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The heterogeneous relationship of education with wellbeing

Authors

Marco Felici[a]

Matthew Agarwala[a]

[a]Bennett Institute for Public Policy, University of Cambridge.

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Abstract

We use the theory of subjective wellbeing (SWB) homeostasis, combined with the properties of education as a positional good, to make predictions about the distinct relationship between education and SWB across the distribution of SWB. Theoretically, we propose that education acts as a *buffer* against negative shocks to SWB, but in the absence of such shocks, might lead to some individuals becoming *frustrated achievers*. Empirically, we conjecture that the relationship between education and SWB should be large, positive, and significant for those with low SWB, but that it should fall in significance and magnitude for those with higher SWB. Using two different datasets on the United Kingdom, we first test these hypotheses in the cross-section and then characterise their longitudinal dynamics in an event study design. Our predictions are confirmed in the cross-section and are consistent with the longitudinal results. We further illustrate how the results follow a geographic gradient.

Keywords: wellbeing, education, heterogeneity.

JEL codes: I24, I26, I31

SECTION 1

Introduction

There is strong public, scientific, and policy interest in identifying the drivers of subjective wellbeing (SWB) and the extent to which policy can influence them. SWB is defined as our experiences and evaluations of life (OECD 2013, Stone and Mackie 2013). It is typically measured by asking people to recall emotions they have felt recently, and to assess how satisfied they are with life on a scale from 1–10. While some drivers of SWB are policy-invariant, such as age (Carstensen et al., 1999; Blanchflower and Oswald, 2008; Weiss et al., 2012; Steptoe et al., 2015), others can be affected by policy, such as income and employment (Diener et al., 1993; Bardasi and Francesconi, 2004; Jebb et al., 2018; Scheuring, 2020). Education is a determinant of both income and employment opportunities and may also affect SWB directly. Previous studies of the education-SWB nexus yield surprising and sometimes conflicting results (Dolan et al. 2008). Many have identified a small but significant positive effect of education on SWB, typically mediated through its effect on income (Layard 2005; Pinquart et al., 2000; Witter et al., 1984) or as a 'positional good' (Salinas-Jimenez et al., 2011; Graham and Pettinato, 2002). Others have noted that education can have a negative effect on SWB, particularly if education raises aspirations which ultimately go unmet (Diener et al., 1999, Binder and Coad, 2011). Further discrepancies arise at different scales of analysis: education is found to have a stronger association with SWB at the city or national level, as compared to the individual level (Florida et al., 2013). In contrast to much of the existing literature that evaluates education-SWB links at the sample mean, we focus on the tails of the SWB distribution, allowing for different effects among those with low, average, and high SWB. This can help explain some of the inconsistency in results across studies: if the SWB returns to education are different depending on whether an individual starts from a high or low point of SWB, averaging may mask these nuanced differences. Moreover, policy might be particularly concerned with those who report low SWB, rather than with the average person, especially as low SWB might coincide with depression (Cummins, 2010).

Investigating the cross-sectional relationship between education and life satisfaction, Binder and Coad (2011) find a positive relationship among those with low life satisfaction, a negative one for those with high life satisfaction, with estimates around 0 for those in the middle. We extend their results in a number of ways. First, we provide a more structured theoretical basis, drawing on SWB homeostasis theory and on the properties of education as a positional good (Cummins 2010). We posit that education acts as a *buffer* against negative shocks to SWB, for example by raising the probability of stable employment, higher income, and a wider set of opportunities in general. At the other end of the scale, viewing education instead as a positional good (Hirsch, 1976), we hypothesise that in the absence of said negative shocks, education can have a negative effect because it is associated with high-pressure and high-competition environments. Empirically, we confirm their results on a separate UK dataset (the Community Life Survey), as well as extending the results in a panel setting using the British Household Panel Survey and Understanding Society datasets, and exploiting recent advances in the difference-in-differences design for event studies where treatment occurs at different times for different units. Using OLS and quantile regression, we show that the cross-sectional association between life satisfaction and education is stronger and positive at lower levels of life satisfaction, weaker or zero for those in the middle intervals (as well as for the overall average, since the middle intervals contain most of the sample) and negative for those at the high end of life satisfaction. Using the imputation technique of Borusyak et al. (2021), we show that increased education is associated with different trajectories of life satisfaction over time, and that those starting out with higher life satisfaction at a young age benefit comparatively less from education, a result that is consistent with the cross-sectional findings. Finally, we discuss the spatial implications of this heterogeneity. Theory suggests that education may act as buffer against negative SWB shocks because it improves access to resources such as income and job security. But these resources are themselves unevenly distributed across space. Thus we might expect to see a geographic component to the relationship between education and life satisfaction.

The paper proceeds as follows. Section 2 discusses the theoretical framework that connects education to SWB. Section 3 describes the survey data used. Section 4 lays down the empirical strategy to identify the cross-sectional and longitudinal relationship between education and life satisfaction across the distribution of life satisfaction. Section 5 presents and discusses the results, focusing on the heterogeneity of the relationship. Section 6 concludes.

SECTION 2

Theoretical Framework

Our conceptual framework for the definition and operationalisation of SWB follows the OECD guidelines on measuring SWB (OECD, 2013). Specifically, we distinguish conceptually three dimensions of SWB: *evaluation*, *affect* and *eudaimonia*. *Evaluation* involves a cognitive effort on the part of the individual to compare their current situation to a standard they have in mind. *Affect*, on the other hand, is the description of an emotional state and pertains to the realm of experience, rather than to that of evaluation. *Eudaimonia*, finally, is yet a different dimension of SWB that concerns a person's sense of purpose. It is about the good functioning of one's psychological processes rather than the evaluation of one's current situation or description of an emotional state. The main focus of this study is on the first dimension, *evaluation*, which we operationalise using reported *life satisfaction* as a measure. Examples of *affect* and *eudaimonia* instead would be reported *happiness* and reported *assessment of life being worthwhile*, respectively. Educational attainment is measured via a binary variable indicating whether or not the individual holds a university degree. This is grounded in the assumption that the increase in opportunities arising from education are discrete in nature (reflecting the division in educational cycles) and the biggest jump occurs when obtaining a degree. We use two different but complementary theories to make predictions about the effect of holding a university degree on life satisfaction. The first is SWB homeostasis, which relies on the notion of Homeostatically Protected Mood (HPMood) and can explain education as a buffer for life satisfaction against negative shocks. The second frames education as a positional good that leads some individuals to be *frustrated achievers* – people who despite reporting high levels of life satisfaction, face downward pressure on SWB due to unmet aspirations.

2.1 SWB homeostasis and low levels of wellbeing

Our empirical investigations are grounded in theories of SWB homeostasis, especially Homeostatically Protected Mood (Cummins 2010; 2014). SWB homeostasis is the notion that individuals' wellbeing has a tendency to revert to a set-point range through the action of a set of buffers. Whilst shocks and life events may temporarily increase or decrease wellbeing, individuals adapt. SWB homeostasis bears a close relationship with set-point theory, in that both rely on the existence of a set-point range for SWB, but while set-point theory assumes that individuals invariably return to their set-point and that therefore non-transitory differences in SWB across individuals are genetically driven (Lykken and Tellegen, 1996), SWB homeostasis allows for and characterises structural departures from the set-point. In fact, the existence empirically of such structural departures from the set-point has been the primary criticism aimed at set-point theory (see for instance Lucas (2007) or Foa et al. (2018)). When adverse external circumstances are sufficiently strong or prolonged to push wellbeing below the set-point range, the individual's system is said to have suffered *homeostatic defeat*, which may be considered a structural change in SWB. HPMood, on the other hand, is defined as the hard-wired positive mood that drives individuals' SWB as well as higher cognitive processes. HPMood is also the set-point that SWB homeostasis defends. Chronic homeostatic defeat can detach individuals from HPMood, placing them into a lower range of SWB. In Cummins' theory, SWB is therefore the result of a combination of the hard-wired, stable HPMood and of emotional states, and the stronger the emotional state relative to HPMood, the bigger the distance of SWB from HPMood. While this is more credibly true for *affect* measures, such as reported *happiness*, which focus on the emotional state and rely less on a cognitive component, *evaluative* measures of SWB such as *life satisfaction* are the result not only of HPMood and of emotional states, but also of cognitive components at the time of response. Our focus on *life satisfaction* means that the answers we observe in the survey will therefore always be driven by HPMood and by a cognitive component, as well as the respondent's emotional state (positive or negative), if it is particularly strong. Estimates for the set-point range typically land towards the upper end of the SWB distribution: 71-90 (Cummins et al. 2014) to 75-90 (Capic et al. 2018) on a 100-point scale. Further, Cummins (2010) posits that "SWB values lying one standard deviation below the normative mean approximate the boundary between homeostatic maintenance and homeostatic defeat", providing the example of the Personal Wellbeing Index (a composite, evaluative measure of SWB), with a mean of 73.40 and a standard deviation 14.54, so that such boundary would be located at 58.9.

We focus on the role of education as an external buffer that increases the probability of accessing external resources such as financial security or a bigger house in a pleasant environment (Cummins 2000; 2010). If education acts as a buffer aiding homeostatic maintenance, we would expect its relationship with life satisfaction to be stronger the further below their set-point range an individual is. That is, we would expect its action to be positive and stronger the closer we get to the lower extreme of the distribution to bring SWB back up to the set-point range. SWB homeostasis theory has been used to highlight the importance of evaluating SWB in the tails of the distribution has been identified in other contexts. Examining the effect of an adolescent intervention designed to improve education and employment outcomes, Tomyn et al. (2015) find the biggest gains are made by those below a baseline score of 50 (on a 0 to 100 normalised scale) and smallest by those above a score of 70, with intermediate results in between these ranges.

2.2 Education as a positional good, frustrated achievers and high wellbeing

While SWB homeostasis can explain a buffer effect of education on SWB when negative shocks occur, it is less useful to make predictions about what should happen at high levels of SWB. To evaluate the relationship at the upper end of the SWB distribution, we frame education as a positional good: one that is more valuable in relation to others' possession of it. As Hirsch (1976, page 3) aptly puts it: "The value to me of my education depends not only on how much I have but also on how much the man ahead of me in the job line has." Being the only person with a university degree places a high value on degree-level education, but this value declines, in relative terms at least, as more and more people gain degree-level education. To compound this effect, individuals with higher educational attainment tend to concentrate together, most notably in urban areas. Self-selection into an environment that rewards and attracts those with degrees might fuel a phenomenon termed *frustrated achievement* (Graham and Pettinato, 2002), whereby those that are most upwardly mobile are also the most negative when it comes to self-assessment. Notice that this does not negate a positive role for education as a buffer against negative shocks. It rather posits that in the absence of said negative shocks, the social competition that characterises environments with high educational attainment can actually have detrimental effects on SWB. Since this effect plausibly kicks in only in the absence of negative shocks, it should concern only those that are higher up in the SWB distribution. A related theoretical interpretation of the role of education as a positional good affecting SWB is described as the "tunnel effect" (Hirschman and Rothschild, 1973). The "tunnel" posits a dynamic relationship between one's position compared to that of others in the society (e.g. one's education compared to the average). Initially, below average education may provoke a degree of optimism, if one believes they too will eventually reach that higher average level. But if the inequality is not resolved over time, those left behind eventually develop negative feelings. The relationship is likened to a traffic jam in a tunnel, hence the name. Although the tunnel effect similarly portrays education as a positional good, it refers to societal changes unfolding over a longer time span than the data permits in the present study.

2.3 Hypotheses testing

The combined framework of SWB homeostasis theory and the positional nature of educational attainment leads us to the following hypotheses:

> *Hypothesis 1*: The difference in life satisfaction between individuals with a degree and those without a degree should be greater the lower the level of individual life satisfaction.

