, the digital switchover reduces all these frequencies when children are younger, and the estimates are significant at the 5% confidence level. The estimates of the digital switchover become positive when children are older, and these are also statistically significant.

Figure A.9: Impact on Frequency of Drinking Alcohol



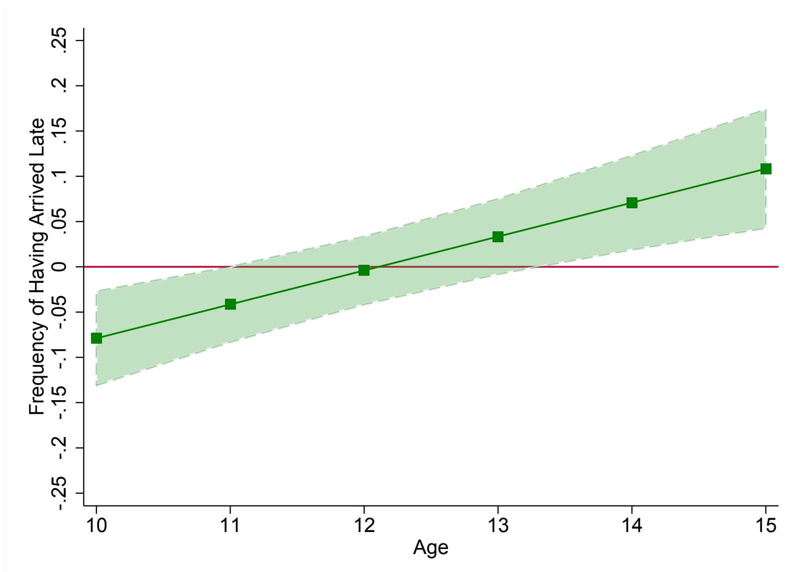
The figure estimates equation (3), but including as control an interaction between the digital switchover dummy and age. I use as dependent variable the frequency of drinking alcohol. I show the average marginal effects of television for the different ages of children.

Figure A.10: Impact on Frequency of Smoking



The figure estimates equation (3), but including as control an interaction between the digital switchover dummy and age. I use as dependent variable the frequency of smoking. I show the average marginal effects of television for the different ages of children.

Figure A.11: Impact on Frequency of Arriving after 9pm

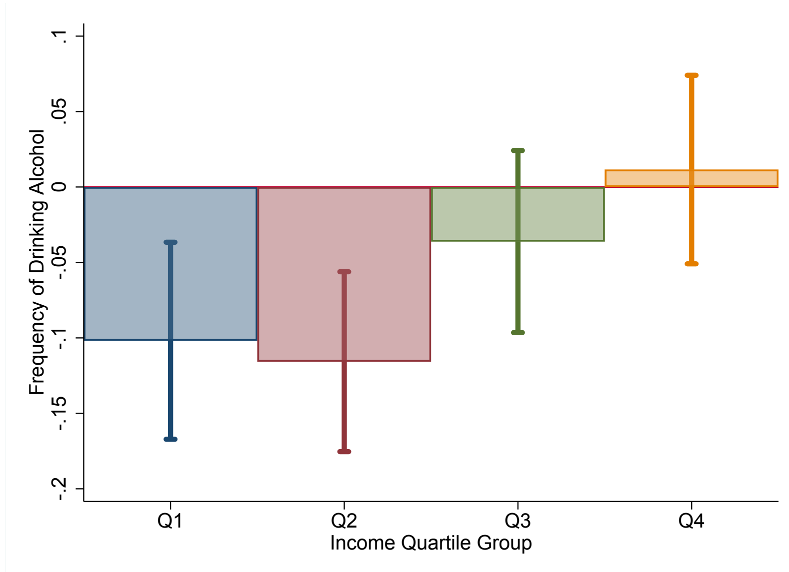


The figure estimates equation (3), but including as control an interaction between the digital switchover dummy and age. I use as dependent variable the frequency of arriving late at home in the last month. I show the average marginal effects of television for the different ages of children.

