Education and Pro-environmental Attitudes and Behaviours: A Nonparametric Regression Discontinuity Analysis of a Major Schooling Reform in England and Wales

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Abstract

There is a widespread belief that a lack of education contributes to public apathy to climate change. Yet, despite the global campaign to promote education as a tool to combat global warming, empirical evidence on the causal effect of education on climate literacy and pro-environmental behaviours remains scarce. Using the raising of the minimum school leaving age law in England from 15 to 16 years of age in September 1972 as a natural experiment, we show that remaining in school as a result of the reform causally reduces people's unwillingness to change their behaviours for the environment and their perception that climate change is too far in the future to worry. However, we find little evidence that more education improves the pro-environmental behaviours of those who were affected by the reform. This raises an important question of whether policies aimed at improving climate change awareness through education can effectively produce long-lasting changes in pro-environmental behaviours.

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1. Introduction

Consistent with Gary Becker's (1964) theory of human capital, in which individuals invest time and money to acquire education in the hope to increase lifetime wealth, many writings in economics have empirically demonstrated that there are substantial financial payoffs to schooling (e.g., Harmon & Walker, 1995; Oreopoulos, 2006; Card, 2001; Trostel et al., 2002). Given that the empirical findings on the financial returns to education are now reasonably well-established, researchers have since moved on to investigate what else schooling does other than enhancing our economic well-being. Consequently, this has led to a growing number of studies showing education to have a causal effect on nonpecuniary outcomes, including a person's physical health (Powdthavee, 2010; Clark & Royer, 2013), their propensity to get a divorce (Oreopoulos & Salvanes, 2011), and their likelihood to vote (Milligan et al., 2004).[2] Thus, these findings suggest that there may be more to schooling than merely a means to increase a person's lifetime income and consumption.

One question of interest is whether more schooling also improves climate change literacy and pro-environmental attitudes and behaviours later on in life. At present, virtually all studies that investigated the link between education and climate literacy, as well as pro-environmental behaviours, were either correlational (see, e.g., Torgler & Garcia-Valiñas, 2007; McCright & Dunlap, 2011; Kahan et al., 2012; Lee et al., 2015) or small-scale experiments that focused on the impact of specially designed education about the causes and consequences of global warming on public understanding of climate change risks of a nonrepresentative sample (Ranney & Clark, 2016; Rumore et al., 2016)[3]. Hence, it remains inconclusive whether

[2] For a comprehensive review of the nonpecuniary returns to education literature, see Oreopoulos and Salvanes (2011).

[3] The findings so far have also been mixed, with many studies reporting a positive association between education and climate change related outcomes (e.g., Callan & Thomas, 2006; Torgler& Garcia-Valiñas, 2007; De Silva & Pownall, 2014) and a few finding the association to be either statistically insignificantly different from zero or negative (e.g., Johnston, 2001; Ek & Soderholm, 2008). Such an apparent divide in the research findings

differences in climate literacy across education groups are the direct result of education affecting people's attitudes towards climate change, or whether these differences are due to other factors that may or may not be directly observable such as differences in early life experiences, family background, political ideologies, and inborn predispositions.

The current study contributes to the literature by using the nationally representative data to estimate the effect of the raising of the minimum school leaving age from 15 to 16 years of age in September 1972 on climate change awareness and pro-environmental behaviours of over 22,000 England- and Wales-born citizens. By applying a nonparametric robust regression discontinuity design (RDD) on the principal components of climate change literacy and pro-environmental behaviours, we find some evidence of a significant education reform effect on specific dimensions of climate change literacy. More specifically, we demonstrate that the introduction of the 1972 compulsory schooling law lowers the principal component that is mainly defined by people's unwillingness to make a behavioural change to save the environment and their perception that climate change is too far in the future to worry. However, there is little evidence that the reform shifted people's beliefs about the causes of global warming and whether the world will soon experience a major environmental disaster. We also find no evidence to suggest that people who were randomly assigned an extra year of education behaved significantly more pro-environmentally friendly, on average.

The paper is structured as follows. Section 2 discusses the background literature and the conceptual framework of this study. Section 3 describes the data, and Section 4 discusses he empirical strategy. Results are laid out and discussed in Section 5. Section 6 concludes.

2. Background literature and conceptual framework

highlights the possibility that there are potentially many confounders in the observed relationship between education and climate change related outcomes.

The early human capital investment models often treat schooling as a black box where individuals use to convert time and money into knowledge-based skills – i.e., skills that enable engineers to build bridges and medical doctors to treat the sick – highly valued in the labour market (see, e.g., Becker, 1964; Ben-Porath, 1967; Mincer, 1974). However, subsequent studies have shown that there are also nonknowledge-based or non-cognitive skills that individuals might even pick up from school, perhaps through different schooling activities as well as interactions with teachers and peers (Oreopoulos & Salvanes, 2011). These include, for example, critical thinking and social skills that have been shown in the literature to correlate strongly and positively with more years of schooling (Soskice, 1993; Cascio & Lewis, 2006; Glaeser et al., 2007). A few studies have even gone further to show that education has a causal effect on some of these nonknowledge-based skills (see, e.g., Dahmann & Anger, 2014).

According to Michael Grossman (2006), skills that individuals learned from school – though he did not explicitly distinguish between knowledge-based and nonknowledge-based skills in his model – enable them to not only become more efficient in carrying out their tasks but also make better decisions than people without the skills in similar situations. Given that this knowledge capital is embedded within the individual and accompanies them wherever they go, Grossman (2006) concluded that it should be of no surprise why these skills will also influence decisions individuals make outside the labour market as well. Grossman's theory of productive and allocative efficiency is often used in the health economics literature to explain why individuals with more schooling tend to have better health-related behaviours (Wagstaff, 1993; Li & Powdthavee, 2015) and can process health information faster and provide more pronounce responses than those with less schooling (Kenkel, 1991; Glied & Lleras-Muney, 2008).

More relevant to this study is the hypothesis that more schooling can also equip individuals with skills to process the information on climate change better and faster than those

with fewer years of education, which would explain why there is a strong positive correlation between educational attainment and climate change awareness across the world (Lee et al., 2015). Yet, despite the empirically clear correlation between schooling and climate change literacy, the causal relationship between the two remains imperfectly understood. There may be, for example, omitted variables such as innate ability (Card, 2001), heritable endowments (Behrman & Rosenzweig, 2002), and time-preference (Fuch, 1982) that explain why some individuals excel at school and, at the same time, are more likely than others to sought out climate change information outside the classroom. One could imagine, for example, that more future-oriented individuals (i.e., those who desire better air quality in older ages) will stay in school for longer as well as have better knowledge about climate change.

To test whether education increases climate change awareness that could, in turn, lead to behavioural change, we need more evidence from large-scale studies that randomly assign children with different levels of education in a model where climate change literacy is an outcome variable. However, to randomly deprive some children of schooling would be highly unethical. As a result, previous attempts at identifying the causal effects of education on a range of outcomes have mainly dealt with the endogeneity issue using either the instrumental variables (IV) method or the quasi-experimental approach. Examples of IV for schooling include the student's state of residence in childhood (Leigh & Dhir, 1997), distance from home to college (Card, 1995), and regional spending on education in regions where the individual was still a student (Berger & Leigh, 1989). However, it is likely that many of these IVs used in the return to schooling literature only affected a small fraction of the general population, which means that the estimated educational effects are merely approximations of the average treatment effects among a small group of people exposed to the instruments (Card, 2001).

More recently, economists have turned to large-scale 'natural' experiments that randomly forced a significant fraction of the general population to remain in school for longer

than they would have otherwise chosen to identify the effects of education on an outcome of interest (Rosenzweig & Wolpin, 2000; Angrist & Krueger, 2001). One of the most widely used natural experiments on education in the economics literature is the raising of the minimum school leaving age laws that affected all children in England and Wales who were born after a specified cut-off date.

Many studies in economics have exploited the education reforms to study the causal effect of education on a variety of outcomes that included, for example, income (Harmon & Walker, 1995; Oreopoulos, 2006), health (Powdthavee, 2010; Clark & Royer, 2013; Davies et al., 2018), civic engagement (Milligan et al., 2004), and happiness (Oreopoulos, 2007). However, empirical evidence on the causal effect of education reform on climate change literacy and pro-environmental behaviours remains scarce. A few notable exceptions are the works by Meyer (2015) and Chankrajang and Muttarak (2017). Using changes in compulsory schooling laws in 20th century Europe in a fuzzy RDD setting, Meyer (2015) found evidence that education causally increased the probability that an individual uses environmentally friendly travel, reduces disposables, recycles, reduces energy consumption, purchases environmentally friendly labelled products and local items, and reduces car usage. Using a different education reform – i.e. the exogenous variation in the supply of state primary schooling – in Thailand as an IV, Chankrajang and Muttarak (2017) showed that education causally improved the probability of taking knowledge-based environmentally actions such as using cloth bags instead of plastic bags and using energy-saving light bulbs, but not cost-saving pro-environmental activities such as unplugging electrical devices when not in use and turning off the tap while brushing teeth or taking a shower. They also found little evidence that education causally increased people's level of concern about global warming or their willingness to pay for environmental tax. But currently, the economics literature is small, and

the econometric evidence on the effect of education on climate change awareness and pro-environmental behaviours continues to be scarce.

To identify the causal effect of compulsory schooling on climate change literacy and pro-environmental behaviours, the current study exploits the minimum school leaving age in England and Wales in 1972. Since the end of World War II, the compulsory schooling age in England and Wales has been raised on two different occasions. The 1944 Education Act first raised the school leaving age from 14 to 15 in April 1947, and then again from 15 to 16 in September 1972. The 1947 raising of the school leaving age (or ROSLA) had been remarkably successful at getting potential leavers to remain in school for at least one more year; one estimate shows that within two years of this policy change, the portion of 14-year-olds leaving school fell from 57 percent to less than 10 percent (Oreopoulos, 2006).

The second ROSLA legislation, which was implemented in September 1972, was also effective at raising compulsory schooling from 15 to 16: within one year of this policy change, the portion of 15-years-old leaving school fell from 35 percent to less than 10 percent. The 1947 change meant that students could not leave school until part way through grade nine, whilst the 1972 change meant that students could not leave school until part way through grade ten.

Ideally, we would have liked to study the effect of both changes in the school leaving age on climate literacy and pro-environmental behaviours. However, as outlined below in the following section, this is not possible to do so because of the small number of observations that we have of the people who were born before and after the first ROSLA's cut-off date (April 1933). As a result, we will be focusing in this paper on the 1972 legislation of raising the school leaving age from 15 to 16 years of age.[4]

[4] There was no introduction of any environmental content into the National curriculum around the time of the 1972 reform. Climate change was included for the first time in the science element of the curriculum in 1989 for students studying key stage 4 (14-16 years old); see https://www.whatdotheyknow.com/request/first_introduction_of_the_subjec (last accessed 17th September

3. Data

3.1. The Understanding Society (UKHLS)

The data set used in this study is the so-called 'Understanding Society' UKHLS (the annual, nationally representative United Kingdom Household Longitudinal Survey), which is explained at, and is downloadable from, site https://www.understandingsociety.ac.uk. In Wave 4, which was conducted between 2012 and 2014, the survey participants completed self-report questionnaires on climate change literacy and pro-environmental behaviours. The full sample size exceeds 30,000 randomly selected individuals.