Hypothesis 2: At very high levels of life satisfaction, the relationship between holding a degree and life satisfaction should be negative.

Because most individuals are expected to lie in the set-point range at any point in time, we would expect instead to see little to no effect of education, on average.

SECTION 3

Data Description

3.1 The Community Life Survey

To investigate our hypotheses, we first utilise waves 1-5 of the Community Life Survey (CLS), a nationally representative repeated cross-section of respondents in England spanning 2012 to 2017 and containing questions on engagement in social and local activities, in addition to demographic and socio-economic characteristics (CO and DCMS 2019.) The CLS also enables us to examine geographic variation in life satisfaction by using Output Area categories in which respondents live. Table 1 reports summary statistics for the full sample of 19,494 observations, by degree status. Mean life satisfaction in both groups sits between 7 and 8, on a 0 to 10 scale, with a standard deviation of around 2. Both groups have similar gender balance and meet with friends or family at similar rates. The share below age 35 (the age variable is not continuous but instead has eight categories), the share reporting good health and the share with a partner are instead noticeably higher for those with a degree.

Table 1: Summary statistics for the estimation sample, CLS

	No degree		Degree	
	Mean	S.D.	Mean	S.D.
Life Satisfaction	7.35	2.12	7.43	1.71
Share below age 35 (%)	21.48	41.07	31.01	46.26
Share female (%)	54.63	49.79	54.44	49.81
Share reporting good health (%)	66.91	47.06	84.39	36.29
Share with a partner (%)	57.67	49.41	69.09	46.22
Share meeting friends or family often (%)	92.22	26.78	91.41	28.03
Observations	14105		5389	

Our theoretical framework suggests that the relationship between life satisfaction and education should differ across the distribution of life satisfaction. Figures 1 and 2 below divide the sample into low (below a reported score of 5) and high (above a reported score of 8) life satisfaction groups, respectively, showing the correlation between LS and education for each group. To show how the relationship is spatial in nature, we take the high and low life satisfaction groups and plot their mean life satisfaction against the share of the sample with a degree in each of eight types of Output Area.[1] A few interesting patterns emerge. First, the relationship between life satisfaction and education is positive and

[1] A description of the eight Output Area classification is found in Appendix A. For more information about the Output Areas classification, including definitions and the creation methodology, see Gale et al. (2016).

significant (p-value = 0.013) at low levels of life satisfaction (Figure 1) but negative and significant (p-value = 0.00003) at high levels of life satisfaction (Figure 2), supporting the claim that the relationship between the two is not constant but depends on where in the distribution of life satisfaction the individual lies. Moreover, the ordering of Output Areas based on the sample share with a degree is largely unchanged between the low and high life satisfaction samples (although the range is wider at high levels of life satisfaction), indicating that individuals sort into different areas based on their degree in a similar fashion across the high and low life satisfaction groups. This is better shown in Figure 3, which compares directly the ordering of Output Areas, by share with a degree, in the two subsamples and suggests that education level accounts for the geographic sorting. As a consequence of this, the ordering of Output Areas based on mean life satisfaction (Figures 1-2, vertical axes) is reversed in the two samples.[2]

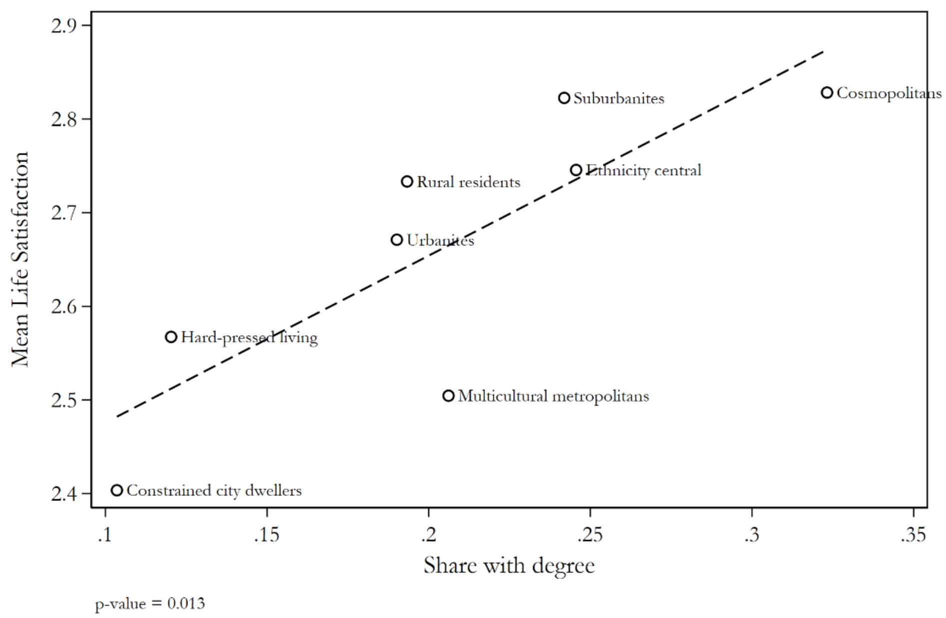

Figure 1: *Life satisfaction and share with a degree for life satisfaction < 5*

[2] To see how the different Output Areas are distributed across England, see an overall map in Fig. 1 of Martin et al. (2018), or, for an interactive visualisation, visit http://oac.datashine.org.uk/

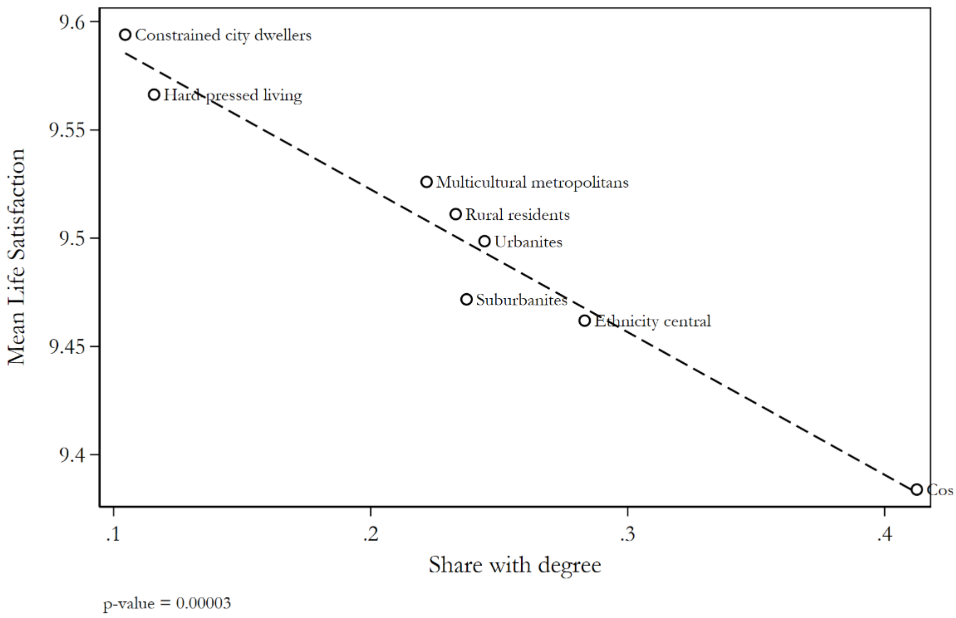

Figure 2: *Life satisfaction and share with a degree for life satisfaction > 8*

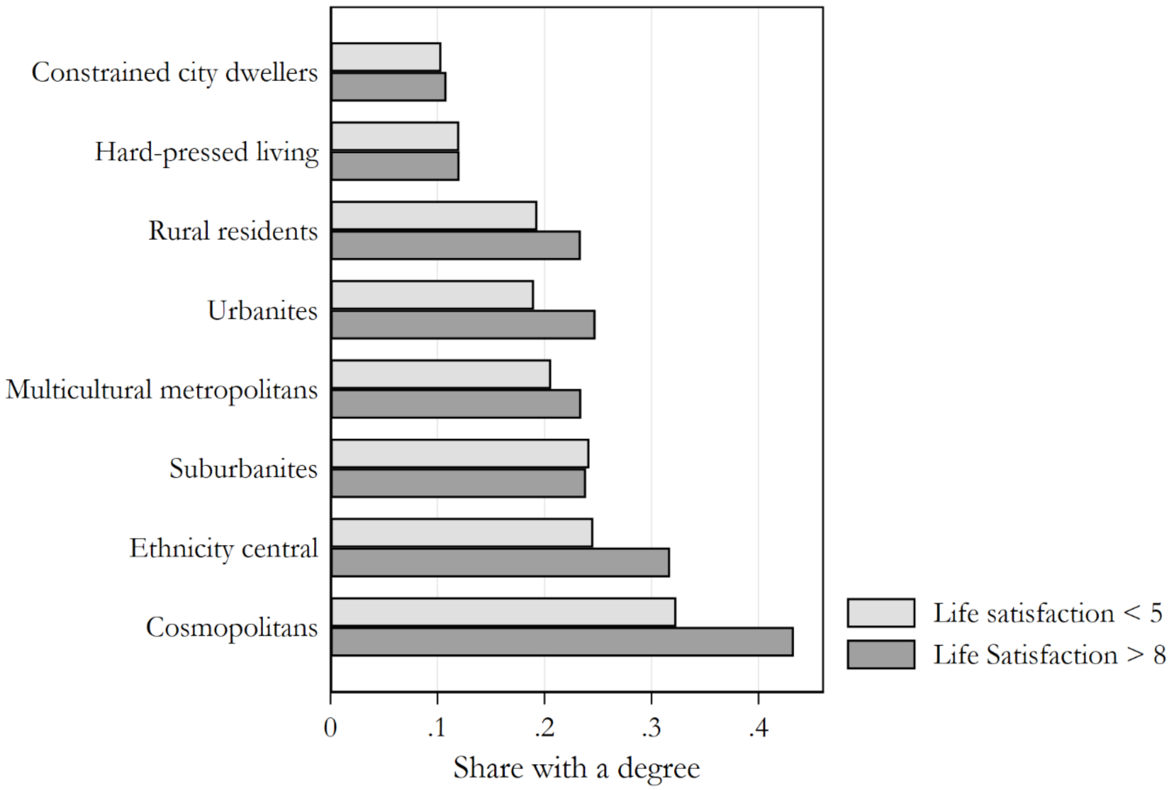

Figure 3: *Ordering of Output Areas by share with degree within the high and low life satisfaction subsamples*

3.2 The British Household Panel Survey and Understanding Society

The second dataset we use is the British Household Panel Survey (BHPS), a representative survey of the United Kingdom at the individual and household level that started in 1991 and continued until 2009, when it was substituted by Understanding Society (US). Crucially, the BHPS/US allows us to follow a same individual over time, including before and after obtaining a university degree. Binder and Coad (2011) used Wave 6 of the BHPS, finding a heterogeneous relationship between education and life satisfaction across the life satisfaction distribution. We expand on their cross-sectional finding by using all available waves of the BHPS/US, and by exploiting the panel to trace the average evolution of life satisfaction before and after obtaining a degree. Overall, we use 28 waves of the combined BHPS/US, excluding from the last wave any observations after December 2019, to avoid the pandemic period (University of Essex, 2021). Our broadest estimation sample includes 525,411 observations across about 90,000 unique individuals.[3] Table 2 shows summary statistics for the sample.

Table 2: Summary statistics for the estimation sample, BHPS/US

	No degree		Degree	
	Mean	S.D.	Mean	S.D.
Life Satisfaction	5.15	1.48	5.27	1.31
Age	47.68	19.58	46.00	15.64
Share female (%)	55.09	49.74	56.01	49.64
Share satisfied with health (%)	62.13	48.51	69.71	45.95
Share with a partner (%)	60.39	48.91	71.09	45.33
Share meeting people on most days (%)*	48.65	49.98	38.59	48.68
Observations	355,543		169,868	

Note: * The sample size for the two groups is 114,883 and 31,806 respectively for this variable.

