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Equality of opportunity and the expansion of higher education in the UK*

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Abstract

Using nine waves of data from *Understanding Society (UKHLS)*, we study the expansion of higher education in the UK and its consequences for levels of and inequalities in income, physical and mental health. University expansion was characterised by a large increase in the proportion of graduates, with higher rates of graduation among individuals from more advantaged socioeconomic backgrounds. Having controlled for birth cohort and lifecycle effects, there is evidence of significant inequality of opportunity (IOp) in the actual outcomes. However, comparing actual outcomes with counterfactual projections, that freeze the likelihood of university graduation and the joint distribution of graduation and circumstances to the pre-1963 levels, we do not detect an impact of the expansion of higher education on IOp in income and only small reductions in IOp in physical and mental health.

Keywords: equality of opportunity; higher education; entropy balancing; high dimensional fixed effects; health; income

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1 Introduction

Equality of opportunity (EOp) is an equity concept that inspires many public policies in contemporary Western societies such as the United States, sometimes known as the *land of opportunity*, the European Union, where the concept is implicitly included in the European Pillar of Social Rights, and in the United Kingdom (UK) Equality Act of 2010. It reflects a meritocratic ethic, with educational achievement often seen as an important pathway through which opportunities may be translated into individual attainments such as income and health, mediated by individual effort. In this context, access to university education may therefore be a key part of achieving EOp (e.g., Jones, 2019). The expansion of participation in higher education over recent decades is of particular relevance because it may have influenced the wellbeing of current generations and also because it is likely to affect the set of parental circumstances that future generations will experience during childhood and, consequently, their future wellbeing (e.g., Greenaway and Haynes, 2003; Blanden and Machin, 2004; Machin and Vignoles, 2004; Chowdry et al., 2013; Crawford et al., 2016). While the expansion of higher education has typically generated beneficial effects among all social classes and increased access to higher education (Shavit and Blossfeld, 1993), it is not clear whether this increased access resulted in changes in inequality in wellbeing. This paper focuses on the long-term expansion of participation in university education in the UK that has occurred since the landmark Robbins Report in 1963 and analyses its consequences for levels of inequality of opportunity (IOp) in income and physical and mental health.

Our aim is to explore the consequences of the expansion of higher education for outcomes later in life. We focus on two dimensions of wellbeing, that have both been used as outcomes in the literature on inequality of opportunity, namely income and individual health, with measures that capture not just physical health but also mental wellbeing especially as many of the existing studies do not differentiate between mental and physical health or focus on physical health (e.g., Carrieri and Jones, 2018; Carrieri et al., 2020; Davillas and Jones, 2020; Jusot et al., 2013; Li Donni et al., 2014; Trannoy et al., 2010). Regarding income we mainly focus on the seminal work on the measurement of IOp (Ferreira and Gignoux, 2011), which employs equivalized household income measures as a measure of the overall advantage/disadvantage at the household level; however, we have also implemented further analysis using individual's own income.

In terms of the inequity literature, the paper contributes to understanding the determinants of observed levels of IOp in specific wellbeing measures, particularly focusing on the long-term expansion of participation in university education in the UK. Among others, the IOp literature includes analysis of income inequality (see Ferreira and Peragine, 2015 for a review), educational attainment relevant to secondary or tertiary education (e.g., Ferreira and Gignoux, 2014; Palmisano et al., 2021) and health (e.g., Brunori et al., 2020; Carrieri and Jones, 2018; Carrieri et al., 2020; Davillas and Jones, 2020; Jusot et al., 2013; Li Donni et al., 2014; Rosa Dias, 2009, 2010; Trannoy et al., 2010). However, a few studies aim to estimate IOp in a set of different wellbeing measures (such as income, life-satisfaction and multidimensional welfare measures) within the same study (Mahler and Ramos, 2019). Despite differences in the methodological approach used, all these studies offer a normative assessment of the distribution of the outcomes of interest according to the EOp framework. Their ultimate scope is to identify, on the basis of a given set of opportunities, inequality that is attributable to circumstances for which individuals should not be held responsible.

While these studies advance our understanding of the fairness (or unfairness) of modern societies, they mostly provide a static analysis of IOp in attainments that are attributed to a set of circumstances that individuals faced at a particular point of their life (for example, during childhood). The majority of existing studies rarely look at the evolution of IOp across generations and how IOp varies when the set of opportunities changes as society evolves.[1] Across generations and time, many societal changes can directly or indirectly increase or decrease the set of opportunities open to members of society — technological change, natural events or large-scale policy reforms may cause changes in the available set of opportunities. Societal changes may affect some generations more deeply than others and, even within the same generations, these changes can still produce very asymmetric consequences across individuals with different socioeconomic backgrounds, affecting IOp in their wellbeing.