We restrict the sample to consist only of those participants who were born in England and Wales between 1930 and 1990.[5] Birth month variable, which requires a special license from the data provider, was also obtained and merged into the main UKHLS data set to create the 'quarter of birth' running variable in the regression discontinuity design.[6]

Education variables. *Age left full-time education*. The participants were asked about their school leaving age (*scend*), which ranged from 10 years old to 23 years old (*Mean* = 16.31, *S.D.* = 1.27). *Remained in school after 15 years of age*. Responses to the school leaving age question were used to generate a binary variable that takes a value of 1 if the participant left school after 15 years of age and 0 otherwise. *Having completed at least one secondary education qualification*. Using the highest completed qualification variable (*qfhigh_dv*), the

2020). Future research may want to return to investigate the effect of environmentally focused education on climate change awareness and pro-environmental behaviours.

[5] One reason for this is because many people who were born after 1990 had not yet completed their schooling in the year of the survey. Nevertheless, qualitatively similar results are obtained when we use the entire UKHLS sample. The results are available upon request.

[6] It is also possible to use 'month of birth' instead of 'quarter of birth' as the running variable in the RDD design. However, while we were not able to reject the null hypothesis of no discontinuity in density when the quarter of birth variable is the running variable (p-value=0.128), there is some evidence of a density discontinuity at the threshold for the month of birth variable (p-value=0.000). While there is unlikely to be a systematic manipulation of the running variable here (McCrary, 2008), the manipulation test suggests the quarter of birth variable is a more preferable running variable than the month of birth variable. See Figures 1A in the Appendix for the plots of density function before and after the threshold.

binary variable was generated to have a value of 1 if the participant has completed at least a secondary education qualification (GCSE/CSE/O-level) and 0 otherwise.

Outcomes. There are two broad types of climate-related variables in the UKHLS data. They are (i) climate change literacy, which reflect individual's knowledge, awareness, and attitudes towards climate change, and (ii) pro-environmental behaviours, which reflect real behaviours related to preserving the environment. We will be analysing each type separately.

Climate change literacy. The participants were asked to self-rate whether they agree or disagree with seven climate change statements that include (1) "Behaviour contributes to climate change" (*scenv_bccc*), (2) "Climate change is beyond control" (*scenv_tlat*), (3) "Climate change is too far in the future to worry" (*scenv_nowo*), (4) "Not worth making changes if others don't" (*scenv_noot*), (5) "Not worth UK making changes" (*scenv_canc*), (6) "Environmental crisis has been exaggerated" (*scenv_crex*), and (7) "Soon experience major environmental disaster" (*scenv_meds*). Possible responses for statements (1) to (7) range from "1. Strongly disagree" to "5. Strongly agree". All climate change literacy outcomes were standardised to have a mean of zero and a standard deviation of 1.

The participants were asked to rate whether they agree or disagree with four attitudes towards pro-environmental lifestyle statements. They are (1) "Being green is an alternative lifestyle" (*scenv_grn*), (2) "Pay more for environmentally friendly products" (*scenv_pmep*), (3) "Current lifestyle is environment friendly" (*scenv_crlf*), (4) "How I feel about current lifestyle and the environment" (*scenv_ftst*), and (5) "Changes to help environment need to fit with lifestyle" (*scenv_fitl*). Possible responses for statements (1) to (3) range from "1. Strongly disagree" to "5. Strongly agree", while for statement (4) range from "1. Likes to do a lot more" to "3. Happy with what I do".

Pro-environmental behaviours. The participants were also asked to self-complete how often they engage in each of the eleven pro-environmental behaviours (*envhabit1*, …,

envhabit9). They are (1) "Leave your TV on standby at night", (2) "Switch off lights in rooms that aren't being used", (3) "Keep the tap running while you brush your teeth", (4) "Put more clothes on when rather than turning on the heater", (5) "Not buying something because of too much packaging", (6) "Buy recycled paper products such as toilet paper or tissues", (7) "Take your own shopping bag when shopping", (8) "Use public transport rather than travel by car", and (9) "Walk or cycle for short journeys less than 2-3 miles". Possible responses to these statements range from "1. Never" to "5. Always". All outcome variables were standardised to have a mean of zero and a standard deviation of 1. We report in Table 1A of the Appendix the descriptive statistics of all outcome variables used in this study for people who left school before 15 years of age and those remained in school after 15 years of age.

3.2. Generating outcome variables using Principal Component Analysis

Given that there are twelve attitudes towards climate change variables and nine pro-environmental behaviours variables that are likely to share common variance, we perform a principal component analysis (PCA) to reduce the dimension of variables in each group for our RDD design. A detailed information on the PCA results can be found in Tables 2A and 3A in the Appendix.

Following Kaiser's (1960) recommendation, we retain three principal components of climate change literacy, and four components of pro-environmental behaviours that have eigenvectors greater than one; see Figures 2A and 3A in the Appendix.

For the attitudes towards climate change components, the first principal component is mostly defined by the following four variables: "Not worth UK making changes" (*scenv_canc*), "Climate change is too far in the future to worry" (*scenv_nowo*), "Not worth making changes if others don't" (*scenv_noot*), and "Environmental crisis has been exaggerated" (*scenv_crex*). This first component, which explains around 30% of the variance, can perhaps be viewed as a

measure of how much people are aware that behavioural change is important for the environment.

The second principal component is mainly defined by "Soon experience major environmental disaster" (*scenv_meds*), "Behaviour contributes to climate change" (*scenv_bccc*), "Pay more for environmentally friendly products" (*scenv_pmep*), and "Climate change is beyond control" (*scenv_tlat*). This second component, which accounts for 12% of the variance, can probably be viewed as a measure of the beliefs that a major environmental disaster is imminent because of climate change.

Finally, the third principal component is defined mainly by "Current lifestyle is environment friendly" (*scenv_crlf*) and "How I feel about current lifestyle and the environment" (*scenv_ftst*). This third component, which explains around 9% of the variance, can be viewed as a measure of how much lifestyles influence climate change. There were two variables – "Changes to help environment need to fit with lifestyle" (*scenv_fitl*) and "Being green is an alternative lifestyle" (*scenv_grn*) – that remained relatively unexplained in the PCA model.

With respect to pro-environmental behaviours, the first principal component is defined mostly by the following variables: "Not buying something because of too much packaging" (*envhabit5*), "Buy recycled paper products such as toilet paper or tissues" (*envhabit6*), and "Take your own shopping bag when shopping" (*envhabit7*). This first component, which accounts for 21% of the variance, can perhaps be viewed as a measure of pro-environmental behaviours related to packaging.

The second principal component is defined mainly by "Use public transport rather than travel by car" (*envhabit8*) and "Walk or cycle for short journeys less than 2-3 miles" (*envhabit9*). This second component, which accounts for 13% of the variance, can be viewed as a measure of pro-environmental behaviours related to transportation.

The third principal component, which accounts for 12% of the variance, is similar to the first component as it is mainly defined by "Leave your TV on standby at night" (*envhabit1*), "Not buying something because of too much packaging" (*envhabit5*), "Buy recycled paper products such as toilet paper or tissues" (*envhabit6*). Hence, we can perhaps view this third component as another measure of pro-environmental behaviours related to packaging as well.

Finally, the fourth principal component, which accounts for 11% of the variance, is mainly defined by "Leave your TV on standby at night" (*envhabit1*), "Switch off lights in rooms that aren't being used" (*envhabit2*), and "Put more clothes on when rather than turning on the heater" (*envhabit4*). We can view this component as a measure of pro-environmental behaviours that are also cost-saving strategies at home.

These PCA outcomes form the dependent variables outlined in the next section.

4. Empirical strategy

To identify the causal effect of education on an outcome of interest, previous studies have either used a dummy variable that represents whether the person was exposed to the new compulsory schooling law as an IV for years of schooling (e.g., Harmon & Walker, 1995) or estimated a parametric RDD equation – either with a sharp or a fuzzy design – with the date of the law as the cut-off point (e.g., Clark & Royer, 2013; Meyer, 2015).

There are many clear advantages to both approaches. One of which is that, when properly implemented, both methods can produce unbiased estimates that have a high internal validity that is almost as good as randomised experiments (Lee & Lemieux, 2010).[7] However, one potential pitfall of these two approaches is that the estimates – whether it is the average treatment effect of the law change or the local average treatment effect of education brought

[7] For recent papers that have successfully implemented the parametric RDD approach, see Dell and Querubin (2018).

about by the law change – are subject to bias from using data that are farther away from the cut-off. To minimise such bias in identifying the causal effect of the law change on climate change literacy, the current study adopts a nonparametric RDD that uses only observations near the cut-off, where the discontinuous change in the probability of treatment assignment occurs.[8]

Nevertheless, the performance of a nonparametric RDD model tends to be sensitive to the choice of bandwidth employed. According to Calonico, Cattaneo, and Titiunik (2014a), traditional bandwidth selectors typically yield a "large" bandwidth that produces confidence intervals for treatment effects that have incorrect coverage probability. To minimise the bias associated with optimal bandwidth selection, we adopt a local polynomial nonparametric RDD with data-driven bandwidth selectors and bias-correction techniques (Calonico, Cattaneo, and Titiunik, 2014a, 2015). This data-driven RDD model has been shown to produce confidence intervals that are close-to-correct empirical coverage probability, thus improving upon the available bandwidth selectors in the literature (Calonico, Cattaneo, and Titiunik, 2014a).

In this paper, we estimate both "sharp" and "fuzzy" RDD models. With respect to the basic setup of the sharp RDD, which allows for the average treatment effect of the law change on our outcome variable to be identified, we assume that there is a pair of potential outcomes – for example, $Y_i(1)$ for what would occur to the participants' educational attainment if they were exposed to the 1972 reform, and $Y_i(0)$ if not exposed. Based on the assumption that the reform is independent of the unobserved confounding factors and has no other direct effects on the outcome, the causal effect of the reform on each of the educational attainment outcomes is given by $Y_i(1) - Y_i(0)$. However, given that in the regression discontinuity setting, only the participants to the right of the cut-off were affected by the reform, whilst all those to the left of

[8] Another reason for choosing a nonparametric RDD model over a parametric one is because the parametric method, which requires researchers to control for global high-order polynomials in their RDD design, often produces extremely noisy estimates that are sensitive to the degree of the polynomial as well as have poor coverage of confidence intervals (Gelman & Imbens, 2019).

the cut-off were not. Hence, we could only observe $E[Y_i(1)|X]$ to the right of the cut-off and $E[Y_i(0)|X]$ to the left of the cut-off, which enabled us to obtain the following quantity

$$\lim_{\varepsilon \downarrow 0} E[Y_i|X = c + \varepsilon] - \lim_{\varepsilon \uparrow 0}[Y_i|X = c + \varepsilon],$$

which would equal to the average treatment effect at the cut-off c,

$$E[Y_i(1) - Y_i(0)|X = c].$$

Here, the running variable, X, is the quarter of birth and the cut-off, c, is September 1957, i.e., the birth month of the first cohorts who would go on to be affected by the 1972 reform. In our UKHLS Wave 4 data, individuals who were born just before and after the cut-off date would have been 55 and 54 years old, respectively. It is also worth noting that this is different from the RDD set up typically seen in the environmental economics literature in which time is the running variable and the event in question might take place further away from the cut-off point, e.g., the installation date of a wind turbine.[9] In this particular analysis, the change in people's schooling level took place immediately on the cut-off date, which is the date of the law change. We separately applied the above equation to Y_i and Z_i as the outcome variable in our analysis.

We follow previous work that applied the same RDD and controlled for the month of birth, to control for seasonality, and sex (see, e.g., Davies et al., 2018). Given that participants were not able to systematically sort themselves around the cut-off, this RDD employs observations just below and above the cut-off as controls and treatment groups to conduct inference on the average effect of the reform on educational and environmental outcomes.