The long panel yields an overall sample with similar mean values across individuals with and without a university degree in terms of life satisfaction, age, and gender. Life satisfaction ranges from 1 (completely dissatisfied) to 7 (completely satisfied). Those with a degree report greater satisfaction with health, are more likely to have a partner, and are less likely to meet others on most days. Due to scale and definitional differences between the BHPS/US and CLS described in the previous section, most variables cannot be directly compared between the surveys. However, the proportion of women and of those with a partner, are similar across the surveys. The disparity in health satisfaction between those

[3] In some estimates, we reduce the sample because of the lack of availability of covariates.

with and without degrees is wider in the CLS, but the overall levels are somewhat similar. The BHPS/US does not report OA classifications and so cannot be compared against the CLS on this dimension.

SECTION 4

Empirical Strategy

Our theoretical framework suggests a specific structural relationship between education and SWB. In the data, this relationship is likely confounded by other variables affecting both SWB and educational attainment, as well as made imprecise unless we account for other drivers of SWB only. Estimating this relationship poses a challenge that we aim to overcome through model specification. In the cross-sectional setting, our baseline model is:

$$LS_i = \alpha + \beta_D \mathrm{Degree}_i + \boldsymbol{\beta}'_X \boldsymbol{X}_i + \beta_t t + \beta_{HPM} HPMood_i + \beta_{PS} PS_i + \varepsilon_i \tag{1}$$

Where LS_i is the reported life satisfaction score, Degree_i is the dummy variable indicating whether an individual has or has not a degree, $\boldsymbol{X}_i$ is the vector of covariates, namely age, gender, marital status, social capital, general health and interview mode (whether the respondent was interviewed face-to-face or online), while t are time period fixed effects, $HPMood_i$ is unobserved and time-invariant HPMood and PS_i is unobserved parents' socio-economic status. ε_i is the error term. Since $HPMood_i$ and PS_i are unobserved there will be a bias. Estimating (1) without $HPMood_i$, for example, leads to the biased coefficient $\beta_{D,bias}$:

$$\beta_{D,bias} = \beta_D + \beta_{HPM}\gamma_D \tag{2}$$

Where γ_D is the coefficient of the regression of $HPMood_i$ on Degree_i; we return to this bias later to discuss attempts to reduce it. The vector of covariates $\boldsymbol{X}_i$ does not include variables such as employment or income, to avoid introducing bias from "bad controls" (Angrist and Pischke 2009). Specifically, having a degree influences both the chances of employment and one's income, so that controlling for these when estimating the effect of education will likely introduce bias. These variables may at the same time reduce bias if they are correlated with unobserved confounders that could drive both reported life satisfaction and chances of obtaining a degree, for instance $HPMood_i$. Thus, the overall effect on bias depends on the relative strength of these two relationships. Specifically, if we assume for simplicity that income is a deterministic function of HPMood and of education, we can write:

$$I_i = \pi + \pi_{HPM} HPMood_i + \pi_D \mathrm{Degree}_i \tag{3}$$

Substituting the formula for $HPMood_i$ obtained from this into (1) and rearranging, we have:

$$LS_i = \left(\alpha - \frac{\beta_{HPM}}{\pi_{HPM}}\right) + \left(\beta_D - \frac{\beta_{HPM}\pi_D}{\pi_{HPM}}\right)\mathrm{Degree}_i + \frac{\beta_{HPM}}{\pi_{HPM}} I_i + \boldsymbol{\beta}'_X \boldsymbol{X}_i + \beta_t t + \varepsilon_i \tag{4}$$

So that the biased coefficient we would estimate is, in this case:

$$\beta_{D,bias} = \beta_D - \frac{\beta_{HPM}\pi_D}{\pi_{HPM}} \tag{5}$$

If income and having a degree are unrelated to each other ($\pi_D = 0$), then the model in equation (4) would allow us to estimate correctly the effect of education on life satisfaction. But we know that π_D is very likely to be big, so will push down the estimated effect of education on life satisfaction. In fact, if the relationship between HPMood and income is small ($\pi_{HPM} \approx 0$), the term $\frac{\beta_{HPM}\pi_D}{\pi_{HPM}}$ could be of substantial magnitude. We argue therefore that controlling for income (or for occupation) is more likely to harm than to help produce unbiased estimates. The conceptual structure behind the model is summarised by the Directed Acyclical Graph (DAG)[4] in Figure 4:

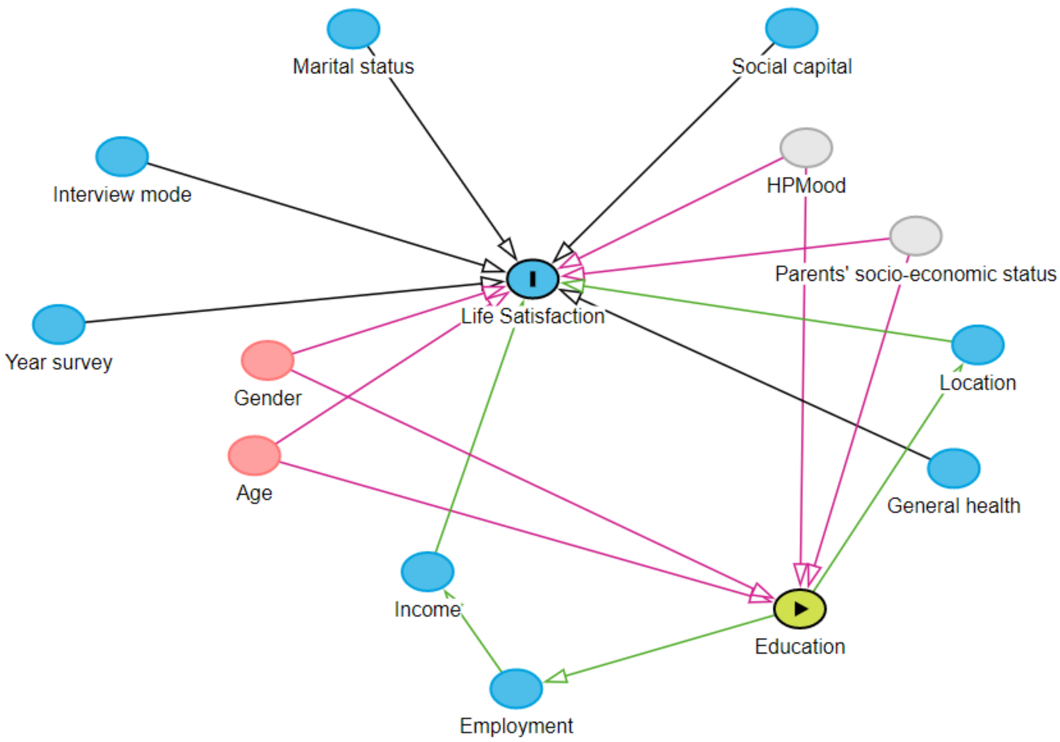

Figure 4: *Directed Acyclical Graph for the model*

Note: The DAG was created using DAGitty (Textor et al., 2011). The green arrows indicate causal pathways of interest. Purple arrows indicate confounder effects while black arrows exogenous drivers of life satisfaction. Pink nodes are observed confounders, grey nodes unobserved confounders, while blue nodes represent variables affecting the outcome without confounding the main effect of interest.

Age and gender are the only observed drivers of both reported life satisfaction and education. Two important, but unobserved, drivers of both life satisfaction and education are HPMood and parents'

[4] See Cunningham (2021) and Pearl (2009) for an introduction and an in-depth treatment of DAGs respectively.

socio-economic status. Income and employment, as well as location, are framed as consequences of education and the mediators through which education affects SWB. Though there could be direct effects of education on life satisfaction, we focus on the indirect effects that come through increased access to resources such as employment or income. Figure 4 is not meant to be exhaustive as to all causal paths between any two variables in the diagram, but rather to highlight the relevant effects underpinning our model.

4.1 Subsetting the sample

We first split the sample in subsamples and estimate specification (1) under different definitions of high and low thresholds for life satisfaction. We argue that subsetting the sample into high and low life satisfaction individuals can account for unobserved characteristics such HPMood or parents' socio-economic status under the assumption that both of these variables determine much of the first order variation in life satisfaction, while the residual variation, within these subsets, is more plausibly attributed to the remaining variables, including educational attainment. An illustration of this reasoning is offered in Figure 5. For the CLS, we consider in turn the samples below a life satisfaction of 5, 6, 7, 8, 9, 10 and the samples above a life satisfaction of 4, 5, 6, 7, 8. For the BHPS/US, we consider in turn the samples below a life satisfaction of 3, 4, 5, 6, 7 and the samples above a life satisfaction of 1, 2, 3, 4, 5.

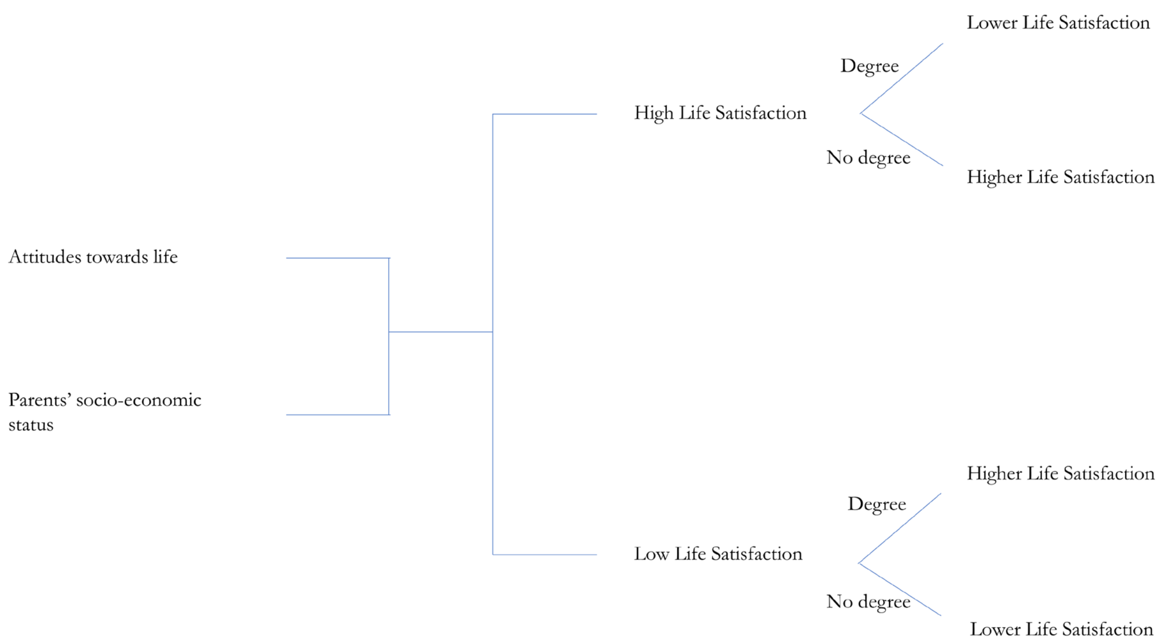

Figure 5: *Diagram connecting unobserved characteristics, education and life satisfaction*

4.2 Interaction with specific groups

Instead of subsetting the sample, a second strategy is that of interacting the degree dummy with a variable that indicates increased or decreased likelihood to experience hardship. One such variable is health. Our model in this case is then:

$$LS_i = \alpha + \beta_D \text{Degree}_i + \beta_{D,Health} \text{Degree}_i \bullet Health_i + \boldsymbol{\beta}'_X \boldsymbol{X}_i + \beta_t t + \beta_{HPM} HPMood_i + \beta_{PS} PS_i + \varepsilon_i \quad (6)$$

The $\beta_{D,Health}$ coefficient will separate the relationship between life satisfaction and education by health group.