A.11 Heterogeneity in Income Using Frequencies as Dependent Variables

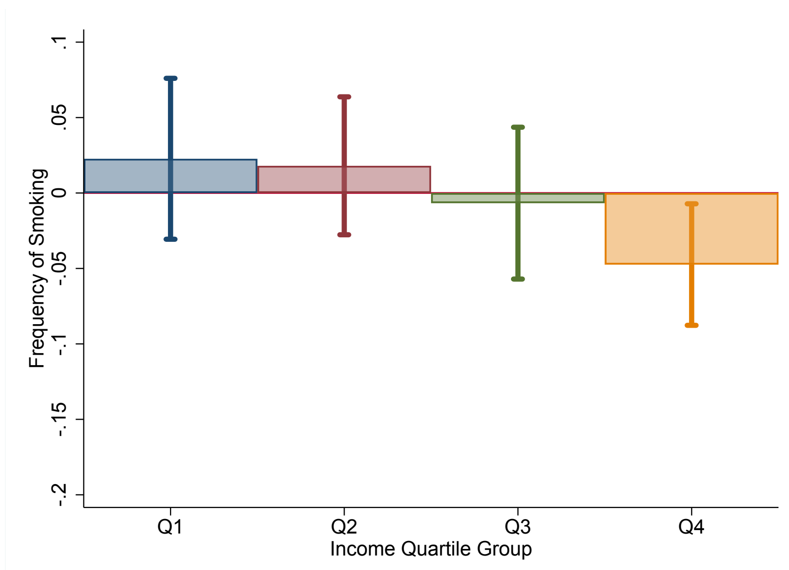
This section explores whether the effect of the digital switchover on the frequency with which children get involved in detrimental activities is heterogeneous in income. For this, I assign children in quartiles attending to their household income, and estimate a specification analogous to (3), where I also control for an interaction between the switchover indicator and the income quartiles. Figures A.12 - A.14 show the average marginal effects of television for the different income quartiles, respectively using as dependent variable the frequency with which children drink alcohol, smoke, or arrive late at home. First, I find that the digital switchover only reduces the frequency with which children drink alcohol when they have a poorer socioeconomic background. The estimates are significant at the 1% confidence level. Second, I show that the impact of television on the frequency with which children smoke is only negative when they live in richer households. The estimate is significant at the 5% confidence level for the fourth quartile of the income distribution. Finally, I show that television has no effect on the frequency with which children arrive late at home for any of the income quartiles.

Figure A.12: Impact on Frequency of Drinking Alcohol



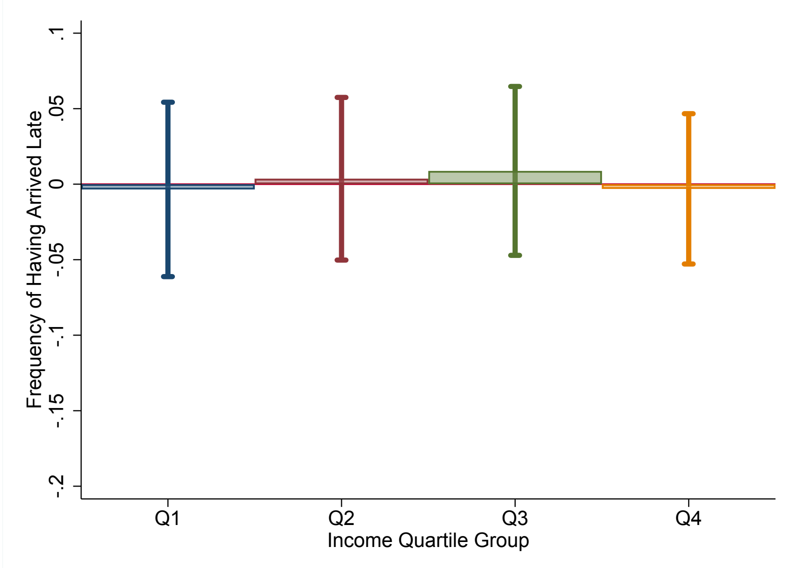
The figure estimates equation (3), but including as control an interaction between the digital switchover indicator and income quartiles, and using as dependent variable the frequency with which children drink alcohol. I show the average marginal effects of television for the different income quartiles of the households where children live.

Figure A.13: Impact on Frequency of Smoking



The figure estimates equation (3), but including as control an interaction between the digital switchover indicator and income quartiles, and using as dependent variable the frequency with which children smoke. I show the average marginal effects of television for the different income quartiles of the households where children live.

Figure A.14: Impact on Frequency of Arriving Late at Home

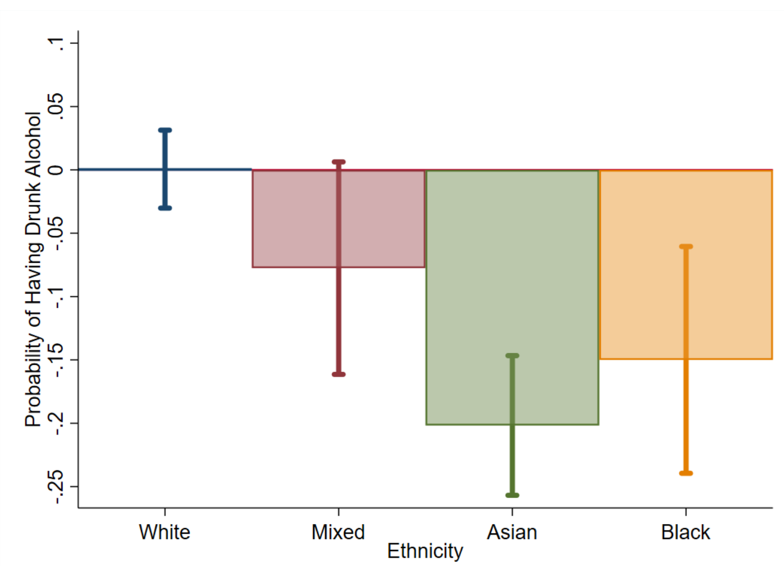


The figure estimates equation (3), but including as control an interaction between the digital switchover indicator and income quartiles, and using as dependent variable the frequency with which children arrived late at home in the last month. I show the average marginal effects of television for the different income quartiles of the households where children live.