[9] See Hausman and Rapson (2018) for a comprehensive discussion on the implementation of an RDD with time as the running variable.

While this RDD setup is widely known as the sharp RDD (e.g., Imbens & Wooldridge, 2009), it can also be thought of as a setup to estimate the intention-to-treat effect in the medical literature (e.g., Hollis & Campbell, 1999), which represents the average effect of a policy on the outcome of both compliant and non-compliant individuals. We estimate the regression discontinuity plots with optimal bandwidths using the winter 2020 version of the rdplot command in Stata (for a full description of the rdplot command and its basic setup, see Calonico, Cattaneo, & Titiunik, 2014b).

Given that not everyone who was exposed to the law change complied to the new law, we also carry out a series of fuzzy RDD to estimate the local average treatment effects (LATE), i.e., the effect of the education reform on climate change literacy and pro-environmental outcomes of the sample whose education was affected by the introduction of the new law. The fuzzy RDD estimates, which are equivalent to the IV estimates, provide policy makers with the causal effects of education on the outcomes of the treated. For example, the LATE estimates can inform policy makers about to the magnitude of the causal effect of staying one additional year in school on climate change literacy of the target group, i.e., the compliers.

The fuzzy RDD also controls for the month of birth, to control for seasonality, and sex, and is estimated with optimal bandwidths using the winter 2020 version of the rdrobust command in Stata (Calonico, Cattaneo, & Titiunik, 2014b). Instead of clustering by the running variable, which has been shown in the literature to produce confidence intervals that have poor coverage properties, standard errors in all regressions were heteroskedasticity-robust adjusted (Kolesár & Rothe, 2018).[10] Also, following a recommendation by Gelman and Imbens (2019), we only apply a local linear RDD regression (i.e., one degree of polynomial) in the main analysis, with higher degrees added on in the robustness checks. The main reason for not

[10] One referee has raised that some spatial dependence in the data might produce standard errors that are biased if they are not clustered by region/administrative unit. This is an important point. However, as we have shown later in the robustness check, a regression model that clustere the standard errors by local authority district continues to produce qualitatively similar results to the one that only adjusts for heteroskedasticity in the standard errors.

controlling for global higher-order polynomials in the main analysis is to prevent poor coverage of confidence intervals in our estimates. We use the default triangular kernel that assigns linear down-weighting to the same observations, although qualitatively similar results can still be obtained using uniform and Epanechnikov kernels. We also present in the main analysis estimates obtained from using different bandwidth selection procedures: one common MSE-optimal bandwidth selector, two different MSE-optimal bandwidth selectors (below and above the cut-off), and one coverage error rate (CER)-optimal bandwidth selector. Finally, all principal component outcomes are standardised to have a mean of zero and a standard deviation of 1.

3. Results

We first estimate a series of sharp robust RDD to obtain the average effects of the law change on education attainment and reported the results in Table 1 and Figures 1a-c. Looking across Table 1's panels and columns, we can see that the 1972 education reform was successful at raising the average education attainment for individuals who were born in or after September 1957 in England and Wales. The results are also statistically robust across different choices of optimal bandwidth. On average, the reform increased the proportion of people remaining in school after 15 years of age by 28-30 percentage points, age left full-time education by 0.3-0.4 years, and the proportion of people with at least a secondary school qualification (GCSE/CSE/O-level) by 9-12 percentage points. This is also evident in Figures 1a-c, which present regression discontinuity plots of different education attainments before and after the reform.

The above estimates of the reform effects on education attainment are substantial by any standards, e.g., compared to England and Wales, most compulsory schooling laws in other countries tend to affect only around 10 percent of those who were exposed to the law change,

which also implies that the LATE estimates of schooling produced by this law change will come close to the population average treatment effects (Oreopoulos, 2006). It is worth noting that participants who were born in July and August could still technically leave school before they turned 16 years old, which explains why noticeably more participants who were affected by the reform but born in the third quarter of each year left school before their 16th birthday.

Table 2 and Figures 2a-c display the sharp RDD estimates on the average effects of the reform on three climate change literacy components, which we interpret as measures of the belief that "behavioural change is not needed to save the environment", "that major environmental disaster is imminent", and that "lifestyle influences climate change". The reform had a negative and statistically significant effect on a measure of people's belief that "behavioural change is not needed to reduce climate change"; the estimated standardised RDD coefficients range from -0.24 to-0.32 across different choices of optimal bandwidth. These are sizeable effects. Given that the standard deviation of the first principal component variable is approximately 1.89, these effects are equivalent to around 13%-17% of the standard deviation, which are similar in terms of size as the effect of being a female compared to being a male in our data.

There is, however, little evidence that the reform caused a significant shift in the other two components: the composite beliefs that a major environment is imminent and lifestyle influences climate change. We can also see a noticeable discontinuous drop in the average "belief that behavioural change is not needed to save the environment" component at the cut-off in Figure 2a.

We next turn to more objectively measured, pro-environmental behaviour components in Table 3 and Figures 3a-c. Despite Table 2's evidence that the reform reduced people's belief that "it is not worth changing behaviours to slow down climate change", there is little evidence that the reform had successfully made these individuals behave significantly more

environmentally friendly that they would have otherwise. For example, the effect of the reform on a measure of pro-environmental behaviour related to the use of packaging is approximately 0.01 with a standard error of 0.1.

We report in Tables 4 and 5 estimates from the fuzzy robust RDD regressions with each education attainment as the endogenous variable. While we continue to find causal evidence that more education as a result of the reform had a negative and sizeable effect on the measure of people's belief that "changes are not necessarily to save the environment", we find little evidence that education also had a significant effect on other measures of climate change awareness and pro-environmental behaviours. For example, using the one common MSE-optimal bandwidth selector to select the optimal bandwidth, we find the effect of remaining in school after 15 years of age = -0.87 standard deviation (robust $p = 0.035$), the effect of spending one more year in full-time education = -0.72 (robust $p = 0.046$), and the effect of having at least a secondary education qualification = -2.54 standard deviation (robust $p = 0.074$)). However, the RDD estimates are close to zero in regressions with other measures of climate change literacy and pro-environmental behaviours. These results are inconsistent with Meyer's (2015) and Chankrajang and Muttarak's (2017) IV estimates, which found an additional year of schooling to have a positive and statistically significant impact on people's willingness to adopt a more environmentally friendly lifestyle.

We also run separate RDD regressions run on each of the pro-environmental attitude and behaviour variables and reported the results in Table 6. Consistent with the earlier tables' results, the reform had a negative and statistically well-determined effect on the perception that "climate change is too far in the future to worry". However, we also show that the reform significantly improved people's belief that behaviour contributes to climate change and lowered people's perception that being green is an alternative lifestyle, which were not two of the main variables defining the first principal component of people's climate change literacy.

Nonetheless, due to the problem of multiple hypothesis testing, the overall interpretation of these RDD estimates should be treated with more caution than those obtained using principal components as the dependent variables.

A number of robustness checks, some suggested by the referees of this paper, were undertaken and reported in the Online Appendix. First, we find the results to be qualitatively similar when the first principal components are replaced by factors that had been obtained from running a factor analysis on the climate change literacy and pro-environmental behaviour variables; see Table 4A for the RDD estimates. The reform only had a negative and statistically significant impact on the first factor of the climate change literacy, which, like the first PCA component, is mainly defined by the individual's unwillingness to change their behaviours to save the environment.

We also carry out a placebo test, the results of which appeared in Table 5A. By using cut-off dates from one year before and one year after September 1957 in a sharp RDD regression, we show that the reform did not have any statistically well-determined effect on the first component of the climate change literacy around these placebo dates. This gives us some reassurance that the negative and statistically significant reform effect on people's belief that change is not necessary to save the environment observed amongst those who were born in September 1957 is genuine and not due to chance.

We test different degrees of polynomial in Table 6A. Here, we show that the negative and statistically robust effect of the education reform on people's unwillingness to change behaviour found in early tables does not depend on the degree of polynomial. The same applies to the nonsignificant finding of the reform effect on the first principal component of the pro-environmental behaviours. Table 7A demonstrates that the results continue to be robust to clustering the standard errors by the running variable as well as by local authority district, while

Table 8A shows that qualitatively similar results can still be obtained when a non-robust RDD is used instead of the robust RDD in the estimation.

Table 9A estimates the sharp RDD regressions by gender, north-south regional divide, and household income. The rationale behind subsample analysis is that the reform may have impacted men and women, individuals from relatively less affluent regions (i.e., the North), and relatively poorer households differently. While there is some evidence that the reform reduced people's unwillingness to change their behaviours for the environment across all subsamples, the RDD estimate is only statistically robust for people in the northern regions, i.e., those residing in the North-East, Yorkshire and the Humber, and the North-West. By contrast, all of the estimated RDD coefficients in the pro-environmental behaviours equation are statistically insignificant and closer to zero in magnitudes across all subsamples. Nevertheless, we should treat the subsample estimates with caution because of the smaller number of observations just before and after the cut-off.

Table 10A reports the sharp RDD estimates on other principal components that we did not include in the main analysis, i.e., components that have an eigenvalue less than 1. We test up to component 7th and 8th for climate change literacy and pro-environmental behaviours, respectively. Consistent with Tables 2 and 3's results, we find little evidence that the reform had a statistically significant impact on any other measures of climate change literacy and pro-environmental behaviours.

Finally, Table 11A and Figure 4A test the stability of the sharp RDD estimate on the measure of people's belief that behavioural change is not necessary to save the environment (Dong & Lewbel, 2015; Cerulli et al., 2017). We do this by estimating the treatment effect derivative (TED) of the sharp RDD estimate. The idea here is to test whether people with other nearby values of X_i around the cut-off would experience similar treatment effects. If they do, i.e., a small change in X_i substantially changes the magnitude and sign of the causal estimate,

then we can conclude that the RDD estimate is sensitive to marginal changes in the running variable and therefore lacks the required external validity. Using the *ted* command in Stata, our TED estimate was 0.003 ($p = 0.956$), which means that we can accept the null hypothesis of statistically insignificant differences in the RDD estimate as we move marginally away from the cut-off. This result suggests that individuals who are slightly further away from the cut-off has the same RDD estimate as those at the cut-off, thus giving more credibility and external validity to the only statistically significant RDD estimate in this paper.

4. Discussions and conclusions

This study uses the nationally representative of individuals in England and Wales and the raising of the minimum school leaving age law in September 1972 as a natural experiment to estimate the causal effects of education on pro-environmental attitudes and behaviours. While previous studies had found the education reform to be successful at improving health, wealth, and well-being for an average person who gained more education as a result of the reform, there is little evidence that the change in the minimum school-leaving age in England and Wales had much of an impact on individual's pro-environmental outcomes. It is not that the reform on raising general education had completely failed to educate people about how behavioural change is necessary to slow down climate change; there is some evidence that it did. However, despite some significant differences in the level of attitudes towards behavioural change to save the environment between participants not affected by the reform and those affected by it, there is little evidence to suggest that more education causes a drastic change in individual's actual pro-environmental behaviours.