4.3 Quantile regression

Quantile regression is an alternative modelling strategy to estimate the relationship between education and SWB across the SWB distribution. Using the same variables as for equation (1), we can express the generic quantile as:

$$Q_\tau(LS_i|\boldsymbol{Z}_i) = \alpha_\tau + \beta_{\tau,D} \text{Degree}_i + \boldsymbol{\beta}'_{\tau,X} \boldsymbol{X}_i + \beta_{\tau,t} t \quad (7)$$

Where $Q_\tau(LS_i|\boldsymbol{Z}_i)$ is the conditional τth quantile of life satisfaction given the vector of characteristics $\boldsymbol{Z}_i$, which corresponds in turn to the right-hand side. Notice that while the variables on the right-hand side are the same as in equation (1), with the exception of $HPMood_i$ and PS_i, the corresponding coefficients are allowed to vary based on the quantile and are in fact indexed by τ. $HPMood_i$ and PS_i are not reported as part of the model for the same reasoning outlined in Figure 4, because it is assumed that these are largely constant within a same quantile. To ensure convergence in the computation of the quantile regression, we carried out a few adjustments on the inclusion and use of specific variables. For the CLS, the gender variable was excluded from the estimation of (7). For the BHPS/US, the variable capturing education was used as a continuous variable going from 1 (no qualifications) to 6 (degree holders), in a similar fashion as Binder and Coad (2011). Moreover, the variable capturing marital status was excluded and the variable for satisfaction with own health was used as continuous. The quantiles considered are the 25th, 40th, 50th, 60th and 75th percentiles for the CLS and the 10th, 25th, 40th, 50th, 60th, 75th and 90th for the BHPS/US.

4.4 Event study design

We then move on to exploit the longitudinal structure of the BHPS and US dataset to estimate the relationship of obtaining a degree with life satisfaction in an event study design, where obtaining a degree is taken as the event. As obtaining a degree is not exogenous, it is particularly important to state under what assumptions we can identify a causal effect of education on life satisfaction. Traditional (dynamic) event study specifications take the form:

$$LS_{\mathrm{it}} = \gamma_{\mathrm{i}} + \lambda_{\mathrm{t}} + \sum_{\tau=-\mathrm{q}}^{-1} \gamma_{\tau} \, \mathrm{Degree}_{\mathrm{i}\tau} + \sum_{\tau=0}^{\mathrm{m}} \delta_{\tau} \, \mathrm{Degree}_{\mathrm{i}\tau} + \mathrm{X}_{\mathrm{it}}' \Gamma + \epsilon_{\mathrm{it}} \qquad (8)$$

Where γ_{i} and λ_{t} are respectively individual and time fixed effects, γ_{τ} are coefficients on the leads τ periods before the event and δ_{τ} are coefficients on the lags τ periods after the event, that is our dynamic effect of interest. Γ are coefficients in case of time-varying controls. The econometrics literature has recently focused on the problems arising in this setup when treatment occurs at different times for different units. Crucially, (8) can recover the causal effect of $\mathrm{Degree}_{\mathrm{i}\tau}$ only under, among other assumptions, *homogenous treatment effects*. This is a strong assumption in general and especially in our case, for our theoretical framework explicitly calls for heterogenous treatment effects (for individuals at different points of the SWB distribution). Among the estimators available that are robust to treatment effect heterogeneity, we resort to that proposed in Borusyak et al. (2021). This is a three-step estimator that first estimates the counterfactual for treated units based on non-treated units (never treated or yet-to-be treated):

$$LS_{\mathrm{it}}(0) = \gamma_{\mathrm{i}} + \lambda_{\mathrm{t}} + \epsilon_{\mathrm{it}} \qquad (9)$$

It then computes the individual level treatment effect based on such counterfactual:

$$\hat{\tau}_{it} = LS_{\mathrm{it}} - \widehat{LS}_{\mathrm{it}}(0) \qquad (10)$$

Finally, it aggregates individual level treatment effects according to the weights $\frac{1}{N}$, where N is the total number of observations for a specific horizon of interest. This estimator is particularly appealing as it is generally more efficient than other available estimators, even under heteroscedasticity, as well as with lower bias in case the assumption of *no anticipation* (which is treated more in detail below) fails. Other than treatment effect heterogeneity, the two crucial assumptions for this estimator are:

1. *Parallel trends*

Parallel trends cannot be tested explicitly as they rely themselves on the counterfactual, so we need to assume that the difference in life satisfaction between those who gain a degree and those who do not would have stayed the same in the absence of treatment (the counterfactual life satisfaction if the person did not obtain a degree, $LS_{\mathrm{it}}(0)$). Formally, this is equivalent to equation (9). Borusyak et al. (2021) suggest testing pre-trends based on non-treated units only, as a placebo test

$$LS_{\mathrm{it}} = \gamma_{\mathrm{i}} + \lambda_{\mathrm{t}} + W'_{it}\varphi + \tilde{\epsilon}_{\mathrm{it}} \tag{11}$$

Where W'_{it} are pre-treatment periods indicators. Such a placebo test is robust to the critique of Roth (2021), as testing only on never or yet-to-be treated units makes the pre-trend coefficients orthogonal to treatment effect estimates.

2. No anticipation

A second assumption is that of no anticipation, meaning that individuals do not respond to treatment prior to the actual treatment:

$$LS_{\mathrm{it}} = LS_{\mathrm{it}}(0) \tag{12}$$

For all individuals and periods for which there is no treatment. Since our treatment is endogenous (individuals decide to gain a degree), there can be a concern that this assumption is violated. At the same time, our theoretical framework implicitly rules out anticipation by considering the effects of gaining a degree as those enjoyed only after its formal achievement. We can test this assumption again by looking at pre-trends coefficient estimated only on never or not-yet-treated units, as for parallel trends. Moreover, as mentioned already, the estimator is minimally biased, among those available, in case this assumption is violated.

We are interested in horizon-specific Average Treatment effects on the Treated (ATT) for the full samples as well as for subsamples. If we were to subset the sample as in the cross-sectional case, that is by retaining observations below or above specific thresholds for life satisfaction, we would break up individual time-series as some individuals would be included only in those time periods where they reported life satisfaction below or above the thresholds. We include instead the entire time-series of individuals based on average life satisfaction between the age of 15 and 22, that is the usual period before obtaining a degree. This way we can capture different types of individuals before any effect of obtaining a degree materialises (under the assumption of no anticipation): by examining those for whom we have life satisfaction data between the ages of 15 and 22, we can see the life satisfaction trajectory before and after obtaining a degree, distinguishing between those who started off very satisfied about their lives and those who were rather unsatisfied when very young. The average life satisfaction between age 15 and 22 for each individual will be therefore:

$$\overline{LS_{i,15-22}} = \sum_{t=15}^{22} LS_{it} \tag{13}$$

Finally, we assume that individuals that report *non-structural* life satisfaction, i.e. due to temporary events that do not fundamentally alter life satisfaction, do not affect the estimation because there is no systematic correlation between their education and their life satisfaction. In other words, we assume that reporting such non-structural low life satisfaction occurs randomly – it is transitory. This can be thought of as the *affect* component of SWB, discussed in the theoretical framework, not being structural.

SECTION 5

Results and Discussion

5.1 Cross-sectional results

Our cross-sectional analyses yield a coherent picture across the Community Life Survey and the BHPS/US data.

5.1.1 Subsetting the sample

Focusing on the lower end of the life satisfaction (LS) distribution, Table 3 regresses LS on education and standard controls. Column 1 reports results for the overall sample. Consistent with previous literature, we find a statistically significant overall positive impact of education on life satisfaction. However, its strength varies across the life satisfaction distribution. Columns 2-7 report restricted samples, gradually extending from those with life satisfaction below 5 (column 2) to those with life satisfaction below 10, in increments of 1. The average association between having a degree and life satisfaction decreases as we extend the sample towards the right of the distribution, although not in a linear fashion. A striking feature of these results is the role of those reporting a life satisfaction of 10/10 in affecting the average estimate. Column 7 includes the whole sample except those who reported 10/10 and the corresponding estimate is 0.251. Including the 10s to evaluate the full sample estimate, the coefficient falls by about two-thirds, to 0.0816. This underscores how the relationship between education and life satisfaction is positive through most of the distribution but has a strong, negative gradient at the very top.

Table 3: Education and life satisfaction from the left of the distribution, CLS

	(1) Full sample	(2) LS < 5	(3) LS < 6	(4) LS < 7	(5) LS < 8	(6) LS < 9	(7) LS < 10
Degree	0.0816***	0.351***	0.139**	0.300***	0.328***	0.258***	0.251***
	(0.0287)	(0.0735)	(0.0589)	(0.0484)	(0.0370)	(0.0295)	(0.0283)
Observations	19494	1562	3242	4969	8649	13988	16738
Adj. R-squared	0.213	0.107	0.101	0.124	0.163	0.195	0.212

Standard errors in parentheses. Common controls: age, gender, marital status, meeting friends and family, general health, year and interview mode fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The result is confirmed by the corresponding pattern obtained by reversing the exercise and extend the sample from the right (high) towards the left side of the distribution (Table 4). Column 6 indicates a significant negative association between education and life satisfaction among those whose life satisfaction is greater than 8. The significant negative association becomes weaker and monotonically so as those with lower levels of life satisfaction are included, ultimately becoming indistinguishable from 0 in column 2.

Table 4: Education and life satisfaction from the right of the distribution, CLS

	(1) Full sample	(2) LS > 4	(3) LS > 5	(4) LS > 6	(5) LS > 7	(6) LS > 8
Degree	0.0816***	-0.0359	-0.141***	-0.151***	-0.154***	-0.163***
	(0.0287)	(0.0230)	(0.0207)	(0.0190)	(0.0178)	(0.0161)
Observations	19494	17932	16252	14525	10845	5506
Adj. R-squared	0.213	0.138	0.121	0.0926	0.0575	0.0652

Standard errors in parentheses. Common controls: age, gender, marital status, meeting friends and family, general health, year and interview mode fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Although we do not include survey weights in the main estimation, as we already include a number of controls that could drive probability of inclusion in the sample, Appendix C reports the equivalents of Tables 3 and 4 using survey weights. The results show very similar patterns, with the exceptions of the full sample estimate, that is not statistically distinguishable from 0 in this case. We repeat the exercise using the BHPS/US. Although the scale of life satisfaction is different (going from 1 to 7) and so are some of the covariates of the model, the results reported in Tables 5 and 6 are qualitatively consistent. Here too the effect is strongest when the top of the distribution is excluded (column 6 of Table 5), so that the estimate of the degree coefficient is 0.0907 when excluding those reporting a life satisfaction of 7 and 0.0107 when including them (that is, using the full sample).

Table 5: Education and life satisfaction from the left of the distribution, BHPS and US

	(1) Full sample	(2) LS < 3	(3) LS < 4	(4) LS < 5	(5) LS < 6	(6) LS < 7
Degree	0.0107*	0.0709***	0.102***	0.00494	0.0602***	0.0907***
	(0.00603)	(0.00627)	(0.00683)	(0.00709)	(0.00673)	(0.00592)
Observations	525411	34733	73329	131474	242535	458367
Adj. R-squared	0.309	0.160	0.201	0.240	0.270	0.297

Standard errors in parentheses, clustered at the individual level over time. Common controls: age, gender, satisfaction with health, marital status and wave fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6 indicates the degree coefficient is negative whenever those at the lowest end of the LS distribution are excluded, and that the magnitude and significance of the coefficient are highest at the top of the distribution (LS = 5, 6 or 7). Since the variable measuring the frequency of meeting people has lower coverage than our other covariates, the estimation was repeated separately including the frequency of meeting people together with age, gender and wave fixed effects and yielded qualitatively consistent results.