Educational reforms are seen as one of the most important social transformations of the second half of the Twentieth Century (Shavit et al., 2007) and a vast amount of interdisciplinary scientific knowledge recognises a key role for education as a primary factor in human development. As one of the most important, large-scale societal changes in the UK, we focus here on the long-run expansion of participation in university education since the 1960s (Greenaway and Haynes, 2003; Blanden and Machin, 2004; Machin and Vignoles, 2004; Chowdry et al., 2013; Crawford et al., 2016).[2] The landmark Robbins Report in 1963 rejected the notion that only a small minority were capable of benefiting from higher education. At that time in the UK about 4 in every 100 young people entered full-time courses at university and only one per cent of working-class girls and three per cent of working-class boys went on to full-time degree level courses (Barr, 2014). There was a rapid expansion of university provision in the decade between 1965 and 1975 and cumulative growth since then. The overall number of universities in the UK has increased threefold since the 1960s (Greenaway and Haynes, 2003). The growth in

[1] A notable exception is Peragine et al. (2014) who explored the association between inequality and economic growth based on the concept of the opportunity growth incidence curves. Moramarco et al. (2020) also propose a framework for the measurement of IOp which introduces a lifetime and intertemporal perspective as it accounts for individuals' income fluctuations over time.

[2] The studies by Blanden and Machin (2004), Machin and Vignoles (2004), Chowdry et al. (2013) and Crawford et al. (2016) focus on the socioeconomic gap in participation in higher education in the UK and the implications for intergenerational mobility over the period of expansion. There are studies that explore the impact of higher education reforms in Italy on EOp but these are limited to individual educational careers at tertiary level or access to universities (e.g., Bratti et al., 2008; Brunori et al., 2012), rather than expanding their analysis to broader wellbeing outcomes (such as income or health attainment). There are also existing studies that examine the association between reforms of the quality of the primary and secondary schools in England and Wales and EOp (e.g., Burgess et al., 2020; Jones et al., 2012, 2014); however, these studies focus on secondary school reforms, rather than on higher education.

the number of institutions happened in stages: with 20 new universities created around the time of the Robbins report and then when former polytechnics and colleges became universities with the end of the binary divide in the early 1990s. Institutions have also expanded their enrolment of students, although the spending available per student has declined substantially (Greenaway and Haynes, 2003). The consequences of this expansion have received considerable attention in the literature (e.g., Greenaway and Haynes, 2003; Blanden and Machin, 2004; Machin and Vignoles, 2004; Chowdry et al., 2013; Crawford et al., 2016). However, the availability of new longitudinal data allows a longer-term follow up of the consequences for inequality of opportunity, based on recent developments in methods for the measurement of inequality.

Using longitudinal data from *Understanding Society: the UK household longitudinal study* (UKHLS), we follow individuals from different generations over a wide time interval covering the period between Wave 1 (2009-11) and Wave 9 (2017-19). This allows us to make like-for-like comparisons of the wellbeing outcomes of interest (income, physical and mental health functioning) across birth cohorts for similar age ranges and for a long period of follow-up. The Baby Boomers, born between 1946 and 1964, were the first generation affected by the expansion that happened from the 1960s onwards, as the oldest members of this generation were aged 17 in 1963 when the Robbins Report was published. Capitalising on the availability of longitudinal data on younger and older generations, we analyse the association of pre-determined individual circumstances (parental education and occupational status, gender and ethnic origin) with our wellbeing outcomes as society evolved over time. Availability of longitudinal data for respondents from the Silent (born 1927-1945), Boomer (1946-1964) and Gen X (1965-1980) generations allows us to make like-for-like comparisons of outcomes for similar age range across generations. We compare actual outcomes with counterfactual projections that keep the likelihood of university graduation and the joint distribution of graduation and social circumstances, fixed at the levels prior to 1963 (which, in practice corresponds to birth years prior to 1946),[3] when the Boomers, the youngest birth cohort affected by the Robbins reform, turned 17.

Specifically, by accounting for fixed effects for both year of birth and year of current age, we estimate the role of pre-determined circumstances for later life outcomes net of potentially confounding by lifecycle and birth cohort effects. We estimate models using actual and counterfactual scenarios. Counterfactual analysis is conducted using entropy balancing to freeze the likelihood of university graduation and the joint distribution of graduation and circumstances to the pre-1963 levels. In subsequent analysis, we explore to what extent differences in the available set of opportunities and their association with our wellbeing outcomes affects IOp. Shapley decomposition techniques are used to quantify the contribution of each of the circumstances to IOp. Comparison to the counterfactual projections reveals how the relative role of each circumstance has changed as society has evolved.

[3] We use the terms "birth cohorts prior to 1946" and "prior to 1963" interchangeably.

Our findings confirm that university expansion led to a large increase in the proportion of graduates among younger cohorts and that this expansion was more pronounced in absolute terms among those from more advantaged socioeconomic backgrounds. Having controlled for birth cohort and lifecycle effects, there is evidence of IOp in the actual outcomes, with significant gradients in income, and physical and mental health functioning by parental education and occupation. However, comparing actual outcomes with counterfactual projections, we do not detect significant effects of the expansion of higher education on IOp in income and only small reductions in IOp in physical and mental health functioning.

2 Methods

2.1 The outcome regression models

Equality of opportunity is rooted in an ethic of 'responsibility-sensitive egalitarianism' (Fleurbaey, 1995; Roemer and Trannoy 2016). It distinguishes between circumstances, for which people are not held personally responsible, and efforts, which may in-part be shaped by circumstances. There are two broad approaches to IOp: the *ex ante* and the *ex post* approach. The *ex post* approach seeks equality of outcomes among people who have exerted the same degree of effort, regardless of their circumstances (Roemer, 1998). The ex ante approach to IOp is based on the principle that there is equality of opportunity if all individuals face the same opportunity set, prior to their efforts and outcomes being realised (Fleurbaey and Schokkaert, 2009; Van de Gaer, 1993). The *ex ante* approach suggests that there are equal opportunities if no differences in outcomes arise from having different circumstances.