There are potentially many explanations for why an increase in formal education causally improved our understanding that we need to change our ways to save the environment but did not lead to a significant change in their pro-environmental behaviours. One leading

explanation for this is that, despite knowing the imminent danger of climate change, each rational agent might still independently choose to consume more of the common good than socially optimal, i.e., "the tragedy of the commons" problem (Hardin, 1968), or to free-ride on the contributions of others to the public goods out of self-interest, or both. Another possible explanation comes from many writings in psychology and behavioural economics, which had found that most people tend to prefer immediate gratification than delayed rewards[11] (e.g., "*I know I should do more for the environment, but driving to work is a lot easier than taking a public transport*"), like to engage in social comparisons[12] (e.g., "*I know I should recycle more, but why should I when most people I know in my neighbourhood don't?*"), and are loss averse[13] (e.g., "*I know I should change to an electric car, but I don't want to stop driving the car that I've been driving for the last ten years*"). The current study contributes to this literature by providing evidence that more schooling is mostly ineffective at changing people's behaviours in an effort to slow down climate change.

It does not follow, however, that we should give up on education in our fight against climate change. It may be true that the application of behavioural economics principles in environmental policies has proven to be much more successful at promoting people's pro-environmental behaviours than merely informing them to change (see, e.g., Ölander & Thøgersen, 2014; Vlaeminck, Jiang & Vranken, 2014; Schubert, 2017). Yet it has also been found that behavioural changes from these *nudge* policies are likely to be much more enduring if the person also identifies themselves as someone who cares deeply about the environment (Mols et al., 2015). In other words, while education may not necessarily cause pro-environmental behaviours, nudge policies may have a much more significant and longer-lasting impact on the responses of better-educated people who may be more aware about the negative

[11] Laibson (1997).
[12] Festinger (1954).
[13] Tversky and Kahneman (1991).

consequences of having a certain lifestyle on climate change. This is primarily because the new behaviours are likely to be consistent with the more correct beliefs about the causes of climate change brought about by more years of schooling.

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Figures 1a-c: Regression discontinuity plots of the 1972 Education Reform effects on education outcomes

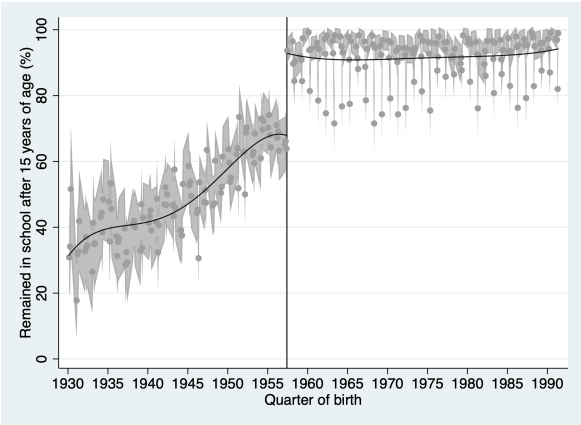


Fig 1a: Proportion of remaining in school after 15 years of age

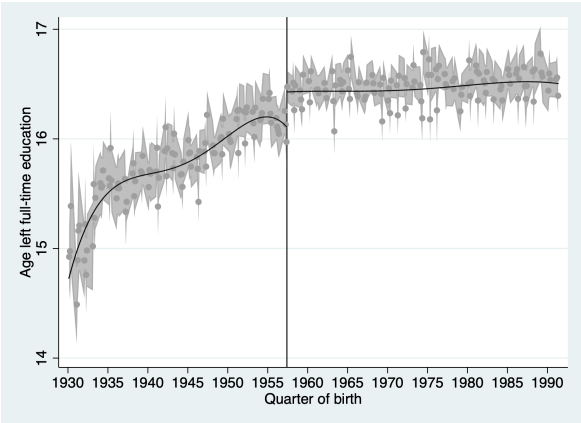


Fig 1b: Age left full-time education

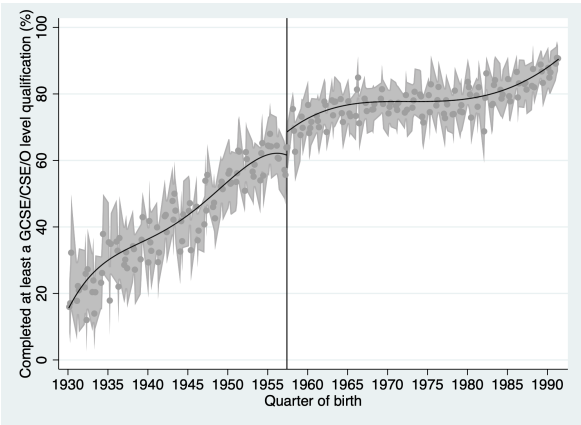


Fig 1c: Proportion of having completed at least a GCSE/CSE/O-level qualification

Note: Each data point represents local averages of respondents' corresponding educational outcome per quarter of birth. The change in the minimum school leaving age law from age 15 to 16 in September 1972 affected all children who were born in or after September 1957, as indicated by the vertical line. The shaded area represents 95% confidence intervals. The regression discontinuity plots controlled for the participants' birth month and sex. N=24,475. The order of polynomial fit = 4.

Table 1: The effect of the 1972 Education Reform effect on education outcomes: Sharp robust regression discontinuity design

	DV: Proportion of remaining in school after 15 years of age		
Panel A	**MSERD**	**MSETWO**	**CERRD**
RD estimate	27.79***	27.29***	30.53***
	(2.674)	(2.491)	(3.239)
Observations	26315	26315	26315
Effective *N* left of cut-off	1732	1732	1202
Effective *N* right of cut-off	2223	6077	1158
Left bandwidth	4.083	4.069	2.454
Right bandwidth	4.083	11.39	2.454
	DV: Age left full-time education		
Panel B	**MSERD**	**MSETWO**	**CERRD**
RD estimate	0.343***	0.358***	0.411***
	(0.0711)	(0.0652)	(0.0884)
Observations	25666	25666	25666
Effective *N* left of cut-off	2079	1633	1198
Effective *N* right of cut-off	2221	5497	1157
Left bandwidth	4.357	3.935	2.623
Right bandwidth	4.357	10.36	2.623
	DV: Proportion of having completed at least a GCSE/CSE/O-level qualification		
Panel C	**MSERD**	**MSETWO**	**CERRD**
RD estimate	8.646***	9.178***	11.59***
	(2.895)	(2.672)	(3.701)
Observations	26315	26315	26315
Effective *N* left of cut-off	2524	2083	1537
Effective *N* right of cut-off	2760	4927	1704
Left bandwidth	5.364	4.796	3.225
Right bandwidth	5.364	9.316	3.225

Note: ***<1%. MSERD = One common mean squared error optimal bandwidth. MSETWO = Two different mean squared error optimal bandwidth. CERRD = One common coverage error probability optimal bandwidth. All regression discontinuity estimates adjust for the month of birth and sex. The running variable is the quarter of birth and the cut-off date is 1st September 1957. Standard errors are heteroskedasticity-robust adjusted. Kernel weights = triangular. Polynomial = 1. Estimates adjusted for mass points in the running variable.

Figures 2a-c: Regression discontinuity plots of the 1972 Education Reform effects on standardised principal components of climate literacy

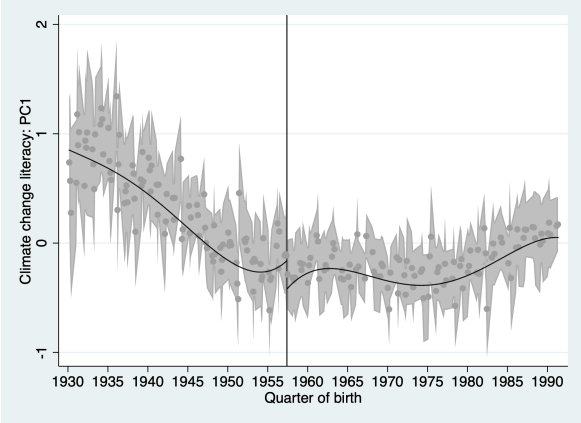


Fig 2a: Component 1: Behavioural change is not needed

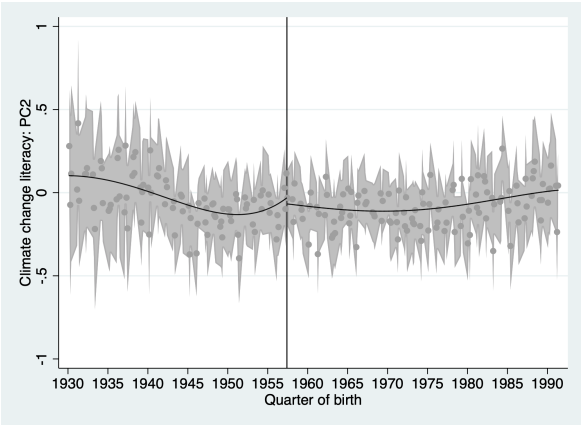


Fig 2b: Component 2: Major environmental disaster is imminent

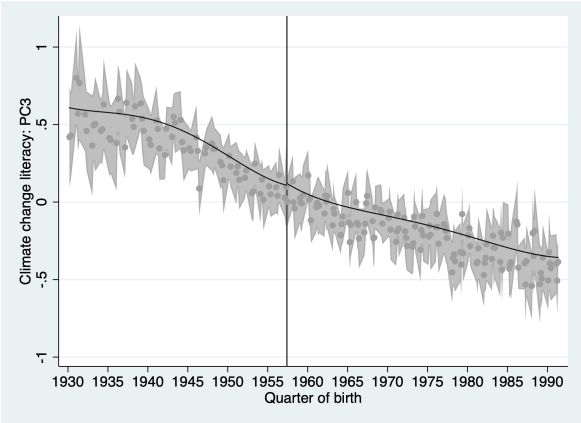


Fig 2c: Component 3: How lifestyle influences climate change

Note: Each data point represents local averages of standardised corresponding climate change literacy outcome per quarter of birth. The change in the minimum school leaving age law from age 15 to 16 in September 1972 affected all children who were born in or after September 1957, as indicated by the vertical line. The shaded area represents 95% confidence intervals. The regression discontinuity plots controlled for the participants' birth month and sex. N=22,044. The order of polynomial fit = 4. Standard errors are heteroskedasticity-robust adjusted. Kernel weights = triangular. Estimates adjusted for mass points in the running variable.

Table 2: The effect of the 1972 Education Reform on principal components of climate change literacy: Sharp robust regression discontinuity design

	DV: Component 1: Behavioural change is not needed		
Panel A	**MSERD**	**MSETWO**	**CERRD**
RD estimate	-0.250**	-0.238**	-0.316**
	(0.121)	(0.115)	(0.152)
Observations	22165	22165	22165
Effective *N* left of cut-off	2194	2194	1414
Effective *N* right of cut-off	2604	3294	1471
Left bandwidth	5.887	5.738	3.570
Right bandwidth	5.887	7.124	3.570
	DV: Component 2: Major environment disaster		
Panel B	**MSERD**	**MSETWO**	**CERRD**
RD estimate	0.0360	0.0114	0.0362
	(0.0687)	(0.0638)	(0.0855)
Observations	22165	22165	22165
Effective *N* left of cut-off	2774	2865	1810
Effective *N* right of cut-off	3294	4718	1916
Left bandwidth	7.195	7.226	4.363
Right bandwidth	7.195	10.16	4.363
	DV: Component 3: How lifestyle influences climate change		
Panel C	**MSERD**	**MSETWO**	**CERRD**
RD estimate	0.0218	0.0219	-0.00202
	(0.0476)	(0.0473)	(0.0609)
Observations	22165	22165	22165
Effective *N* left of cut-off	3319	3635	2194
Effective *N* right of cut-off	4107	3997	2365
Left bandwidth	8.905	9.217	5.399
Right bandwidth	8.905	8.812	5.399

Note: **<5%. MSERD = One common mean squared error optimal bandwidth. MSETWO = Two different mean squared error optimal bandwidth. CERRD = One common coverage error probability optimal bandwidth. Dependent variables are standardised with a mean of 0 and a standard deviation of 1. All regression discontinuity estimates adjust for the month of birth and sex. The running variable is the quarter of birth and the cut-off date is 1st September 1957. Standard errors are heteroskedasticity-robust adjusted. Kernel weights = triangular. Polynomial = 1. Estimates adjusted for mass points in the running variable.