Table 6: Education and life satisfaction from the right of the distribution, BHPS and US

	(1) Full sample	(2) LS > 1	(3) LS > 2	(4) LS > 3	(5) LS > 4	(6) LS > 5
Degree	0.0107***	-0.0143**	-0.0274***	-0.0185***	-0.0621***	-0.0758***
	(0.00349)	(0.00580)	(0.00529)	(0.00419)	(0.00333)	(0.00246)
Observations	525411	513958	490678	452082	393937	282876
Adj. R-squared	0.309	0.283	0.250	0.230	0.186	0.169

Standard errors in parentheses, clustered at the individual level over time. Common controls: age, gender, satisfaction with health, marital status and wave fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

These estimates can be compared to the existing literature. Using British and international data, and taking the whole sample, Clark (2018) reports a total effect of a one standard deviation in education, counting both direct and indirect effects, of 0.1 on life satisfaction. Our sample average result of 0.0816 for the CLS is equivalent to about 0.18 in standard deviations and is therefore almost twice as much. But the result for the CLS at low levels of life satisfaction, 0.351, is equivalent to about 0.78 in standard deviations, almost eight times the average estimate reported by Clark (2018). The estimates for the BHPS/US are lower but show a similar pattern: the sample average result is about 0.02 in standard deviations, while the largest estimate, the result for those reporting a life satisfaction below 4, corresponds to about 0.22 in standard deviations. Florida et al. (2013) estimate the relationship between a composite index of SWB that goes from 0 to 100 and the share of individuals with a degree or above at the metropolitan level, in the United States, and find an average effect of around 30 points, which translated to our scale is 0.3, comparable to our findings at the low levels of life satisfaction for the CLS. Although the models and samples vary, these comparisons underscore the importance of investigating the whole distribution: if the same heterogeneity that we document here holds in other contexts, the average association of education and life satisfaction tells us little about what is going on in the tails of the distribution, potentially limiting its usefulness for policy.

5.1.2 Interaction

One alternative to subsetting the sample is to interact the degree dummy with another covariate that would affect LS. We chose to use a subjective assessment of own health for this purpose. In the CLS, this is a categorical variable with five levels, from very good to very bad health. From our hypothesis, we would expect to observe a coefficient growing in magnitude as we go from the interaction with very good health to that of very bad health. If “very good health” captures those with very high life satisfaction, we could even expect the interaction to have a negative coefficient.

Table 7: Education and life satisfaction interaction model, CLS

	(1) No interactions	(2) Interactions
Degree	0.0816***	0.00951
	(0.0287)	(0.0448)
Relative to very good health:		
Degree int. good health		0.0683
		(0.0574)
Degree int. fair health		0.154*
		(0.0863)
Degree int. bad health		0.427*
		(0.223)
Degree int. very bad health		0.632
		(0.466)
Observations	19494	19494
Adj. R-squared	0.213	0.213

Standard errors in parentheses
Common controls: age, gender, marital status, meeting friends and family, general health, year and interview mode fixed effects
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column 2 of Table 7 reports these interaction coefficients, as compared to the baseline average coefficient in column 1. While the first coefficient, that corresponds to the interaction with the highest self-reported health category, is not negative and the standard errors around the others are wide enough not to be able to conclusively distinguish them from 0, the increasing pattern in the point estimates is clear. Such patterns are substantially more pronounced and better identified when using the additional power of the BHPS/US large sample, where the self-assessed health variable goes from "completely dissatisfied" to "completely satisfied". Estimating a similar model (Table 8), we see how the coefficient on "Degree" (equivalent to the interaction with the reference level "Completely satisfied with own health") is negative and the coefficients on the interactions increase as we move towards those individuals with worse assessments of own health. Notice that the absolute value of the interaction coefficients exceeds the reference coefficient of -0.123 already for the "neither satisfied nor dissatisfied" category (0.155).

Table 8: *Education and life satisfaction interaction model, BHPS and US*

	(1) No interactions	(2) Interactions
Degree	0.0107*	-0.123***
	(0.00603)	(0.0121)
Relative to completely satisfied with health:		
Degree int. mostly satisfied		0.0905***
		(0.0123)
Degree int. somewhat satisfied		0.112***
		(0.0148)
Degree int. neither Sat nor Dissat		0.155***
		(0.0191)
Degree int. somewhat dissatisfied		0.283***
		(0.0192)
Degree int. mostly dissatisfied		0.236***
		(0.0253)
Degree int. completely dissatisfied		0.336***
		(0.0433)
Observations	525411	525411
Adj. R-squared	0.309	0.310

Standard errors in parentheses, clustered at the individual level over time. Common controls: age, gender, marital status, satisfaction with health, wave fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.1.3 Quantile regression

An additional empirical strategy to observe how the relationship between education and life satisfaction changes across the distribution of life satisfaction is to estimate directly the association at different quantiles. Figure 6 shows coefficients on the degree dummy at the 25th, 40th, 50th, 60th and 75th percentiles of the life satisfaction distribution, using the CLS. This estimation technique reveals a familiar story: in the low segment of the distribution, specifically at the 25th percentile, the coefficient on the degree dummy is positive and significant, with a point estimate around 0.2. The estimate is undistinguishable from 0 from the 40th to the 60th percentile, and turns negative at a point estimate of about -0.1 for the 75th percentile. These estimates are comparable to the baseline results obtained by OLS above. It is natural to compare these results to Binder and Coad (2011), who also used quantile regression, although the data comes from a different survey and the variables included in the model were partly different. The results are remarkably (qualitatively) similar: they found a significant (0.1% level) coefficient on the 25th percentile of 0.0392, at the 50th percentile of 0.0158 (significant at a 5% level), a coefficient indistinguishable from 0 at the 75th percentile and of −0.0450 (significant at the 0.1% level) at the 90% percentile. Once more, the relationship of having a degree with life satisfaction goes from positive to negative as we move from left to right in the life satisfaction distribution. Finally, we extend the dataset used by Binder and Coad (2011) to use all waves of the British Household Panel Survey and Understanding Society which have available observations for our variables of interest and repeat the quantile regression exercise, albeit with a modified set of covariates to ensure convergence across the entire distribution. Figure 7 reports the results, which are qualitatively consistent with those from the CLS, and also quantitatively similar to those found by Binder and Coad (2011) in a much smaller sample (and with a partly different set of covariates) from the same survey.

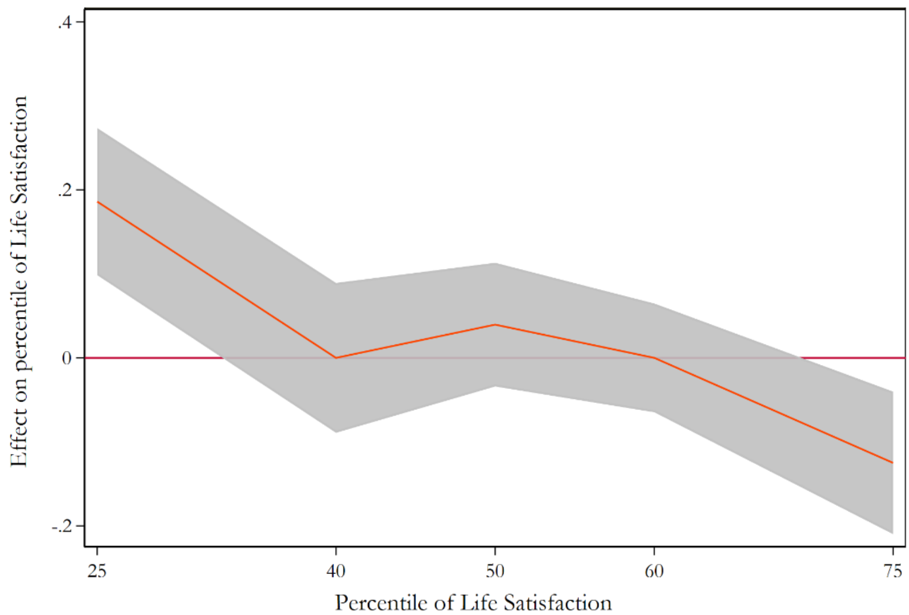

Figure 6: *Quantile regression coefficients across the distribution of life satisfaction, CLS*

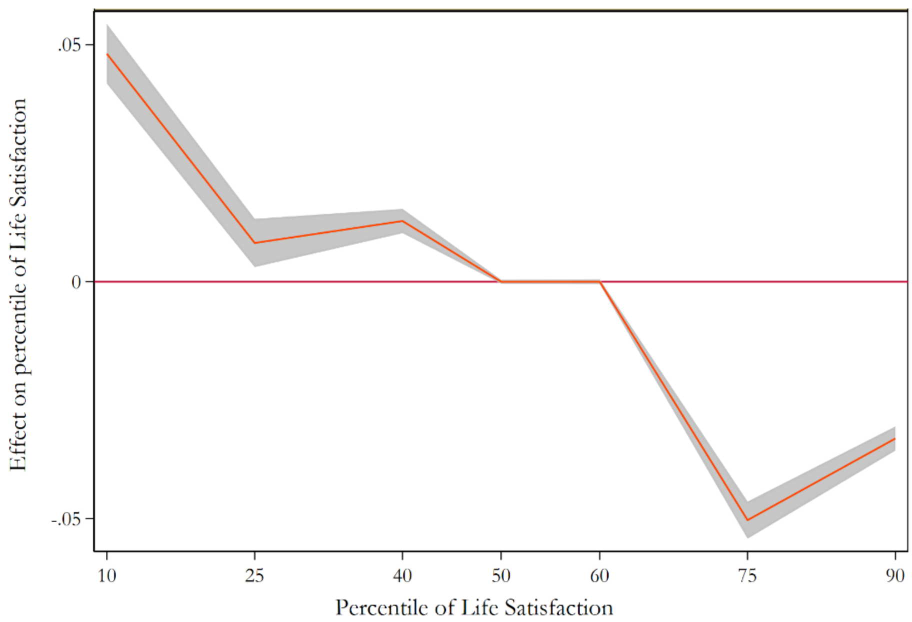

Figure 7: *Quantile regression coefficients across the distribution of life satisfaction, BHPS/US*

5.2 Longitudinal dynamics

We now turn from cross-sectional to longitudinal dynamics, extending the results of Binder and Coad (2011) in a panel context. Results are summarised in a series of event study plots. The horizontal axis for each plot reports the time distance, in terms of survey waves, from the event of obtaining a degree (which corresponds to time 0). The vertical axis reports the coefficient magnitude. Each plot is divided in two parts. One in red, containing the periods leading up to degree attainment (pre-trends), and another in blue containing the periods in which a degree is obtained and all subsequent waves. The coefficients and standard errors for the pre-trends are obtained through the placebo test of Borusyak et al. (2021) and when not different from 0 provide evidence in favour of the assumption of no anticipation (since there does not appear to be a treatment effect before the event) as well as of parallel trends, as one can expect pre-trends to continue in the absence of treatment. The coefficients for the event period and subsequent periods give instead an estimate of horizon-specific ATTs.