The notion of *ex ante* IOp focuses on the distribution of outcomes that are available for a given set of circumstances prior to an individual's specific level of effort being realised (for example, Ramos and Van de Gaer, 2016). *Ex ante* IOp then rests on the comparison of opportunity sets and, given utilitarian reward, these are reflected in the mean outcome for a given set of circumstances. We adopt the direct *ex ante* parametric approach proposed by Ferreira and Gignoux (2011, 2014). An advantage of the parametric approach is that, unlike nonparametric tests for IOp, it does not suffer from a curse of dimensionality. Another advantage is that individual efforts do not have to be observed to implement this approach. Moreover, it has been shown that the *ex ante* analysis can be interpreted as the lower-bound estimates of overall IOp, i.e. the inequality attributed to all circumstances (e.g., Ferreira and Gignoux, 2011).

Following the IOp literature (Bourguignon et al., 2007; Davillas and Jones, 2020; Ferreira and Gignoux, 2011; Roemer, 1998, 2002), the first step in our analysis is to derive and estimate reduced form regressions for the outcomes of interest, as a function of circumstances, that allow for lifecycle and birth-cohort fixed effects. We begin with a structural model for outcomes and (unobserved) efforts, assuming that circumstances are not affected by efforts, while efforts may be influenced by circumstances:

$$y_{it} = f(C_{it}, E_{it}, , X_{it}, u_{it}) \tag{1}$$

$$E_{it} = g(C_{it}, X_{it}, v_{it}) \tag{2}$$

where y_{it} is the outcome of interest measuring individual attainments for each individual (i) at time (t), C_{it} is a vector of observed circumstances, E_{it} is a vector of all relevant efforts and X_{it} are controls for age and birth cohort effects; v_{it} and u_{it} are unobserved error terms which capture the random variation in the realised effort and outcomes, often called 'luck' in the IOp literature (e.g., Davillas and Jones, 2020). The variation in E that is independent of C is represented by v_{it}, while u_{it} captures random variations in our outcomes that are independent of both C and E.

Assuming additive separability and linearity of $f(.)$ and $g(.)$, the linear reduced form, that forms the basis for our analysis of *ex ante* inequality of opportunity, can be derived (e.g., Carrieri et al., 2020):

$$y_{it} = C_{it}\psi + X_{it}\beta + \varepsilon_{it} \tag{3}$$

where the coefficients ψ reflect the total contribution of circumstances and include both the direct effect of circumstances on the outcome of interest, and the indirect effect of circumstances through efforts. In equation (3) X is modelled using year of birth and year of age fixed effects. In practice, we employ a higher dimensional fixed effects regression, where birth year and year of age fixed effects are absorbed into the estimation (Guimarães and Portugal, 2010; Correia, 2017).[4] Typically, in the case that there is more than one higher dimensional fixed effect, explicit introduction of dummies for each of the units (groups) in the estimation models may not be an option, given that the number of groups is often too large. However, in our case and given our sample size (99,409 person-year observations), the number of age and birth year cohort dummies to be included in our models to account for fixed effects (i.e., 44 age dummies and 41 birth year cohort dummies) is not too large to rule out their explicit introduction in our regression models.[5]

Note that the set of effort factors do not need to be defined or observed in order to derive the reduced form (3). The mean-based direct parametric approach to measure *ex ante* IOp is based on using predictions from the reduced form in equation (3), with the age and birth cohort fixed effects absorbed:

$$\widetilde{y_{it}} = C_{it}\hat{\psi} \tag{4}$$

[4] Correia (2017) has developed a Stata command, reghdfe, that is used in our paper; it is an improved version of the generalized within–estimator of Guimarães and Portugal (2010) which has faster running time and performs well with large datasets and high–dimensional fixed effects.

[5] Our regression results are identical when estimating higher dimensional fixed effects regression models (using the user-written reghdfe command in Stata) and when age and birth year cohort dummies are included in our regression models directly, but the former computes predictions that are marginal to the fixed effects and only vary with the measured circumstances.

where $\hat{\psi}$ represents the estimates of the coefficients in equation (3) (e.g., Abatemarco, 2015; Ferreira and Gignoux, 2011, Li Donni et al., 2014; Rosa Dias, 2010; Trannoy et al., 2010;). The predicted outcomes are the same for all individuals who have identical circumstances (Ferreira and Gignoux, 2011). It should be explicitly noted here that these predictions capture the association between C and our outcomes, net of the potential role of age and birth-cohort effects; i.e. they are marginal to the high dimensional fixed effects for age and birth cohort and capture only the variation in our outcomes that is associated with observed C.