A.12 Heterogeneity in Ethnicity

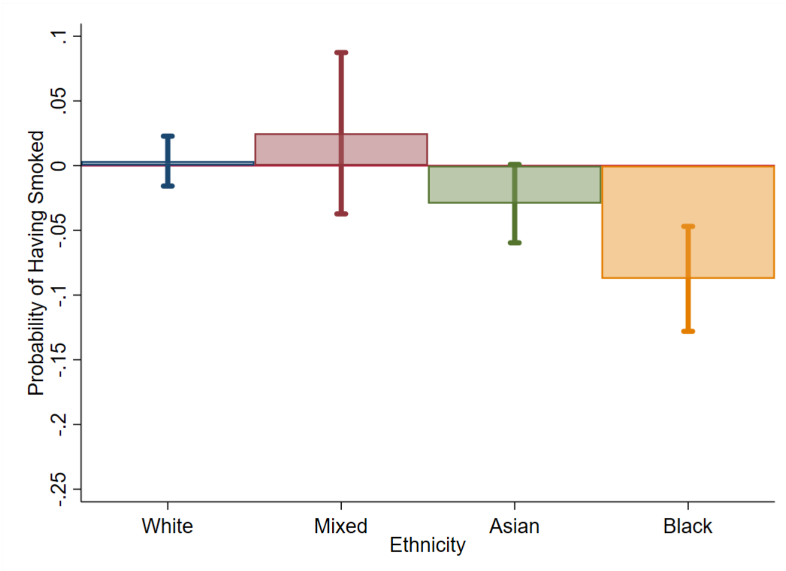
This section further explores whether the impact of the digital switchover on the probability of getting involved in detrimental activities is heterogeneous in ethnicity. To do so, I first assign children into four groups: (i) white, (ii) mixed, (iii) asian and (iv) black. I then estimate my baseline specification but controlling for an interaction between the digital switchover variable and a set of dummies that indicate whether the child pertain to any of the previous four groups. Figures A.15-Figures A.17 respectively show the estimates when I use as dependent variable the probability of having drunk alcohol, smoked or arrived late at home in the last month. As shown, the effect of television on time use is driven by asian and black children.

Figure A.15: Impact on Probability of Having Drunk Alcohol



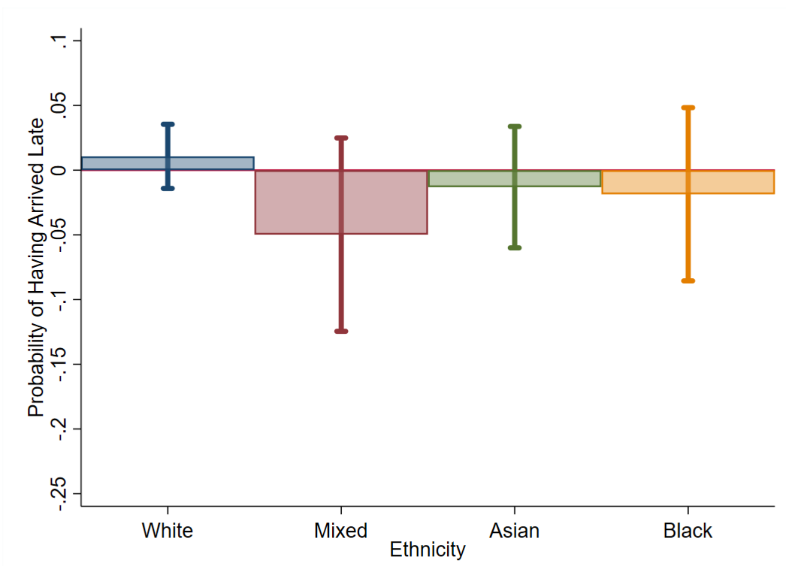
The figure estimates equation (3), but including as control an interaction between the digital switchover indicator and a set of dummies for the ethnicity of children. I use as dependent variable the probability of children having drunk alcohol. I show the average marginal effects of television for the different ethnicities.

Figure A.16: Impact on Probability of Having Smoked



The figure estimates equation (3), but including as control an interaction between the digital switchover indicator and a set of dummies for the ethnicity of children. I use as dependent variable the probability of children having drunk alcohol. I show the average marginal effects of television for the different ethnicities.

Figure A.17: Impact on Probability of Having Arrived Late at Home



The figure estimates equation (3), but including as control an interaction between the digital switchover indicator and a set of dummies for the ethnicity of children. I use as dependent variable the probability of children having drunk alcohol. I show the average marginal effects of television for the different ethnicities.