Figures 3a-c: Regression discontinuity plots of the 1972 Education Reform effects on principal components of pro-environmental behaviours

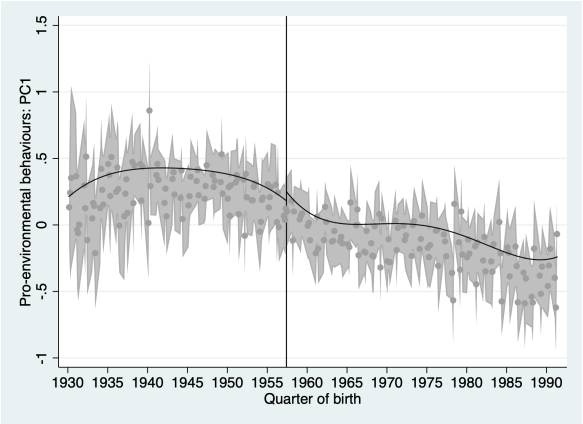


Fig 3a: Component 1: Pro-environmental behaviours (packaging #1)

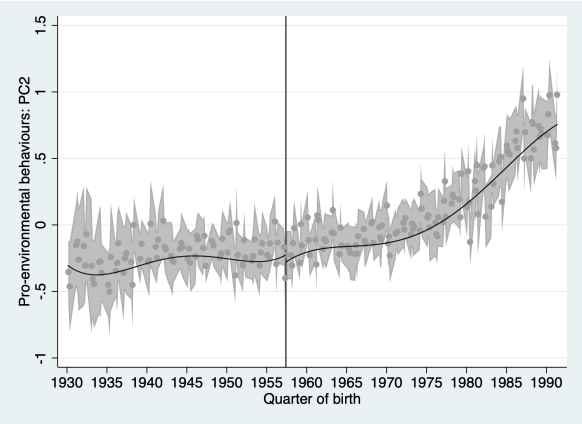


Fig 3b: Component 2: Pro-environmental behaviours (transportation)

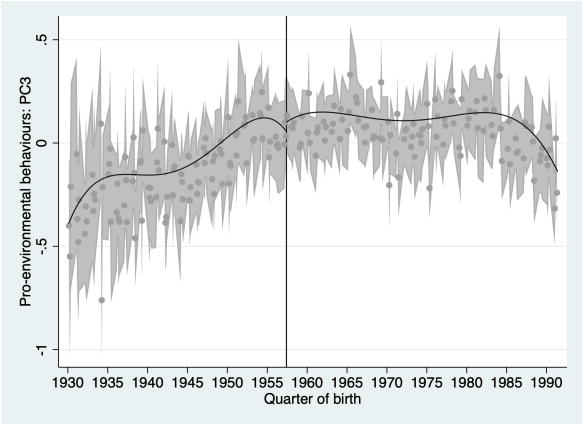


Fig 3c: Component 1: Pro-environmental behaviours (packaging #2)

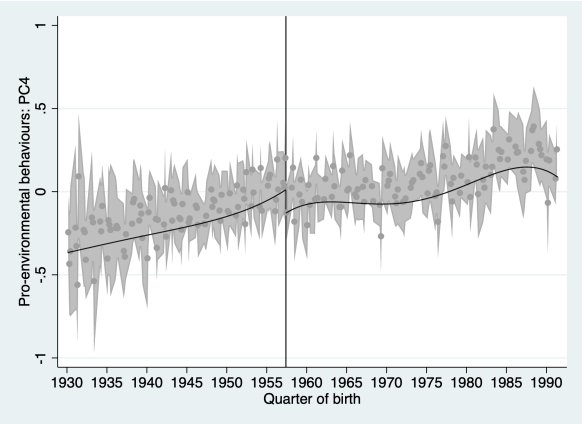


Fig 3d: Component 4: Pro-environmental behaviours (cost-saving strategies at home)

Note: Each data point represents local averages of the corresponding pro-environmental behaviours per quarter of birth. The outcome variables are standardised to have a mean of 0 and a standard deviation of 1. The change in the minimum school leaving age law from age 15 to 16 in September 1972 affected all children who were born in or after September 1957, as indicated by the vertical line. The shaded area represents 95% confidence intervals. The regression discontinuity plots controlled for the participants' birth month and sex. N=20,974. The order of polynomial fit = 4. Standard errors are heteroskedasticity-robust adjusted. Kernel weights = triangular. Estimates adjusted for mass points in the running variable.

Table 3: The effect of the 1972 Education Reform on principal components of pro-environmental behaviours: Sharp robust regression discontinuity design

	DV: Component 1: Packaging #1		
Panel A	**MSERD**	**MSETWO**	**CERRD**
RD estimate	0.00525	0.00248	0.0498
	(0.0750)	(0.0734)	(0.0959)
Observations	21089	21089	21089
Effective *N* left of cut-off	2742	2742	1698
Effective *N* right of cut-off	3179	3628	1827
Left bandwidth	7.529	7.595	4.576
Right bandwidth	7.529	8.086	4.576
	DV: Component 2: Transportation		
Panel B	**MSERD**	**MSETWO**	**CERRD**
RD estimate	-0.0548	-0.0431	-0.0617
	(0.0593)	(0.0563)	(0.0761)
Observations	21089	21089	21089
Effective *N* left of cut-off	2411	2495	1325
Effective *N* right of cut-off	2706	3179	1722
Left bandwidth	6.545	7.052	3.978
Right bandwidth	6.545	7.559	3.978
	DV: Component 1: Packaging #2		
Panel C	**MSERD**	**MSETWO**	**CERRD**
RD estimate	0.0760	0.0581	0.0575
	(0.0748)	(0.0662)	(0.0954)
Observations	21089	21089	21089
Effective *N* left of cut-off	1698	1698	970
Effective *N* right of cut-off	1827	3179	1175
Left bandwidth	4.669	4.929	2.838
Right bandwidth	4.669	7.679	2.838
	DV: Component 4: Cost-saving strategies at home		
Panel D	**MSERD**	**MSETWO**	**CERRD**
RD estimate	-0.101*	-0.0989*	-0.0979
	(0.0553)	(0.0530)	(0.0703)
Observations	21089	21089	21089
Effective *N* left of cut-off	2835	3495	1698
Effective *N* right of cut-off	3628	3179	2068
Left bandwidth	8.013	9.872	4.871
Right bandwidth	8.013	7.654	4.871

Note: MSERD = One common mean squared error optimal bandwidth. MSETWO = Two different mean squared error optimal bandwidth. CERRD = One common coverage error probability optimal bandwidth. Dependent variables are standardised with a mean of 0 and a standard deviation of 1. All regression discontinuity estimates adjust for the month of birth and sex. The running variable is the quarter of birth and the cut-off date is 1st September 1957. Standard errors are heteroskedasticity-robust adjusted. Kernel weights = triangular. Polynomial = 1. Estimates adjusted for mass points in the running variable.

Table 4: The local average treatment effects of education on principal components of climate change literacy: Fuzzy robust regression discontinuity design

	DV: Component 1: Behavioural change is not needed		
Panel A	**Stayed in school after 15 years**	**Age left full-time education**	**Completed GCSE/CSE/O-level**
RD estimate	-0.870**	-0.720**	-2.543*
	(0.440)	(0.351)	(1.535)
Observations	22165	21596	22165
Effective *N* left of cut-off	2576	2262	2865
Effective *N* right of cut-off	3056	2804	3294
Left bandwidth	6.872	6.083	7.263
Right bandwidth	6.872	6.083	7.263
	DV: Component 2: Major environmental disaster		
Panel B	**Stayed in school after 15 years**	**Age left full-time education**	**Completed GCSE/CSE/O-level**
RD estimate	0.0877	0.110	0.123
	(0.257)	(0.224)	(0.809)
Observations	22165	21596	22165
Effective *N* left of cut-off	3411	2940	4234
Effective *N* right of cut-off	4207	3291	4863
Left bandwidth	9.064	7.549	10.80
Right bandwidth	9.064	7.549	10.80
	DV: Component 3: How lifestyle influences climate change		
Panel C	**Stayed in school after 15 years**	**Age left full-time education**	**Completed GCSE/CSE/O-level**
RD estimate	0.112	0.0731	0.344
	(0.194)	(0.178)	(0.630)
Observations	22165	21596	22165
Effective *N* left of cut-off	3737	3315	4678
Effective *N* right of cut-off	4452	3759	5206
Left bandwidth	9.889	8.350	11.38
Right bandwidth	9.889	8.350	11.38

Note: **<5%, *<10%. One common mean squared error optimal bandwidths are used in the estimation. Dependent variables are standardised with a mean of 0 and a standard deviation of 1. All regression discontinuity estimates adjust for the month of birth and sex. The running variable is the quarter of birth and the cut-off date is 1st September 1957. Standard errors are heteroskedasticity-robust adjusted. Kernel weights = triangular. Polynomial = 1. Estimates adjusted for mass points in the running variable.

Table 5: The local average treatment effects of education on principal components of pro-environmental behaviours: Fuzzy robust regression discontinuity design

	DV: Component 1: Packaging #1		
Panel A	**Stayed in school after 15 years**	**Age left full-time education**	**Completed GCSE/CSE/O-level**
RD estimate	-0.0318	-0.0302	-0.0754
	(0.309)	(0.321)	(1.038)
Observations	21089	20553	21089
Effective *N* left of cut-off	3098	3395	3098
Effective *N* right of cut-off	3858	4061	3628
Left bandwidth	8.883	9.286	8.677
Right bandwidth	8.883	9.286	8.677
	DV: Component 2: Transportation		
Panel B	**Stayed in school after 15 years**	**Age left full-time education**	**Completed GCSE/CSE/O-level**
RD estimate	0.0811	-0.0784	0.417
	(0.220)	(0.226)	(0.825)
Observations	21089	20553	21089
Effective *N* left of cut-off	3953	3095	4372
Effective *N* right of cut-off	4705	3625	5040
Left bandwidth	10.74	8.389	11.66
Right bandwidth	10.74	8.389	11.66
	DV: Component 1: Packaging #2		
Panel C	**Stayed in school after 15 years**	**Age left full-time education**	**Completed GCSE/CSE/O-level**
RD estimate	0.203	0.118	0.410
	(0.258)	(0.232)	(0.829)
Observations	21089	20553	21089
Effective *N* left of cut-off	2411	2739	2742
Effective *N* right of cut-off	3082	3531	3534
Left bandwidth	6.969	7.927	7.947
Right bandwidth	6.969	7.927	7.947
	DV: Component 4: Cost-saving strategies at home		
Panel D	**Stayed in school after 15 years**	**Age left full-time education**	**Completed GCSE/CSE/O-level**
RD estimate	-0.437*	-0.436*	-1.515
	(0.238)	(0.248)	(0.987)
Observations	21089	20553	21089
Effective *N* left of cut-off	3007	3095	3495
Effective *N* right of cut-off	3628	3625	4417
Left bandwidth	8.250	8.534	9.954
Right bandwidth	8.250	8.534	9.954

Note: *<10%. One common mean squared error optimal bandwidths are used in the estimation. Dependent variables are standardised with a mean of 0 and a standard deviation of 1. All regression discontinuity estimates adjust for the month of birth and sex. The running variable is the quarter of birth and the cut-off date is 1st September 1957. Standard errors are heteroskedasticity-robust adjusted. Kernel weights = triangular. Polynomial = 1. Estimates adjusted for mass points in the running variable.