2.2 *Measures of ex ante inequality of opportunity*

IOp can be estimated using an inequality measure ($I(.)$) applied to the vector of predicted outcomes $\tilde{y}$:

$$\theta_a = \mathrm{I}(\tilde{y}). \tag{5}$$

A relative measure of IOp, expressing IOp as a fraction of the overall inequality in our outcomes ($I(y_i)$), can be obtained by:

$$\theta_r = \frac{\mathrm{I}(\tilde{y})}{I(y)}. \tag{6}$$

For income, we use the mean logarithmic deviation (MLD) inequality index (Ferreira and Gignoux, 2011). Income is a ratio-scale outcome and MLD is a path-independent decomposable inequality measure that satisfies the typical axiomatic properties used in the inequality measurement literature (Ferreira and Gignoux, 2011; Wendelspeiss Chávez Juárez and Soloaga, 2014). For the PCS-12 and MCS-12 outcomes the variance (and variance share) is used as our inequality measure, being a path-independent decomposable measure that is more appropriate for outcomes that are not ratio-scaled (Ferreira and Gignoux, 2011; Wendelspeiss Chávez Juárez and Soloaga, 2014). We should note that our IOp analysis does not account for unobserved circumstances that are not available in the dataset. However, equations (5) and (6) can be interpreted as lower-bound estimates of inequality due to all predetermined circumstances (Davillas and Jones, 2020; Ferreira and Gignoux, 2011).

2.3. *Decomposition of IOp*

Following estimation of equations (5) and (6), a Shapley decomposition is used to explore the contribution of each of the circumstances to the total IOp in our wellbeing measures (Davillas and Jones, 2020; Shorrocks, 2013; Wendelspeiss Chávez Juárez and Soloaga, 2014). Unlike other decomposition methods, the Shapley decomposition is path independent and exactly additive (all components sum up exactly to the total IOp). To satisfy path independence, the Shapley decomposition allows for inequality measures for all possible permutations of circumstances to be estimated and, then calculates the average marginal effect of each circumstance variable on the total IOp (Davillas and Jones, 2020; Shorrocks, 2013; Wendelspeiss Chávez Juárez and Soloaga, 2014).

2.4 Using entropy balance reweighting to create counterfactual projections

Our counterfactual projections are based on the notion of holding constant the likelihood of being a university graduate and having different levels of circumstances – in effect, fixing the opportunity set in terms of the likelihood being a graduate. This provides a hypothetical benchmark in which the proportions of people holding a degree and having each level of circumstances is rolled forward from the pre-Robbins period, all else held constant. In reality, in the absence of the expansion of higher education, many other things may have changed so these counterfactual projections should not be regarded as forecasts and the analysis is not intended to be causal. Our analysis can be viewed as simulating a hypothetical scenario that is motivated by the use of opportunity sets to define ex ante inequality of opportunity rather than an attempt to conduct causal inference for the expansion of university education. The counterfactual projection is achieved by a reweighting approach (e.g. DiNardo et al., 1996; Fortin et al., 2011; Firpo & Pinto, 2015). We use entropy balance reweighting to adjust the likelihood of being a university graduation and the joint distribution of graduation and circumstances, to the levels prior to 1963.

Entropy balancing minimizes an entropy distance metric subject to balancing constraints (for example, equality of means of the covariates between the comparison groups) and normalizing constraints that ensure non-negative weights (Hainmueller, 2012; Hainmueller and Xu, 2013). This generates weights to be applied in the regressions and other analyses. While entropy balancing operates on the moments of the univariate distributions for each control variable separately, it is possible to extend the algorithm so that balancing applies to their interactions and hence their co-moments. Other matching or propensity score adjustments often result into low level of covariate balance in practice or rely on time-consuming searches over propensity score models to find a suitable balancing solution (Hainmueller, 2012). Entropy balancing directly incorporates information about the known sample moments and adjusts the weights to obtain exact covariate balance for all moments and co-moments included in the reweighting scheme.

In practice, our entropy balancing approach computes the mean of the covariates in the the pre-1946 birth cohorts; then, finds a set of entropy weights such that the corresponding means of the reweighted group of individuals in the post-1945 birth cohorts match the means from the pre-1946 birth cohorts. A binary measure of graduation along with its interactions with each of the circumstance variables are used as covariates in the entropy balancing algorithm. This balances the overall level of graduation as well as the joint distribution of graduation and the categorical measures of circumstances.

The counterfactual analysis is implemented by estimating equations (3)-(6) after accounting for the entropy balancing weights. This implicitly changes the balance of circumstances between weighted and unweighted samples. At the same time this also means a reweighting of the wellbeing outcomes and hence of the relationship between our outcome variables and C (equations 3 and 4) along with our measures of IOp (equations 5 and 6). Comparisons between the actual and counterfactual scenarios allows us to explore the role of the expansion of higher education on our outcomes, their association with C and, hence, on measures of IOp. Shapley decomposition analysis is also implemented for both actual and counterfactual IOp measures to explore the contribution of each circumstance variable to the total IOp.

Beyond our base-case counterfactual analysis, we have estimated counterfactuals for the case where we only freeze the likelihood of university graduation to the pre-1963 levels as sensitivity analysis. This additional counterfactual analysis provides a robustness check for our results in the case of a less restrictive scenario that does not require freezing the likelihood of university graduation and the joint distribution of graduation and circumstances but only the graduation likelihood; the joint distribution evolves over time and for elder cohorts, its evolution may or may not be linked to educational reforms. Although it is not our aim to provide causal inferences on any education reform, these additional counterfactual analyses may provide further robustness to our base-case results. As in the case of our base-case counterfactual analysis, entropy balance reweighting is used to adjust the likelihood of being a university graduate to the levels prior to 1963, and the derived entropy balancing weights are then used to estimate IOp measures.