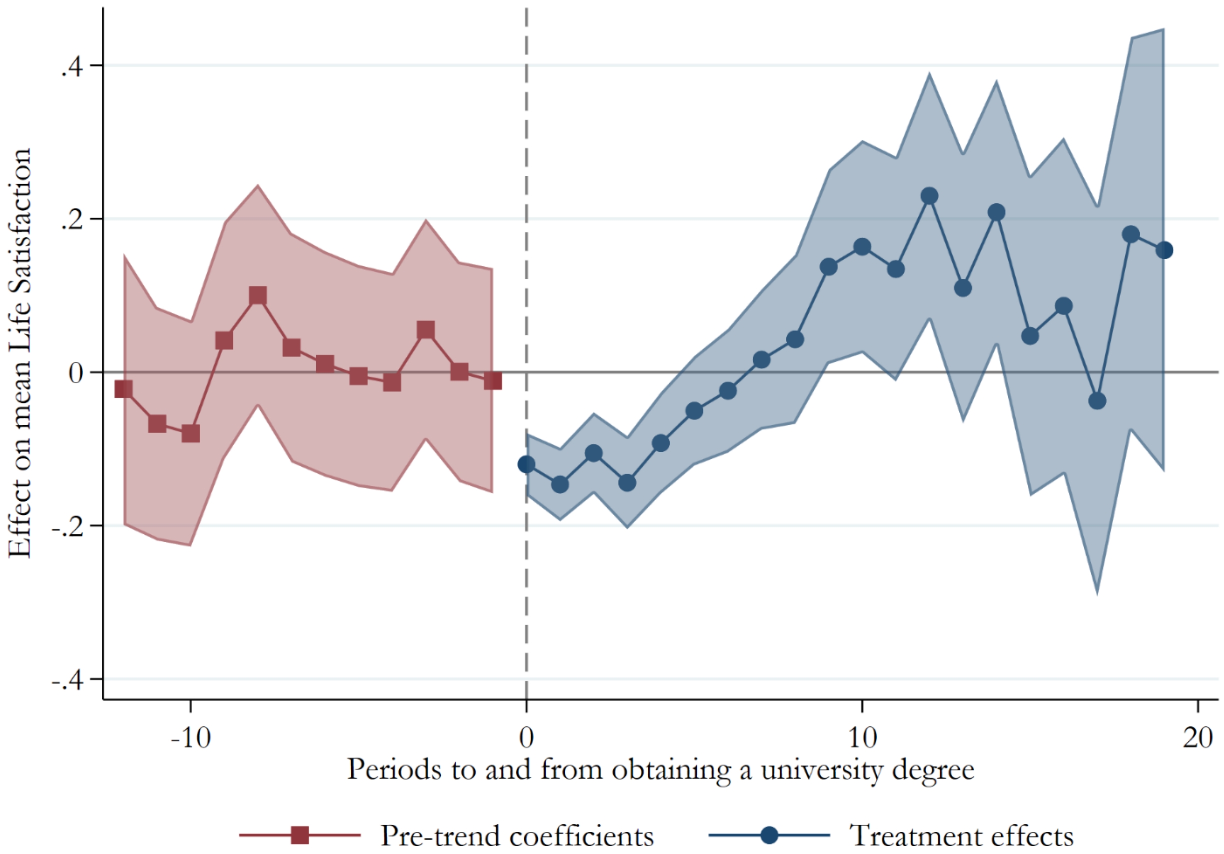

Figure 8: *Overall dynamic effects of obtaining a degree*

Figure 8 shows the event plot for the overall sample. There is evidence to support the assumptions of parallel trends and no anticipation, because the coefficients on pre-trends are not statistically distinguishable from 0. The event of obtaining a degree appears to cause a drop in life satisfaction of about 0.1 points, which persists for about four periods after the event. The effect on life satisfaction initially converges back to 0 after the fourth period, to then turn positive and increasing in magnitude starting from the ninth period after the event and until about fourteen periods after the event. The effect appears to eventually disappear, together with the precision of the estimate. On average, obtaining a university degree appears to decrease life satisfaction in the years following the conclusion of the degree, but to steadily increase it in the later years. What happens when we look separately at those who were very satisfied with their lives before age 23 and at those who were rather unsatisfied?

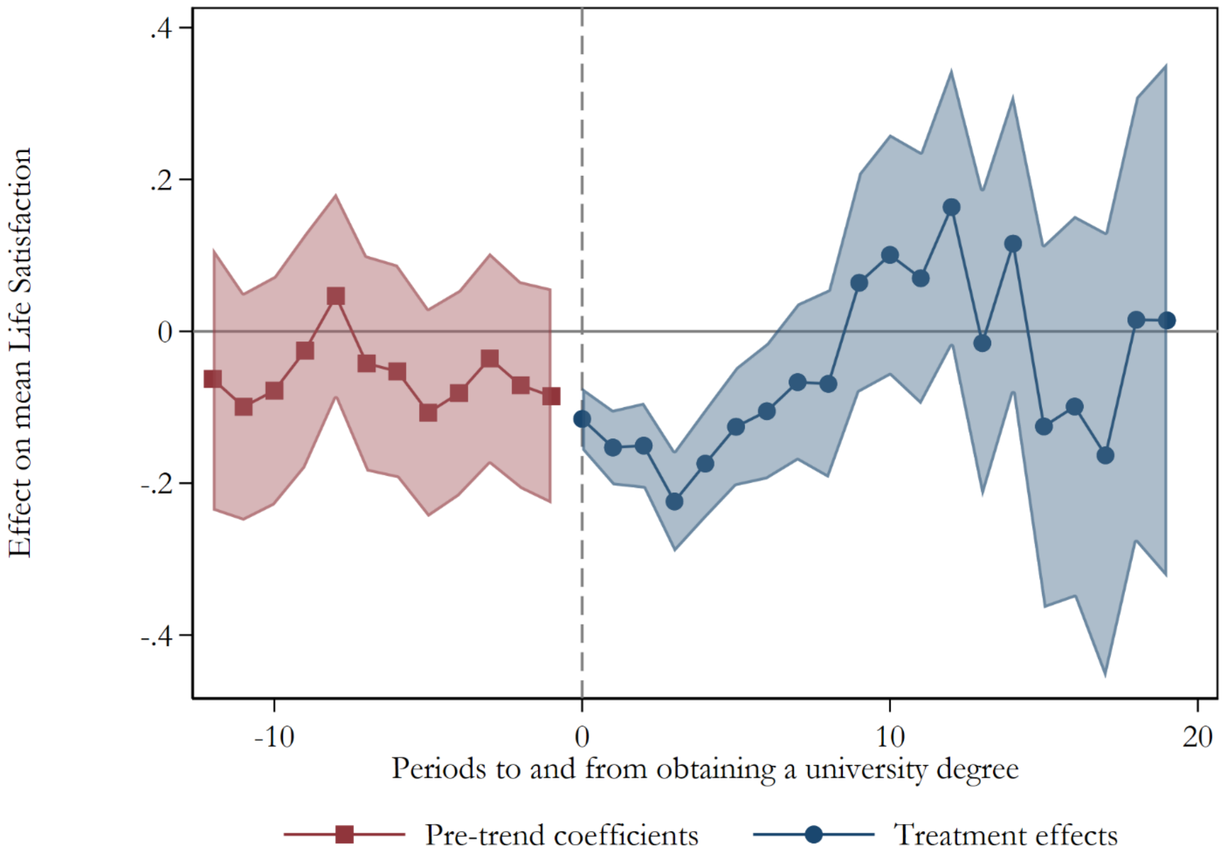

Figure 9: *Dynamic effects of obtaining a degree for those with LS > 5 between age 15 and 22*

Figure 9 replicates Figure 8 exclusively for those individuals for whom we have available data between age 15 and 22 and who reported a mean life satisfaction score above 5 in that interval. The pattern we observe is very similar to that of the overall sample, yet we can observe a level effect in the coefficients after the event. The negative effect of obtaining a degree on life satisfaction in the early years after completing it appears to last two periods longer and despite an upsloping trend, there is no distinguishable positive effect at later years. Those who started out "optimists" at a young age seem to benefit the least, in life satisfaction terms, from obtaining a degree. This is consistent with our hypotheses and with the cross-sectional findings. Finally, Figure 10 replicates Figure 8 only for those individuals for whom we have available data between age 15 and 22 and who reported a mean life satisfaction score below 6 in that interval. In this case, the negative effect of obtaining a degree appears to end markedly earlier than in the previous cases, with an effect indistinguishable from 0 as early as the second period after the event. Marginally positive effects are noticeable already in the fifth period and then again in the eight, tenth, twelfth, thirteenth, and fifteenth. The point estimates of this model are also larger. Compare for instance the highest treatment effect coefficient in this model, about 0.35, to the highest in the model considering the entire sample, just above 0.2. Those who started out with comparatively lower life satisfaction in young age benefit the most, in life satisfaction terms, from obtaining a degree. This result too is consistent with our hypothesis and with the cross-sectional results. Moreover, it speaks to the theoretical insight from SWB homeostasis theory that education can serve as a buffer against negative shocks to SWB by opening up different life trajectories. On average, this means decreasing life satisfaction in the short-term and increasing it in the medium to long term.

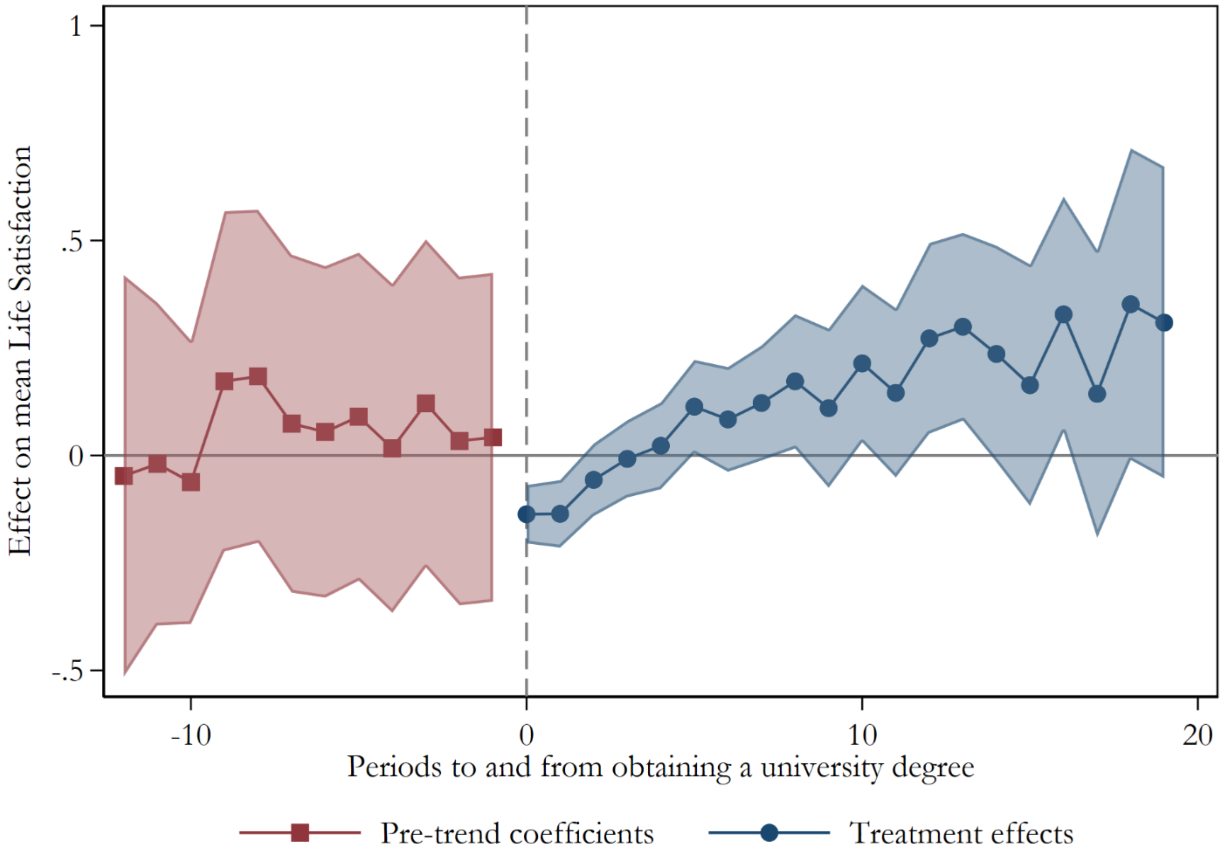

Figure 10: *Dynamic effects of obtaining a degree for those with LS < 6 between age 15 and 22*

5.3 A geographical characterisation

Finally, we discuss the spatial patterns of our results using the CLS. Figures 11 and 12 mirror Figures 1 and 2 but after accounting for covariates. Instead of the original responses mapped to the eight Output Areas, in this case we compute, for both the life satisfaction and degree variables, the residuals from our main model estimated for the sample with life satisfaction below 5 (Figure 11) and above 8 (Figure 12). This way, we can observe the relationship between life satisfaction and having a degree, net of confounders. Comparing Figures 1 and 11, and then 2 and 12, the message remains the same: the positive gradient at low levels of LS, and the negative gradient at high levels of LS, follow a spatial pattern. Deprived areas (Hard-pressed living and Constrained city dwellers, see Appendix A) have the lowest degree-level attainment and LS in Figure 11 (the low LS subsample). In Figure 12 (the high LS subsample), these deprived areas have the highest LS but lowest proportion of degree educated people. This is consistent with the theoretical insight from SWB homeostasis that education operates as a buffer against negative SWB shocks by opening up different life trajectories (as suggested also by our event study results) and access to different geographical areas.