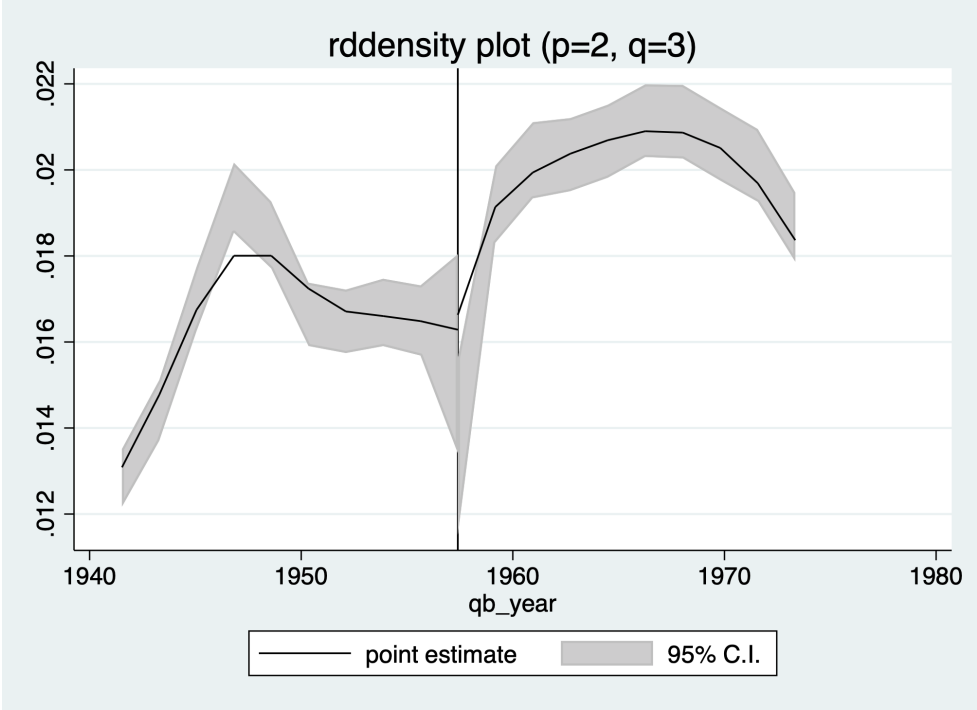
Table 6: Unpacking the climate change literacy and pro-environmental behaviour variables

Standardised outcome variables	***RD Estimate***
Behaviour contributes to climate change	0.157**
	(0.0635)
Climate change is beyond control	-0.0361
	(0.0483)
Climate change is too far in the future to worry	-0.110*
	(0.0621)
Not worth making changes if others don't	-0.0834
	(0.0653)
Not worth UK making changes	-0.0513
	(0.0623)
Environmental crisis has been exaggerated	0.0117
	(0.0483)
Soon experience major environmental disaster	0.0191
	(0.0522)
Being green is an alternative lifestyle	-0.0877**
	(0.0442)
Pay more for environmentally friendly products	0.0815
	(0.0614)
Current lifestyle is environment friendly	0.0335
	(0.0400)
How I feel about current lifestyle and the environment	-0.0105
	(0.0307)
Leave your TV on standby at night	0.0415
	(0.111)
Switch off lights in rooms that aren't being used	-0.0215
	(0.0419)
Keep the tap running while you brush your teeth	-0.0393
	(0.0876)
Put more clothes on when rather than turning on heater	-0.0834
	(0.0640)
Not buy something because of too much packaging	0.0328
	(0.0609)
Buy recycled paper products such as toilet paper or tissues	0.182**
	(0.0894)
Take your own shopping bag when shopping	-0.0334
	(0.0681)
Use public transport rather than travel by car	0.0751
	(0.0660)
Walk or cycle for short journeys less than 2-3 miles	-0.149**
	(0.0724)

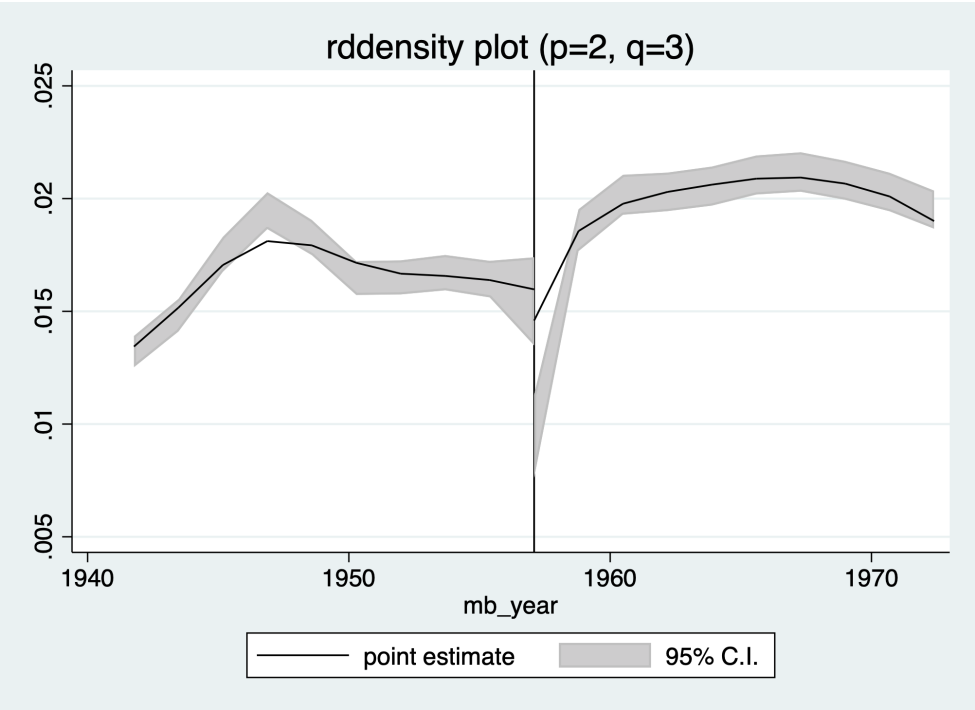
Note: Outcome variables are standardised to have a mean of zero and a standard deviation of 1, with more positive values indicating an increase in the level of agreement with the statement. All regression discontinuity estimates adjust for the month of birth and sex. The running variable is the quarter of birth and the cut-off date is 1st September 1957. One common MSE optimal bandwidth selector was used to select the optimal bandwidths in all regressions. Standard errors are heteroskedasticity-robust adjusted. Kernel weights = triangular. Polynomial = 1. Estimates adjusted for mass points in the running variable.

Online Appendix

Figure 1A: Regression discontinuity density plots



(i) Quarter of birth-year as the running variable; robust t-statistics = -1.36 (*p*-value = 0.174).



(ii) Birth month-year as the running variable; robust t-statistics = -4.33 (*p*-value = 0.000)

Table 1A: Descriptive statistics by education

Unstandardized outcome variables	Left school by 15 years of age (A)			Remained in school after 15 years of age (B)					Test of mean differences across years of schooling groups	
	N	Mean	S.E.	N	Mean	S.E.	Min	Max	Mean differences (B-A)	*p*-values
Behaviour contributes to climate change	5298	3.193	.013	17119	3.368	.007	1	5	0.174***	(0.000)
Climate change is beyond control	5301	2.817	.014	17109	2.586	.007	1	5	-0.231***	(0.000)
Climate change is too far in the future to worry	5313	2.917	.015	17117	2.496	.008	1	5	-0.421***	(0.000)
Not worth making changes if others don't	5312	2.89	.015	17128	2.673	.008	1	5	-0.218***	(0.000)
Not worth UK making changes	5309	3.1	.016	17116	2.679	.009	1	5	-0.421***	(0.000)
Environmental crisis has been exaggerated	5294	3.207	.014	17118	2.938	.008	1	5	-0.269***	(0.000)
Soon experience major environmental disaster	5296	3.256	.014	17112	3.259	.008	1	5	0.003	(0.846)
Being green is an alternative lifestyle	5229	2.65	.009	17057	2.383	.005	1	4	-0.267***	(0.000)
Pay more for environmentally friendly products	5313	2.905	.014	17133	2.993	.008	1	5	0.088***	(0.000)
Current lifestyle is environment friendly	5322	2.82	.013	17137	2.678	.006	1	5	-0.142***	(0.000)
Changes to help environment need to fit with lifestyle	5328	2.732	.007	17134	2.587	.004	1	5	-0.145***	(0.000)
How I feel about current lifestyle and the environment	5306	2.718	.012	17121	2.841	.007	1	3	0.123***	(0.000)
Leave your TV on standby at night	5899	2.588	.024	18067	2.793	.014	1	5	0.205***	(0.000)
Switch off lights in rooms that aren't being used	5929	4.515	.012	18295	4.379	.007	1	5	-0.136***	(0.000)
Keep the tap running while you brush your teeth	5840	2.606	.022	18266	2.608	.012	1	5	0.002	(0.937)
Put more clothes on when rather than turning on heater	5901	3.45	.018	18229	3.528	.009	1	5	0.078***	(0.000)
Not buy something because of too much packaging	5785	1.558	.012	18088	1.678	.007	1	5	0.120***	(0.000)
Buy recycled paper products such as toilet paper or tissues	5758	2.336	.018	17825	2.406	.009	1	5	0.070***	(0.000)
Take your own shopping bag when shopping	5768	3.947	.019	18021	3.598	.011	1	5	-0.349***	(0.000)
Use public transport rather than travel by car	5465	2.175	.019	17484	2.075	.01	1	5	-0.100***	(0.000)
Walk or cycle for short journeys less than 2-3 miles	5386	2.741	.02	17809	2.933	.01	1	5	0.193***	(0.000)

Note: ***<1%.