3 Data

Data come from *Understanding Society (UKHLS)* a longitudinal, nationally representative study of the UK. We use the General Population Sample (GPS) component of UKHLS, a random sample of the general population. We use data for Waves 1-9, and we restrict the sample to those born in the UK, as we are interested in the expansion of higher education in the UK.

3.1 Generations and higher education reforms in the UK

Given the span of the longitudinal data available in our dataset, there are five commonly defined "generations" that can be identified: the Silent Generation; Baby Boomers; Gen X; Gen Y or Millennials; and Gen Z.[6] Table 1 contains the birth years range for each generation (birth years for the youngest and oldest members of each generation) along with the age range for each generation at the time of key higher education reforms that have contributed to changes in higher education in the UK: the post-Robbins expansion of universities [1963], the creation of the new "post-92" universities from polytechnics and colleges [1992] and the expansion of university tuition fees and student loans [1998] (Greenaway and Haynes, 2003).

The age ranges for the youngest and oldest members of each generation in the first (Wave 1) and our last wave (Wave 9) of our data panel are shown in Table 1. For example, the youngest members of the Silent Generation (born in 1945) are likely to be observed in the

[6] We use labels for generations that are in common usage for expositional purposes. Note that the regression analysis controls for birth cohorts using fixed effects for the exact year of birth.

age range 64-66 in UKHLS Wave 1 (depending on the exact field-work dates, i.e., between 2009-11). Given that we focus on the role of the long-term expansion of university places, the Boomers (born between 1946-1964) were the first generation affected by this period of expansion as the oldest members of this generation were aged 17 in 1963 (when the Robbins Report was published). Respondents who were born before 1946 were much less likely to be affected by the expansion as they were aged 18 and over during the expansion of university places ("pre-Robbins" cohorts or the Silent Generation, see Table 1).

Table 1. Generations available in UKHLS and major higher education reforms

Cohort	Date of birth	Aged 18	Age in 1963: Robbins expansion	Age in 1992: new universities	Age in 1998: fees	Age in 2009-11: UKHLS Wave 1†	Age in 2017-19: UKHLS wave 9†
Silent	1927	1945	36	65	71	82-84	90-92
	1945	1963	18	47	53	64-66	72-74
Boomers	1946	1964	17	46	52	63-65	71-73
	1964	1982		28	34	45-47	53-55
Gen X	1965	1983		27	33	44-46	55-54
	1980	1998		12	18	29-31	37-39
Gen Y/Millennials	1981	1999		11	17	28-30	36-38
	1996	2014			2		21-23
Gen Z	1997	2015					20-22
	2001	2019					16-18

† Age intervals reflect the oldest and youngest members for each generation calculated as the difference between birth year and the period when fieldwork for the UKHLS Wave 1 (2009-2011) and UKHLS Wave 9 (2017-2019) is conducted.

Given the panel structure of the data, we restrict our working sample so that we are able to make like-for-like comparisons of outcomes for each cohort for the similar age range (by using birth cohort and age fixed effects in our regression models). We have, thus, restricted our working sample to exclude the youngest two generations (Gen Y/ Millennials and Gen Z); to achieve like-for-like balance in the age range by cohort we further limit our sample to those below the age of 73 years old (reflecting the oldest age observed for Boomers in our dataset) and to over 29 years old (reflecting the youngest age observed for Gen X). As a result of this, there is limited sample size for the birth cohorts born between 1935 and 1940 and, thus, we exclude those respondents from our final sample.

We create a dichotomous indicator for holding an undergraduate university degree or a university higher degree (e.g., MSc, PhD); this is based on a derived variable that measures the respondent's highest academic qualification, which is updated in each UKHLS wave to include the most recent qualifications of new entrants.

3.2 Outcomes (y)

We use three measures of wellbeing that are available in all nine UKHLS waves used here: income, the Physical Component Summary (PCS-12) score of the SF12 and the Mental Component Summary (MCS-12) score of the Short-form 12 instrument SF12.

We follow the work of Ferreira and Gignoux (2011) on the measurement of IOp, which employs equivalized household income measures as a measure of the advantage/ disadvantage at the household level. Household income in the month prior to the interview is provided as a derived variable in the dataset. Our household income measure is equivalized, using the modified OECD scale, to capture the different household composition across households. The modified OECD scale adjusts household income to reflect different needs in resources of single adults, any additional adults, and children in various age groups in the household. We have longitudinal data on total household income as well as for the modified OECD scale to capture differences in individual's household composition over time. Household income data are also deflated, using the Retail Price Index, to express income in January 2010 prices. In addition to household income, we have provided results in the Appendix for individual's own income. Individual's own monthly income is available as a derived variable in the dataset, and it is deflated to be expressed in January 2010 prices.

The SF-12 is a self-administered, generic (not disease-specific) measure of health that contains 12 questions covering two dimensions: physical and mental health. The SF-12 reflects the current health status of the respondents and all questions are asked in each of the nine UKHLS waves used here. The PCS-12 and MCS-12 scores are provided as derived variables by the dataset; they are constructed from responses to the twelve health related questions using explorative factor analysis (Ware et al., 1995). For this study we use the PCS-12 and the MCS-12 separately; these measures are reliable instruments developed to measure physical and mental health in large scale surveys with higher values of sensitivity and specificity compared to other brief health scales (Burdine et al., 2000; Gill et al., 2007; Ware et al., 1995; Ziebarth, 2010). Both the PCS-12 and the MCS-12 are used in the existing literature as measures of physical and mental health (e.g. Marcus, 2013; Schmitz, 2011; Ziebarth, 2010). By definition, PCS-12 scores have values between 0 and 100 and are standardized to have a mean of 50 and a standard deviation of 10; higher values indicate better physical and mental health, respectively.