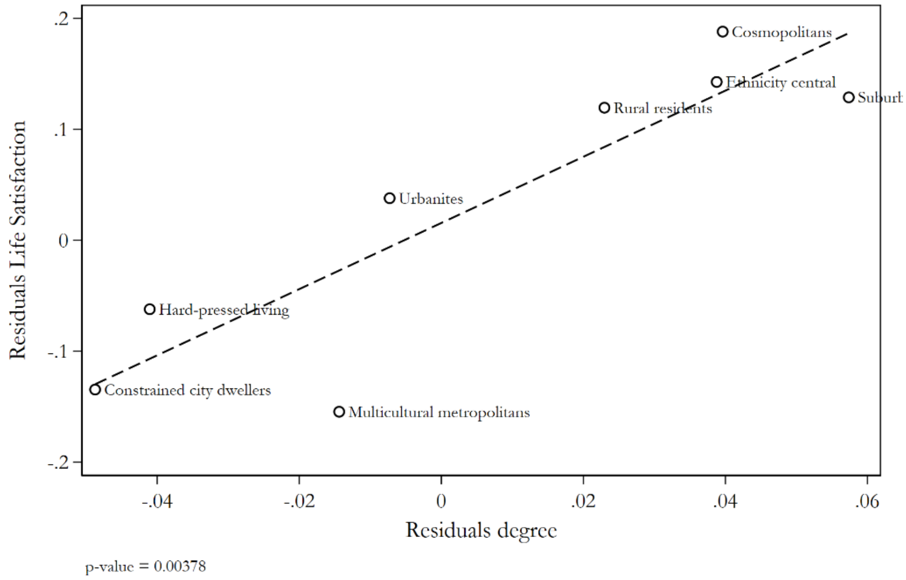

Figure 11: *Residual life satisfaction and share with a degree for life satisfaction < 5, CLS*

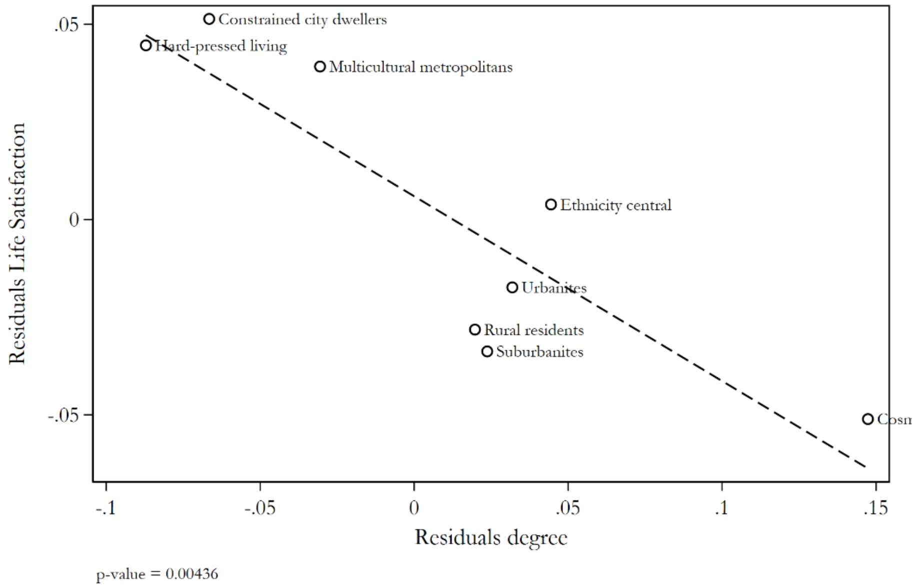

Figure 12: *Residual life satisfaction and share with a degree for life satisfaction* > 8

SECTION 6

Conclusions

This paper puts forward testable predictions concerning the relationship between education and SWB across the distribution of SWB. Because education can be both a buffer against negative shocks to SWB and a positional good, there are theoretical arguments to expect positive effects of education on SWB at low levels of SWB and negative effects at high levels of it. Binder and Coad (2011) had already provided evidence of such dynamics in the cross-section using life satisfaction as their measure of SWB. We extend their results both cross-sectionally and longitudinally. Cross-sectionally, we employ OLS and quantile regression to show that the relationship between education and life satisfaction at the mean or at the median is small or close to zero, while it is larger and positive at low levels of life satisfaction and negative at high levels. Longitudinally, we show that higher educational attainment is associated with different trajectories in life satisfaction over time and that those individuals starting off with higher life satisfaction in younger age benefit less from education than those starting off with lower life satisfaction, a result that echoes our cross-sectional conclusions. One implication of our results is that, because education is associated with both life satisfaction and access to resources (e.g. employment, income), and these resources are concentrated spatially, there will be a geographical gradient in the relationship between education and life satisfaction. Within the sample of individuals with low life satisfaction, those in more deprived areas, as compared to better off areas, will report both relatively less education and relatively lower life satisfaction. On the contrary, within the sample of individuals with high life satisfaction, those in more deprived areas will report relatively less education but relatively higher life satisfaction. A connected implication is that the level of aggregation when estimating the effect of education on life satisfaction matters. Cities, parts of cities, a wider region including country-side areas will all have different underlying distributions of life satisfaction and will potentially yield very different results in terms of the effect of education on life satisfaction.

One limitation of our study is that we do not provide credibly exogenous variation in education when estimating its effect on life satisfaction. Our longitudinal approach relies on an ultimately untestable assumption of parallel trends and the results would be considerably stronger if supported by an instrumental variable approach. Another limitation is that we assume that the interpersonal and intertemporal (for a same individual) comparisons in life satisfaction are valid, in the sense that they are based on a same scale. This is not necessarily the case as different individuals might attach different meanings to the points on a life satisfaction scale, or because, for a same person, such meaning may change over time, a phenomenon known as scale norming (for recent evidence on this, see Fabian, 2021). Finally, our empirical results are limited to the UK and more research is warranted to confirm this relationship in other contexts.

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APPENDIX A

Description of Output Areas

The classification in eight Output Areas is based on the methodology described in Gale et al. (2016). We report below a description of each of them based on the *Pen Portraits and Radial Plots for the 2011 Area Classification for Output Areas* by the Office for National Statistics (ONS 2015a and 2015b).

Rural residents: Population living in rural areas that are, compared to the national average, more sparsely populated, with higher homeownership rates and detached houses, lower unemployment, older age, higher marriage and civil partnership rates and higher educational attainment, and less ethnic integration.

Cosmopolitans: Population living in urban areas that are, compared to the national average, more densely populated, with lower homeownership rates and more flats, lower unemployment, younger age, with a higher proportion of single persons and students, higher educational attainment and more ethnic integration.

Ethnicity central: Population living in urban areas that are, compared to the national average, more densely populated, with lower homeownership rates and more flats, higher unemployment, younger, with a higher proportion of divorce and separation, higher educational attainment and more ethnic integration.

Multicultural metropolitans: Population living between urban and suburban areas that have, compared to the national average, more densely populated, average homeownership rates and more terraced houses, higher unemployment, younger, with higher proportions of single persons and average marriage and civil partnership rates, average educational attainment and more ethnic integration.

Urbanites: Population living in urban areas that have, compared to the national average, average population density, higher homeownership rates and flats, below average unemployment, average age and marriage and civil partnership rates, higher educational attainment and average ethnic integration.

Suburbanites: Population living in outskirts of urban areas that have, compared to the national average, average population density, higher homeownership rates and detached houses, below average unemployment, average age and higher marriage and civil partnership rates, higher educational attainment and lower ethnic integration.

Constrained city-dwellers: Population living in urban areas that have, compared to the national average, higher population density, lower homeownership and more flats, above average unemployment, above average age and higher divorce or separation rates, lower educational attainment and lower ethnic integration.

Hard-pressed living: Population living in the surroundings of urban areas that have, compared to the national average, slightly above average population density, average homeownership and more terraced houses, above average unemployment, average age and marriage and civil partnership rates but higher divorce or separation rates, lower educational attainment and lower ethnic integration.

APPENDIX B

Additional result tables

Table A1: Covariates for Table 2

	(1) Full sample	(2) LS < 5	(3) LS < 6	(4) LS < 7	(5) LS < 8	(6) LS < 9	(7) LS < 10
25-34	-0.317***	-0.0385	-0.0984	-0.115	-0.196***	-0.287***	-0.287***
	(0.0587)	(0.139)	(0.110)	(0.0874)	(0.0687)	(0.0585)	(0.0572)
35-44	-0.405***	0.0540	-0.0552	-0.222**	-0.231***	-0.266***	-0.326***
	(0.0608)	(0.143)	(0.112)	(0.0913)	(0.0720)	(0.0608)	(0.0592)
45-54	-0.391***	-0.170	-0.174	-0.292***	-0.310***	-0.319***	-0.337***
	(0.0630)	(0.144)	(0.115)	(0.0944)	(0.0752)	(0.0636)	(0.0616)
55-64	-0.0134	0.0920	0.0206	-0.0533	-0.123	-0.0469	-0.0317
	(0.0637)	(0.151)	(0.119)	(0.0975)	(0.0777)	(0.0645)	(0.0622)
65-74	0.500***	0.212	0.255**	0.0915	0.100	0.270***	0.380***
	(0.0641)	(0.170)	(0.127)	(0.104)	(0.0833)	(0.0666)	(0.0634)
75-84	0.555***	0.108	0.244	0.0127	0.0911	0.298***	0.446***
	(0.0768)	(0.209)	(0.151)	(0.130)	(0.103)	(0.0820)	(0.0772)
85+	0.478***	0.0493	-0.141	-0.0492	0.182	0.205*	0.260**
	(0.118)	(0.304)	(0.242)	(0.198)	(0.150)	(0.124)	(0.119)
Female	0.0824***	-0.0582	0.0165	-0.0175	0.00362	0.00979	0.0404
	(0.0263)	(0.0676)	(0.0511)	(0.0429)	(0.0339)	(0.0273)	(0.0260)
Cohabiting (ref: Married/civil partnered)	-0.237***	0.224**	0.0449	-0.0256	-0.0870*	-0.149***	-0.204***
	(0.0426)	(0.106)	(0.0813)	(0.0681)	(0.0526)	(0.0432)	(0.0419)
Single	-0.795***	-0.140	-0.253***	-0.313***	-0.419***	-0.575***	-0.683***
	(0.0412)	(0.0897)	(0.0712)	(0.0599)	(0.0483)	(0.0412)	(0.0402)
Separated	-0.953***	-0.354*	-0.504***	-0.435***	-0.646***	-0.765***	-0.853***