Table 2A: Principal components analysis (PCA) of the attitudes towards climate change variables

```
Principal components/correlation                Number of obs    =     22,165
                                                Number of comp.  =          3
                                                Trace            =         12
    Rotation: (unrotated = principal)           Rho              =     0.5140
```

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.65388	2.17329	0.3045	0.3045
Comp2	1.4806	.446535	0.1234	0.4279
Comp3	1.03406	.181633	0.0862	0.5140
Comp4	.852429	.0318491	0.0710	0.5851
Comp5	.82058	.019999	0.0684	0.6535
Comp6	.800581	.0694751	0.0667	0.7202
Comp7	.731106	.039252	0.0609	0.7811
Comp8	.691854	.05489	0.0577	0.8388
Comp9	.636964	.146659	0.0531	0.8918
Comp10	.490305	.029098	0.0409	0.9327
Comp11	.461207	.114779	0.0384	0.9711
Comp12	.346428	.	0.0289	1.0000

Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Unexplained
scenv_crlf	-0.1560	-0.0995	0.7888	.2532
scenv_fitl	-0.2582	-0.1936	0.1222	.6857
scenv_tlat	0.2610	0.3467	0.2107	.5273
scenv_nowo	0.3776	0.1515	0.1347	.4268
scenv_noot	0.3570	0.2555	-0.0896	.4298
scenv_canc	0.3865	0.1873	0.0081	.4027
scenv_ftst	0.2203	-0.2051	0.4274	.5716
scenv_grn	0.2704	0.1824	0.0877	.6758
scenv_bccc	-0.2172	0.4604	-0.0588	.51
scenv_pmep	-0.2558	0.3846	0.2844	.4583
scenv_meds	-0.2635	0.5024	0.0713	.3672
scenv_crex	0.3431	-0.1462	0.1121	.5256

Note: scenv_crlf = current lifestyle is environmentally friendly (1 = do nothing environmentally friendly, …, 5 = do everything environmentally friendly); scenv_fitl = changes to help environment need to fit with lifestyle (1= strongly agree, …, 5 = strongly disagree); scenv_tlat = climate change is beyond control (1 = strongly disagree, …, 5 = strongly agree); scenv_nowo = climate change is too far in future to worry (1 = strongly disagree, …, 5 = strongly agree); scenv_noot = not worth making changes if others don't (1 = strongly disagree, …, 5 = strongly agree); scenv_canc = not worth UK making changes (1 = strongly disagree, …, 5 = strongly agree); scenv_ftst = how I feel about current lifestyle and the environment (1= like to do lots more, …, 3 = happy with what I do); scenv_grn = being green is an alternative lifestyle (1= disagree strongly, …, 4 = agree strongly); scenv_bccc = behaviour contributes to climate change (1 = strongly disagree, …, 5 = strongly agree); scenv_pmep = pay more for environmentally friendly products (1 = strongly disagree, …, 5 = strongly agree); scenv_meds = soon experience major environmental disaster (1 = strongly disagree, …, 5 = strongly agree); scenv_crex = environmental crisis has been exaggerated (1 = strongly disagree, …, 5 = strongly agree).

Figure 2A: **Scree plot of eigenvalues after PCA of the attitudes towards climate change variables**

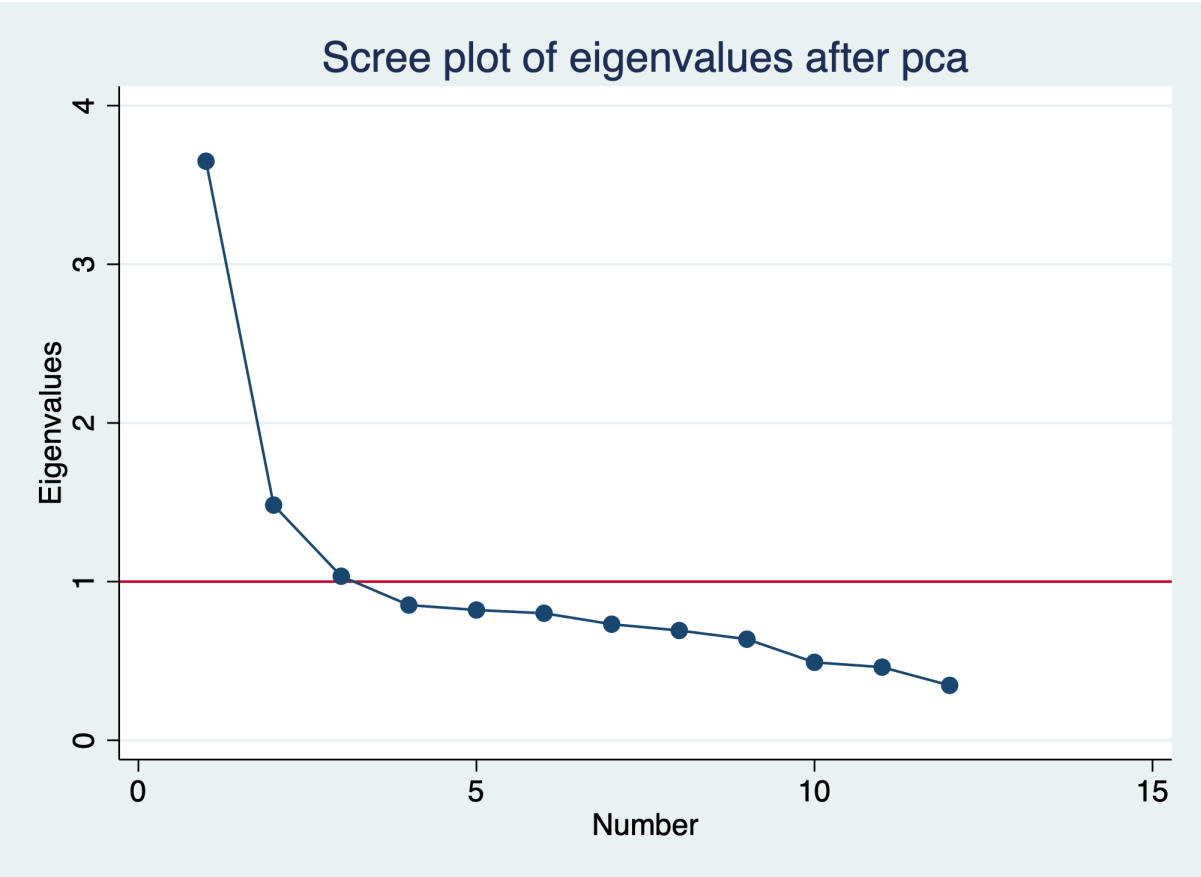


Table 3A: Principal components analysis (PCA) of the pro-environmental behaviour variables

```
Principal components/correlation                Number of obs    =     21,091
                                                Number of comp.  =          4
                                                Trace            =          9
    Rotation: (unrotated = principal)           Rho              =     0.5734
```

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.89183	.701896	0.2102	0.2102
Comp2	1.18993	.129268	0.1322	0.3424
Comp3	1.06066	.0429317	0.1179	0.4603
Comp4	1.01773	.168219	0.1131	0.5734
Comp5	.849513	.014756	0.0944	0.6677
Comp6	.834757	.0335511	0.0928	0.7605
Comp7	.801206	.096254	0.0890	0.8495
Comp8	.704952	.0555318	0.0783	0.9278
Comp9	.64942	.	0.0722	1.0000

Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Unexplained
envhabit1	-0.2177	0.0605	0.4948	0.5428	.3466
envhabit2	0.2540	-0.2048	-0.3188	0.5930	.3625
envhabit3	-0.3020	0.3221	0.3489	0.1455	.5534
envhabit4	0.3419	-0.1088	0.0041	0.5052	.5053
envhabit5	0.3929	-0.0983	0.5337	-0.1288	.3776
envhabit6	0.4077	-0.1064	0.4630	-0.1539	.4206
envhabit7	0.3678	-0.3118	-0.0823	-0.1705	.5917
envhabit8	0.3014	0.6410	-0.0879	-0.0446	.3292
envhabit9	0.3651	0.5565	-0.1343	0.0774	.3543

Note: (*envhabit1*, …, *envhabit9*). They are (1) "Leave your TV on standby at night", (2) "Switch off lights in rooms that aren't being used", (3) "Keep the tap running while you brush your teeth", (4) "Put more clothes on when rather than turning on the heater", (5) "Not buying something because of too much packaging", (6) "Buy recycled paper products such as toilet paper or tissues", (7) "Take your own shopping bag when shopping", (8) "Use public transport rather than travel by car", and (9) "Walk or cycle for short journeys less than 2-3 miles". Possible responses to these statements range from "1. Never" to "5. Always".

Figure 3A: Scree plot of eigenvalues after PCA of the pro-environmental behaviour variables

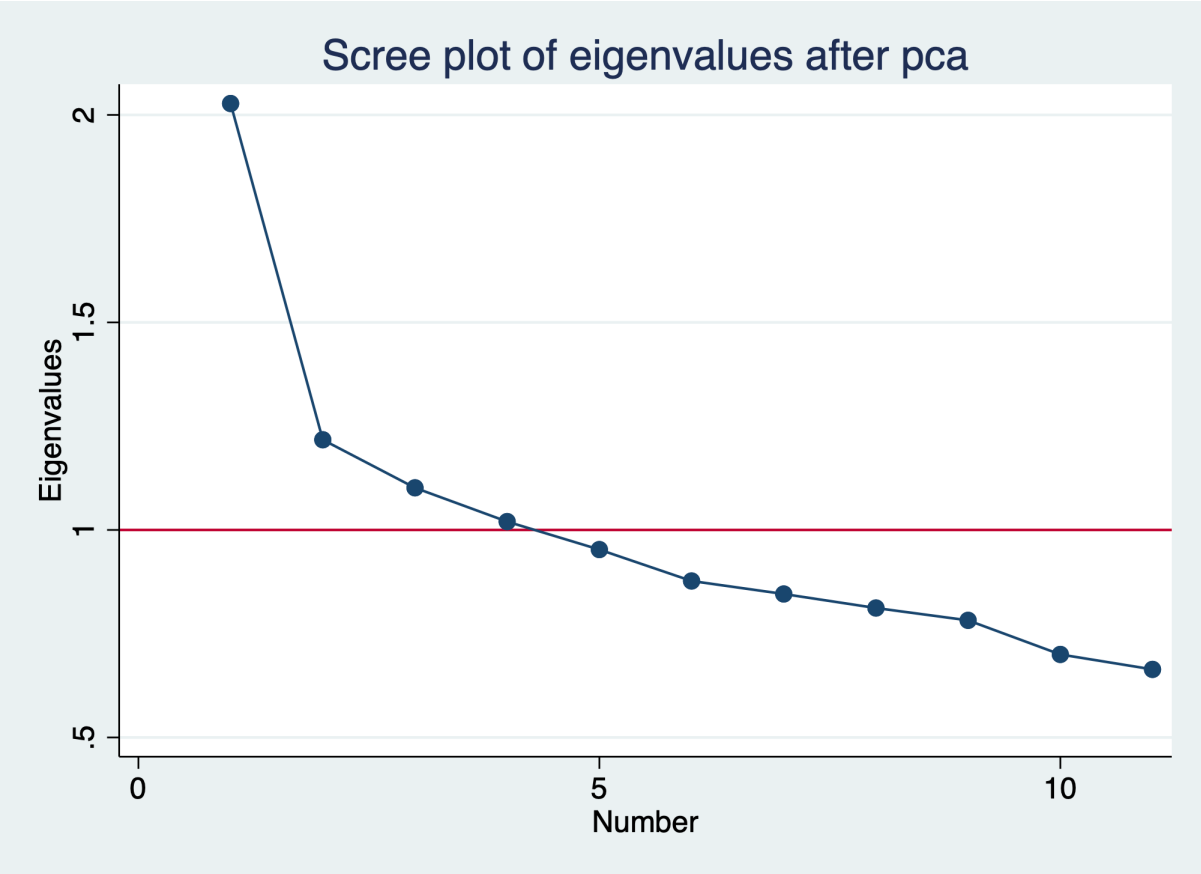


Table 4A: The and local average treatment effects of the 1972 Education Reform on factors of climate change literacy and pro-environmental behaviours: Sharp and fuzzy robust regression discontinuity designs

	DV: Component 1: Behavioural change is not needed			
Panel A	**Sharp RDD**	**Fuzzy RDD: Stayed in school after 15 years**	**Fuzzy RDD: Age left full-time education**	**Fuzzy RDD: Completed GCSE/CSE/O-level**
RD estimate	-0.116**	-0.407*	-0.339**	-1.189
	(0.0574)	(0.211)	(0.169)	(0.732)
Observations	22165	22165	21596	22165
Effective *N* left of cut-off	2194	2576	2262	2865
Effective *N* right of cut-off	2706	3056	2804	3294
Left bandwidth	5.980	6.806	6.023	7.218
Right bandwidth	5.980	6.806	6.023	7.218
	DV: Component 1: Packaging #1			
Panel B	**Sharp RDD**	**Fuzzy RDD: Stayed in school after 15 years**	**Fuzzy RDD: Age left full-time education**	**Fuzzy RDD: Completed GCSE/CSE/O-level**
RD estimate	0.00384	-0.0420	-0.0263	-0.0366
	(0.0401)	(0.162)	(0.175)	(0.549)
Observations	21089	21089	20553	21089
Effective *N* left of cut-off	2742	3495	3492	3098
Effective *N* right of cut-off	3179	4064	4061	3628
Left bandwidth	7.363	9.678	9.594	8.591
Right bandwidth	7.363	9.678	9.594	8.591

Note: **<5%, *<10%. One common MSE optimal bandwidth selector was used to select the optimal bandwidth. See Table 1's notes for the rest of the model's description.