3.3 Socioeconomic Circumstances (C)

The choice of measured circumstance factors follows recent empirical literature, informed by the normative framework of equity in wellbeing outcomes, such as health and income or earnings (e.g., Bourguignon et al., 2007; Carrieri and Jones, 2018; Checchi and Peragine, 2010; Davillas and Jones, 2020; Ferreira and Gignoux, 2011; Jusot et al., 2013; Rosa Dias, 2009, 2010). In the presence of unobserved circumstances, our IOp measures should be interpreted as a lower-bound estimate of overall IOp (Ferreira and Gignoux, 2011). Parental socioeconomic status (SES) is regarded as an important source of IOp in wellbeing, being beyond individual's control and exerting a lasting effect on individual's adult health and income (Bourguignon et al., 2007; Checchi and Peragine, 2010; Davillas and Jones, 2020). In this study we use both parental occupational status and parental education to proxy childhood SES. Occupational status of the respondent's mother and father, when the respondent was aged 14, is measured using two categorical variables (one for each parent) with four categories: not working or lowest-skilled occupation (skill level 1) [reference group]; occupations that require a longer period of work-related training/ work experience (skill level 2); occupational skill level 3 that includes technical and trades occupations and proprietors of small businesses; highest occupational category (skill level 4) that includes professional occupations and high level managerial positions. These occupational categories are created following the skill level structure of the Standard Occupational Classification 2010.[7] Parental education is measured using separate categorical variables for mother and father education. These are five category variables measured as: left school with no qualification (reference group); left school with some qualification; post-school qualification/certificate; degree (university or other higher-education degree). Descriptions and mean values for all variables used in our analysis are available in Table A1 (Appendix).

After excluding missing data on all variables used in our analysis, our working sample contains 99,409 observations across the nine UKHLS waves. As our sample is restricted to those born in the UK, an individual who studied for a higher education qualification abroad to be included in our sample needs to be born in the UK, study abroad, then return to the UK to be sampled in UKHLS. Although we cannot identify these with absolute certainty given the structure of the relevant UKHLS questionnaire, there are a dozen person-year observations that may have got their undergraduate degree outside the UK, keeping our results essentially identical.

4 Results

4.1. Descriptive statistics and entropy balancing

To demonstrate the efficacy of the entropy balancing algorithm, Table 2 presents the mean values for the proportion of graduates and the interactions between being a graduate and the categorical levels of circumstances, for the pre-1963 (pre-Robbins) and for the post-

[7] The structure of our questionnaire does not separate those mothers who were out of labour force due to (temporary) unemployment when the respondent was aged 14. Moreover, those of occupational skill level 1 often have jobs which are seasonal/temporary occupations. Given that preliminary analysis also shows that the coefficient for a "not working" mother does not differ systematically from the "occupation skill level 1" category in the majority of the cases, we have grouped these two categories.

Robbins period, with and without entropy balancing weights. Comparisons reveal substantial differences for the birth cohorts before and after 1946 and that these differences are eliminated using our entropy balancing weights. For example, our entropy balancing weights adjust the post-1946 birth cohort university degree levels to the pre-1946 levels, i.e., a 16% prevalence rate and all of the joint frequencies, given by the interaction terms, are balanced. Table A2 (Appendix) provides a comparison of the mean values of circumstances with and without the entropy balancing weights.

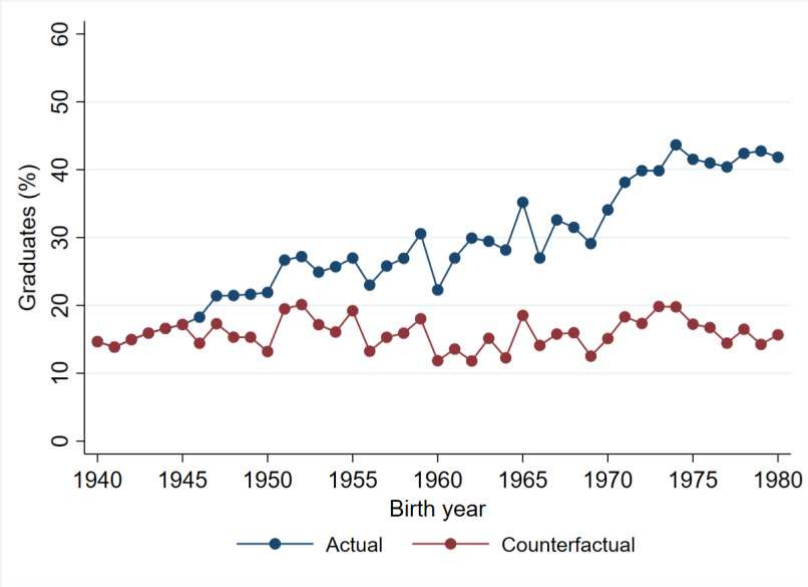
Figure 1 presents plots of the actual and counterfactual university graduation rates (the proportion of those holding a university degree) by birth year. For the counterfactual scenario entropy balancing keeps the likelihood of graduation to the levels experienced by those cohorts not affected by the Robbins reform (pre-1946 cohorts). As expected, given the scope of the Robbins principle to expand university participation to include all those "who are qualified by ability and attainment", there is sharp increase in graduates by birth cohort, with an increasing gap between actual and counterfactual predictions in the proportion of graduates for younger birth cohorts. For example, the proportion of university graduates is around 42% for the 1980 birth cohort, much higher than the corresponding proportion (around 15%) in the counterfactual scenario. As shown in Figure 1, university graduation rates for actual and counterfactual analysis coincide for the 1940-1945 cohorts as these are not reweighted.