	(0.101)	(0.188)	(0.148)	(0.131)	(0.114)	(0.0985)	(0.0979)
Divorced/Legally dissolved partnership	-0.709***	-0.341***	-0.322***	-0.343***	-0.421***	-0.521***	-0.611***
	(0.0545)	(0.121)	(0.0928)	(0.0800)	(0.0665)	(0.0558)	(0.0535)
Widowed	-0.661***	-0.280*	-0.200*	-0.324***	-0.412***	-0.556***	-0.656***
	(0.0628)	(0.165)	(0.111)	(0.0959)	(0.0801)	(0.0657)	(0.0628)
Meet fr. or fam more than once a day (ref: Never)	1.017***	0.783***	0.561**	0.666***	0.903***	1.033***	1.129***
	(0.226)	(0.284)	(0.259)	(0.241)	(0.230)	(0.213)	(0.213)
Once a day	1.027***	0.999***	0.716***	0.974***	1.143***	1.175***	1.284***
	(0.222)	(0.275)	(0.251)	(0.233)	(0.224)	(0.209)	(0.209)
2-3 times per week	0.887***	0.940***	0.741***	0.963***	1.188***	1.190***	1.258***
	(0.220)	(0.262)	(0.243)	(0.227)	(0.220)	(0.206)	(0.207)
About once a week	0.746***	1.013***	0.700***	0.879***	1.016***	1.009***	1.083***
	(0.220)	(0.263)	(0.243)	(0.227)	(0.220)	(0.207)	(0.207)
About once a fortnight	0.654***	0.875***	0.592**	0.828***	0.932***	0.943***	1.032***
	(0.223)	(0.277)	(0.253)	(0.235)	(0.225)	(0.210)	(0.210)
About once a month	0.568**	0.994***	0.524**	0.654***	0.885***	0.869***	0.918***
	(0.224)	(0.270)	(0.251)	(0.235)	(0.226)	(0.211)	(0.211)
Less often than once a month	0.304	0.846***	0.443*	0.694***	0.686***	0.574***	0.624***
	(0.225)	(0.271)	(0.250)	(0.233)	(0.225)	(0.212)	(0.212)
Health Good (ref: Very good)	-0.599***	0.178	0.143*	0.0476	-0.133***	-0.310***	-0.441***
	(0.0286)	(0.113)	(0.0832)	(0.0644)	(0.0431)	(0.0308)	(0.0287)
Fair	-1.308***	0.129	0.0397	-0.193***	-0.567***	-0.893***	-1.113***
	(0.0386)	(0.115)	(0.0865)	(0.0698)	(0.0515)	(0.0402)	(0.0384)
Bad	-2.527***	-0.334**	-0.610***	-0.927***	-1.546***	-2.025***	-2.345***
	(0.0826)	(0.134)	(0.110)	(0.0969)	(0.0851)	(0.0795)	(0.0792)
or very bad?	-3.889***	-0.858***	-1.423***	-1.989***	-2.796***	-3.507***	-3.830***
	(0.179)	(0.159)	(0.156)	(0.151)	(0.154)	(0.159)	(0.164)
Year of interview=2013	0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Year of interview=2014	0.136***	0.0161	0.00314	0.0600	0.101*	0.112**	0.127***
	(0.0430)	(0.137)	(0.0920)	(0.0760)	(0.0586)	(0.0449)	(0.0425)
Year of interview=2015	0.216***	0.148	0.0794	0.141*	0.202***	0.192***	0.220***
	(0.0426)	(0.134)	(0.0921)	(0.0760)	(0.0580)	(0.0449)	(0.0422)
Year of interview=2016	0.176***	0.0891	-0.0202	0.0855	0.184***	0.204***	0.222***
	(0.0478)	(0.144)	(0.100)	(0.0827)	(0.0645)	(0.0500)	(0.0474)
Year of interview=2017	0.213***	0.187	0.0414	0.129	0.125*	0.133**	0.188***
	(0.0590)	(0.158)	(0.114)	(0.0949)	(0.0754)	(0.0611)	(0.0583)
Face to face interview	0.706***	-0.0211	0.280***	0.257***	0.333***	0.489***	0.525***
	(0.0367)	(0.109)	(0.0739)	(0.0618)	(0.0478)	(0.0380)	(0.0363)
Observations	19494	1562	3242	4969	8649	13988	16738

Adj. R-squared	0.213	0.107	0.101	0.124	0.163	0.195	0.212

Table A2: Covariates for Table 3

	(1) Full sample	(2) LS > 4	(3) LS > 5	(4) LS > 6	(5) LS > 7	(6) LS > 8
25-34	-0.317***	-0.191***	-0.120***	-0.0770**	-0.0144	-0.0207
	(0.0587)	(0.0463)	(0.0421)	(0.0391)	(0.0376)	(0.0326)
35-44	-0.405***	-0.254***	-0.155***	-0.168***	-0.133***	-0.0400
	(0.0608)	(0.0473)	(0.0427)	(0.0398)	(0.0386)	(0.0339)
45-54	-0.391***	-0.200***	-0.0941**	-0.0941**	-0.0662*	-0.0316
	(0.0630)	(0.0486)	(0.0438)	(0.0406)	(0.0390)	(0.0343)
55-64	-0.0134	0.0451	0.0972**	0.0743*	0.00536	-0.00447
	(0.0637)	(0.0497)	(0.0447)	(0.0412)	(0.0394)	(0.0341)
65-74	0.500***	0.414***	0.412***	0.309***	0.142***	0.0277
	(0.0641)	(0.0508)	(0.0456)	(0.0420)	(0.0398)	(0.0335)
75-84	0.555***	0.461***	0.462***	0.311***	0.155***	0.00986
	(0.0768)	(0.0606)	(0.0531)	(0.0493)	(0.0460)	(0.0377)
85+	0.478***	0.472***	0.339***	0.277***	0.252***	0.103**
	(0.118)	(0.0923)	(0.0839)	(0.0772)	(0.0712)	(0.0521)
Female	0.0824***	0.0732***	0.0796***	0.0711***	0.0609***	0.0195
	(0.0263)	(0.0209)	(0.0184)	(0.0170)	(0.0158)	(0.0134)
Cohabiting (ref: Married/civil partnered)	-0.237***	-0.175***	-0.145***	-0.117***	-0.0582**	-0.0124
	(0.0426)	(0.0345)	(0.0308)	(0.0284)	(0.0268)	(0.0236)
Single	-0.795***	-0.527***	-0.398***	-0.302***	-0.166***	-0.0580**
	(0.0412)	(0.0318)	(0.0286)	(0.0265)	(0.0257)	(0.0228)
Separated	-0.953***	-0.596***	-0.423***	-0.256***	-0.163***	-0.0364
	(0.101)	(0.0749)	(0.0655)	(0.0599)	(0.0575)	(0.0538)
Divorced/Legally dissolved partnership	-0.709***	-0.478***	-0.355***	-0.265***	-0.153***	-0.0309
	(0.0545)	(0.0421)	(0.0369)	(0.0340)	(0.0323)	(0.0272)
Widowed	-0.661***	-0.458***	-0.289***	-0.216***	-0.0736**	0.0150
	(0.0628)	(0.0507)	(0.0438)	(0.0403)	(0.0368)	(0.0277)
Meet fr. or fam more than once a day (ref: Never)	1.017***	0.464***	0.106	0.0159	-0.0261	-0.100
	(0.226)	(0.166)	(0.146)	(0.134)	(0.125)	(0.0821)
Once a day	1.027***	0.386**	-0.0227	-0.0789	-0.105	-0.194**
	(0.222)	(0.164)	(0.144)	(0.132)	(0.123)	(0.0807)
2-3 times per week	0.887***	0.237	-0.156	-0.227*	-0.215*	-0.245***
	(0.220)	(0.161)	(0.142)	(0.131)	(0.122)	(0.0798)
About once a week	0.746***	0.171	-0.170	-0.205	-0.183	-0.226***

	(0.220)	(0.162)	(0.142)	(0.131)	(0.122)	(0.0801)
About once a fortnight	0.654***	0.111	-0.235	-0.245*	-0.231*	-0.282***
	(0.223)	(0.164)	(0.145)	(0.133)	(0.124)	(0.0824)
About once a month	0.568**	0.120	-0.232	-0.283**	-0.220*	-0.213**
	(0.224)	(0.165)	(0.145)	(0.133)	(0.125)	(0.0833)
Less often than once a month	0.304	-0.0516	-0.336**	-0.238*	-0.147	-0.177**
	(0.225)	(0.166)	(0.146)	(0.135)	(0.126)	(0.0842)
Health Good (ref: Very good)	-0.599***	-0.518***	-0.421***	-0.329***	-0.204***	-0.0698***
	(0.0286)	(0.0234)	(0.0210)	(0.0193)	(0.0177)	(0.0148)
Fair	-1.308***	-0.997***	-0.705***	-0.501***	-0.257***	-0.0464**
	(0.0386)	(0.0310)	(0.0275)	(0.0254)	(0.0241)	(0.0205)
Bad	-2.527***	-1.448***	-0.874***	-0.523***	-0.224***	0.0702
	(0.0826)	(0.0634)	(0.0588)	(0.0563)	(0.0563)	(0.0428)
or very bad?	-3.889***	-1.557***	-0.613***	-0.299**	0.0763	0.120
	(0.179)	(0.162)	(0.157)	(0.150)	(0.133)	(0.0770)
Year of interview=2013	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)
Year of interview=2014	0.136***	0.0721**	0.0516*	0.0300	0.0225	0.00920
	(0.0430)	(0.0349)	(0.0304)	(0.0280)	(0.0258)	(0.0206)
Year of interview=2015	0.216***	0.120***	0.0706**	0.0382	0.0345	-0.0151
	(0.0426)	(0.0348)	(0.0304)	(0.0281)	(0.0257)	(0.0204)
Year of interview=2016	0.176***	0.105***	0.0339	0.000401	-0.0169	-0.0387
	(0.0478)	(0.0385)	(0.0337)	(0.0310)	(0.0287)	(0.0241)
Year of interview=2017	0.213***	0.149***	0.0934**	0.0958**	0.0764**	0.0192
	(0.0590)	(0.0469)	(0.0416)	(0.0382)	(0.0357)	(0.0304)
Face to face interview	0.706***	0.457***	0.396***	0.296***	0.175***	0.132***
	(0.0367)	(0.0295)	(0.0259)	(0.0238)	(0.0223)	(0.0194)
Observations	19494	17932	16252	14525	10845	5506
Adj. R-squared	0.213	0.138	0.121	0.0926	0.0575	0.0652

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

APPENDIX C

Robustness to the use of survey weights, CLS

Table A4: Table 2 re-estimated using survey weights

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full sample	LS < 5	LS < 6	LS < 7	LS < 8	LS < 9	LS < 10
Degree	0.0296	0.402***	0.198**	0.305***	0.281***	0.232***	0.211***
	(0.0376)	(0.115)	(0.0787)	(0.0636)	(0.0480)	(0.0378)	(0.0364)
Observations	19494	1562	3242	4969	8649	13988	16738
Adj. R-squared	0.196	0.110	0.109	0.121	0.160	0.187	0.197

Standard errors in parentheses

Common controls: age, marital status, meeting friends and family, general health, year and interview mode fixed effects

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

Table A5: Table 3 re-estimated using survey weights

	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	LS > 4	LS > 5	LS > 6	LS > 7	LS > 8
Degree	0.0296	-0.0767**	-0.151***	-0.154***	-0.174***	-0.153***
	(0.0376)	(0.0322)	(0.0283)	(0.0262)	(0.0243)	(0.0215)
Observations	19494	17932	16252	14525	10845	5506
Adj. R-squared	0.196	0.128	0.109	0.0802	0.0562	0.0561

Standard errors in parentheses

Common controls: age, marital status, meeting friends and family, general health, year and interview mode fixed effects

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

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