Table 5A: Placebo test: A sharp robust regression discontinuity design using different cut-off dates

	RD Estimates
1) Sharp RD on component 1 of climate change literacy	
i) C1 = People born September 1957	-0.250**
	(0.121)
ii) C2 = People born September 1956	0.0214
	(0.108)
iii) C3 = People born September 1958	0.0451
	(0.103)
2) Sharp RD on component 1 of pro-environmental behaviours	
i) C1 = People born September 1957	0.00525
	(0.0750)
ii) C2 = People born September 1956	-0.0734
	(0.0694)
iii) C3 = People born September 1958	-0.0759
	(0.0641)

Note: **<5%. One common MSE optimal bandwidth selector was used to select the optimal bandwidth. See Table 1's notes for the rest of the model's description.

Table 6A: Testing different degrees of polynomial

	RD Estimates
3) Sharp RD on component 1 of climate change literacy	
i) Order of polynomial = 2	-0.284**
	(0.132)
ii) Order of polynomial = 3	-0.323**
	(0.146)
iii) Order of polynomial = 4	-0.379**
	(0.177)
4) Sharp RD on component 1 of pro-environmental behaviours	
i) Order of polynomial = 2	0.0261
	(0.0888)
ii) Order of polynomial = 3	0.0373
	(0.104)
iii) Order of polynomial = 4	0.0779
	(0.134)

Note: **<5%. One common MSE optimal bandwidth selector was used to select the optimal bandwidth. See Table 1's notes for the rest of the model's description.

Table 7A: Clustered standard errors by the running variable and local authority district (LAD)

	Sharp RD on component 1 of climate change literacy	Sharp RD on component 1 of pro-environmental behaviours
1) Clustering by running variable		
RD estimate	-0.297***	0.0102
	(0.0649)	(0.0609)
Observations	22044	20974
Effective *N* left of cut-off	2194	2674
Effective *N* right of cut-off	2365	3179
Left bandwidth	5.333	7.284
Right bandwidth	5.333	7.284
2) Clustering by local authority district		
RD estimate	-0.257**	0.0175
	(0.125)	(0.0808)
Observations	20871	19708
Effective *N* left of cut-off	2096	2614
Effective *N* right of cut-off	2583	3231
Left bandwidth	5.965	7.895
Right bandwidth	5.965	7.895

Note: **<5%. One common MSE optimal bandwidth selector was used to select the optimal bandwidth. See Table 1's notes for the rest of the model's description. There are 386 LAD clusters.

Table 8A: Non-robust sharp regression discontinuity design

	Sharp RD on component 1 of climate change literacy	Sharp RD on component 1 of pro-environmental behaviours
RD estimate	-0.304*	0.0579
	(0.161)	(0.116)
Observations	22165	21089
Left bandwidth	3.219	3.115
Right bandwidth	3.219	3.115

Note: Optimal bandwidth from Imbens, G., & Kalyanaraman, K. (2012). Optimal bandwidth choice for the regression discontinuity estimator. *Review of Economic Studies*, *79*(3), 933-959.

Table 9A: Sharp robust regression discontinuity design by subsamples on the first components of climate change awareness and pro-environmental behaviours

	DV: Component 1: Behavioural change is not needed					
VARIABLES	**Men**	**Women**	**Southern regions**	**Northern regions**	**Household income below median**	**Household income above median**
RD estimate	-0.268	-0.176	-0.109	-0.318**	-0.209	-0.212
	(0.170)	(0.146)	(0.165)	(0.153)	(0.156)	(0.153)
Observations	9819	12346	10617	11548	11020	11145
Effective *N* left of cut-off	1302	1437	1230	1448	1478	1309
Effective *N* right of cut-off	1429	1584	1343	1693	1410	1675
Left bandwidth	7.800	6.334	6.430	7.121	8.430	6.289
Right bandwidth	7.800	6.334	6.430	7.121	8.430	6.289
	DV: Component 1: Packaging #1					
VARIABLES	Men	Women	Southern regions	Northern regions	Household income below median	Household income above median
RD estimate	0.0687	-0.0574	0.193	-0.0938	0.0589	-0.0305
	(0.108)	(0.0943)	(0.122)	(0.0993)	(0.120)	(0.109)
Observations	9161	11928	10046	11043	10256	10833
Effective N left of cut-off	1963	1964	1963	1963	1960	1966
Effective N right of cut-off	1354	1686	978	1603	1150	1261
Left bandwidth	1582	2088	1091	1907	1164	1625
Right bandwidth	8.700	8.249	5.516	8.357	6.825	6.379

Note: **<5%. One common MSE optimal bandwidth selector was used to select the optimal bandwidth. See Table 1's notes for the rest of the model's description.

Table 10A: Sharp robust regression discontinuity on higher-order principal components

Panel A	**Climate change literacy: PC4**	**Climate change literacy: PC5**	**Climate change literacy: PC6**
RD estimate	-0.00220	-0.0205	-0.0146
	(0.0428)	(0.0410)	(0.0483)
Observations	22165	22165	22165
Effective *N* left of cut-off	4234	4234	2944
Effective *N* right of cut-off	4718	4974	3294
Left bandwidth	10.54	10.85	7.554
Right bandwidth	10.54	10.85	7.554
Panel B	**Pro-environmental behaviours: PC5**	**Pro-environmental behaviours: PC6**	**Pro-environmental behaviours: PC7**
RD estimate	0.0162	0.0473	0.00958
	(0.0492)	(0.0562)	(0.0434)
Observations	21089	21089	22165
Effective *N* left of cut-off	2742	2123	3319
Effective *N* right of cut-off	3534	2706	3762
Left bandwidth	7.910	6.019	8.578
Right bandwidth	7.910	6.019	8.578

Note: **<5%. One common MSE optimal bandwidth selector was used to select the optimal bandwidth. See Table 1's notes for the rest of the model's description.

Table 11A: Testing the stability of the RDD estimate on the belief that behavioural change is not needed

```
*******************************************************************************
************************ DISCONTINUITY IN THE OUTCOME ************************
*******************************************************************************
(sum of wgt is .8621159442749481)

Linear regression                                      Number of obs     =      9,427
                                                       F(5, 9421)        =       2.92
                                                       Prob > F          =     0.0122
                                                       R-squared         =     0.0012
                                                       Root MSE          =     1.9218
```

y1	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
_x_1	.0607524	.0433361	1.40	0.161	-.0241957	.1457004
_x_2	.0078891	.0041706	1.89	0.059	-.0002862	.0160645
_T	-.2541174	.1284631	-1.98	0.048	-.5059329	-.0023019
_T_x_1	.0033416	.0599308	0.06	0.956	-.1141356	.1208188
_T_x_2	-.0136584	.0057304	-2.38	0.017	-.0248913	-.0024256
_cons	-.0734841	.0911851	-0.81	0.420	-.2522266	.1052584

```
(10,767 missing values generated)
(18,915 missing values generated)
(0 real changes made)
(29 missing values generated)
(29 missing values generated)
```

```
************************ Test of significance for LATE ************************

        LATE:  _b[_T]
```

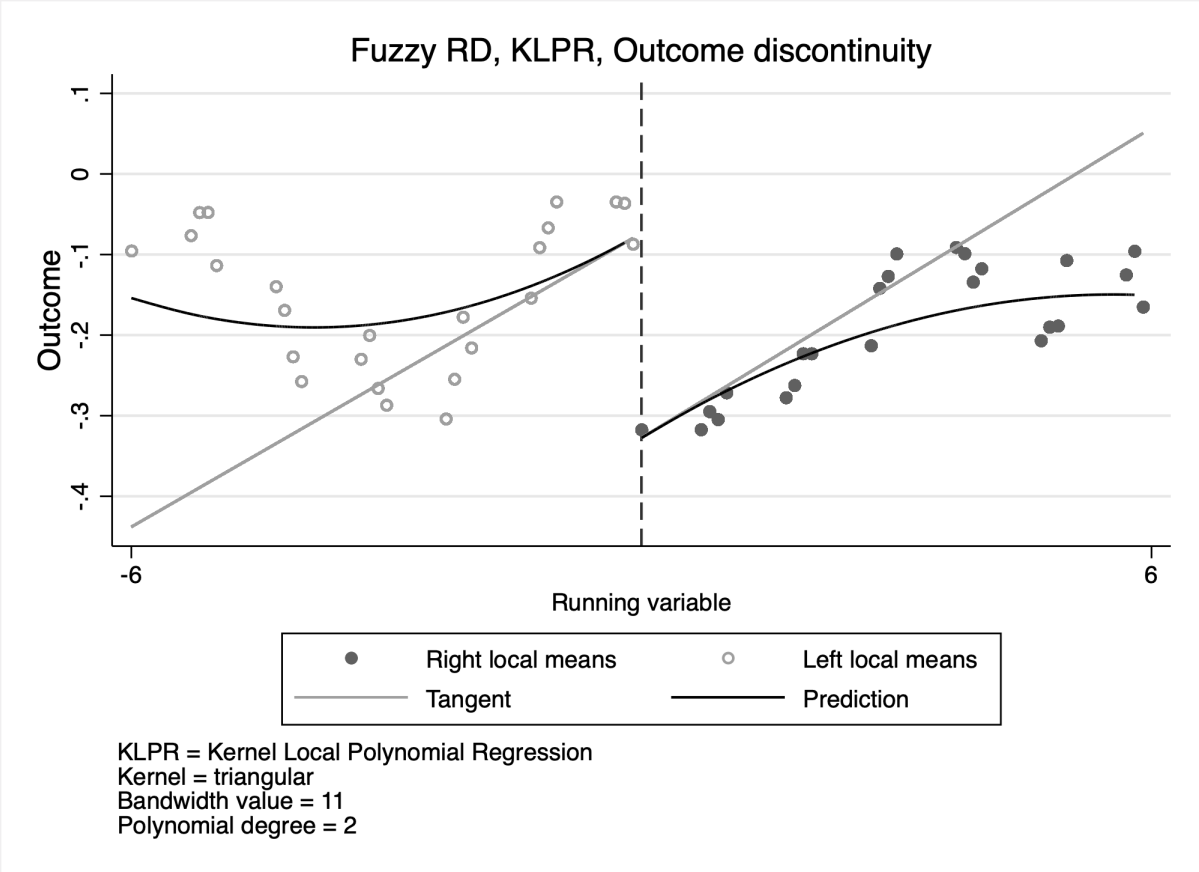
y1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
LATE	-.2541174	.1284631	-1.98	0.048	-.5059006	-.0023343

```
************************ Test of significance for TED ************************

         TED:  _b[_T_x_1]
```

y1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
TED	.0033416	.0599308	0.06	0.956	-.1141206	.1208037

Figure 4A: The treatment effect derivative plot



Note: See Cerulli et al. (2017).