Table 2. Entropy balancing for cohorts affected by the 1963 Robbins reform (birth cohort≥1946) and for the pre-1946 birth cohorts

	Pre-Robbins cohorts	Post-Robbins cohorts	Post-Robbins cohorts
		Unweighted	Weighted
Degree	0.16	0.30	0.16
Proportion who are graduates and have circumstance level:			
Male	0.11	0.13	0.11
White	0.16	0.29	0.16
Mother's education			
Some qualification	0.04	0.11	0.04
Post school quals/certs	0.02	0.07	0.02
University/higher education degree	0.01	0.03	0.01
Father's education			
Some qualification	0.02	0.07	0.02
Post school quals/certs	0.04	0.10	0.04
University/higher education degree	0.02	0.06	0.02
Mother's occupation			
Skill level 2	0.03	0.09	0.03
Skill level 3	0.01	0.03	0.01
Skill level 4 (high-skilled)	0.01	0.06	0.01
Father's occupation			
Skill level 2	0.03	0.06	0.03
Skill level 3	0.08	0.12	0.08
Skill level 4 (high-skilled)	0.04	0.10	0.04

Notes: UKHLS waves 1-9. Details of the working sample are available in the data sub-section.

Figure 1. Actual and counterfactual university graduation rates (%) by birth cohort.

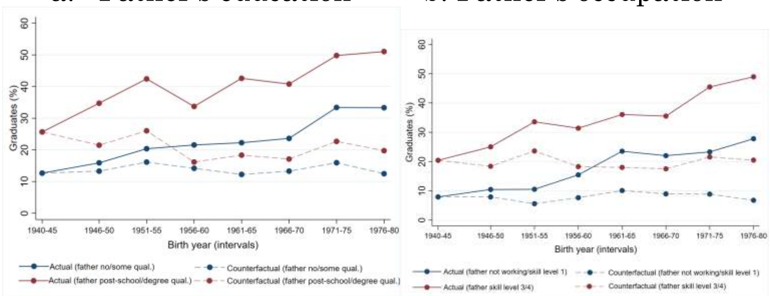


Notes: UKHLS waves 1-9. Details on the working sample are available in the data sub-section. The predicted proportion of graduates is based on linear probability models of the probability of holding a degree on birth cohorts separately for the actual and counterfactual analysis.

To illustrate how rates of graduation vary with parental circumstances, Figure 2 presents the actual and counterfactual university graduation rates by birth year (expressed in intervals), separately for the higher and lower categories of father's education and occupational (the corresponding results for mother's education and occupation are presented in Figure A1, Appendix). The actual data show that rates of graduation increased over time for all groups but the gap in rates of graduation between the higher and lower groups did not converge (in line with Blanden and Machin, 2004 and Crawford et al., 2016). Machin and Vignoles (2004) and Chowdry et al. (2013) have shown that much of this socioeconomic gradient in participation in the UK is attributable to differences in educational attainment at school and that the link between this achievement and parental socioeconomic status has increased during the period of university expansion. Moreover, a recent study argues that more advantaged families are better able to access and utilize universally available programmes (Heckman and Landersø, 2021). Similar patterns are observed in the case of the corresponding university graduation rates by mother's education and occupational categories (Figure A1, Appendix). Overall, our results show that the expansion of university places may have been more beneficial (in absolute terms) for those of more advantaged socioeconomic backgrounds, as shown by the absolute difference in the actual and counterfactual predictions for those with low and high parental background.

Figure 2. Actual and counterfactual university graduation rates (%) by birth cohort: analysis by father's education and occupation

a. Father's education b. Father's occupation



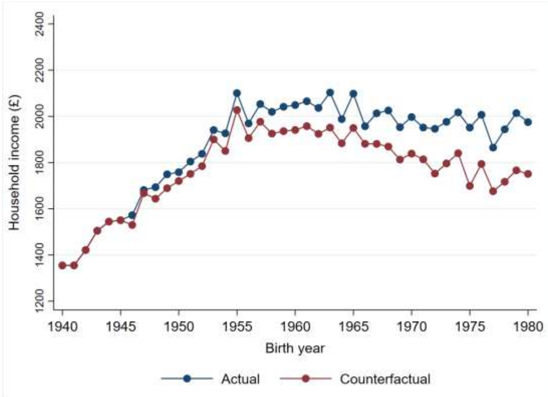
Notes: UKHLS waves 1-9. Details on the working sample are available in the data sub-section. The predicted proportion of graduates is based on linear probability models of the probability of holding a degree on birth cohorts separately by father education and occupation categories for the case of actual and counterfactual analysis.

Figure 3 plots the overall trends in the wellbeing outcomes by birth cohort. In Panel A, the graph shows an inverted U-shaped relationship between real equivalised income and year of birth with the peak corresponding to the Baby Boomers who are currently between their mid-fifties and mid-seventies. This is in line with Hood and Joyce (2013) who use UK Family Expenditure Survey data; they also find a rapid improvement in economic outcomes across birth cohorts that peaked among cohorts born between the 1960s and 1970s. For all post-1945 birth cohorts, household income is higher for the actual data than the counterfactual. The gap between actual and counterfactual income predictions increases for younger birth cohorts. For example, the difference between the actual and counterfactual predicted household income is around £224 for the youngest birth cohort (1980), which is equivalent to 20 percent of the standard deviation of income in our dataset (across waves and generations).

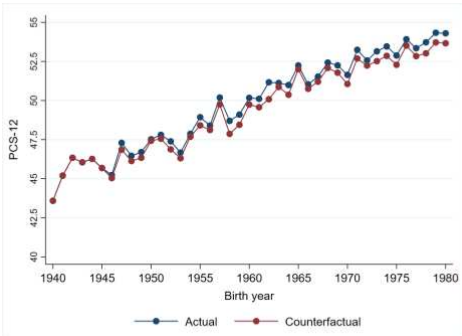
Figure 3, Panel B shows a monotonically increasing relationship between physical health functioning (PCS-12) and year of birth, reflecting the relationship between physical health and age. This is broadly in line with Morciano et al. (2015), who provide evidence of a positive birth-cohort trend in functional difficulties which is largely concentrated among men. There is a much lower (as compared to income) difference in the actual and counterfactual projections of physical health functioning across all the post-1945 birth cohorts. For example, in the case of the youngest birth cohort (1980), the difference between actual and counterfactual PCS-12 predictions is equivalent to around 6% of the standard deviation of the PCS-12 score (i.e., a difference of 0.633 PCS-12 units).

Figure 3. Actual and counterfactual outcomes by birth cohort

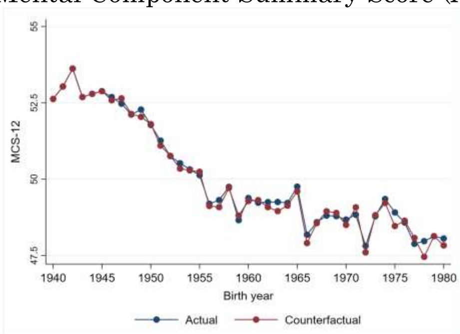
(a) Household income



(b) Physical Component Summary Score (PCS-12)



(c) Mental Component Summary Score (MCS-12)



Notes: UKHLS waves 1-9. Details on the working sample are available in the data sub-section. The predicted outcomes (income, physical or mental health functioning) are based on regression models on birth cohorts separately for the actual and counterfactual analysis.

On the other hand, Panel C shows that the relationship between the mental health component of the SF-12 and year of birth is monotonically decreasing, with poorer mental health reported by younger people. This result is in line with recent literature that documents an increase in mental health disorders across younger generations in the US and UK. For instance, Rothert et al. (2017), who use data from the Behavioral Risk Factor Surveillance System, found that self-reported mental health declined over time in the US. Zheng and Echave (2021), using data from the National Health and Nutrition Examination Surveys (1988–2016) and the National Health Interview Surveys (1997–2018) and also found that mental health disorders have increased continuously from Baby Boomers through late Generation X and Generation Y in the US. Avendano, De Coulon and Nafilyan (2020) exploit a compulsory schooling reform in 1972 in the UK and find that the reform increased educational attainment as well as, for some individuals, the prevalence of depression and other mental health conditions. Their results do not imply that higher educational attainment per se leads to poorer mental health but rather that forcing low achieving teenagers to remain in a formal academic environment may have unintended consequences on their mental health.

Overall, the descriptive analysis suggests that cohort trends differ for the three outcomes we consider and that the counterfactual reweighting changes the trend for income but has a more limited effect on the health outcomes. The regression analysis, that follows, controls for cohort trends in outcomes along with age effects using fixed effects.

4.2. Regression models

Table 3 presents results from our regression models of household income on circumstances, adjusted for birth cohort and age fixed effects. Separate models are estimated for actual and counterfactual scenarios. The results show a strong positive parental (for both mother's and father's) education gradient in household income, in both the actual and counterfactual analyses. For example, the average (monthly) income gap of those respondents whose mother holds a university/higher education degree, as opposed to no qualifications, is £280, ceteris paribus; the corresponding income gap is lower at £228 for the counterfactual analysis. Moreover, mother's and father's occupation (at the respondent's age of 14) play a long-lasting role in respondent's future household income. Specifically, in both the case of actual and counterfactual analysis, we observe positive gradients with parental occupational skill levels, which are steeper for father's as opposed to mother's occupational status. The average monthly income gap for those having a father with a high skilled job (skill level 4), as opposed to those with a non-working/low skilled father, is £425; the corresponding gap is lower (£397) for the counterfactual analysis. On average, men have £135 more household income (in the month prior to the interview) than women, which is lower than the relevant gap (£186) that would have been observed if with rates of graduation fixed to pre-1946 levels (counterfactual analysis).

Table 4 presents the results for our measure of physical health functioning (PCS-12). These show that men have, on average, better physical health than women (0.74 versus 1.138 for the actual and counterfactual analyses, respectively). Mother's and father's education play a systematic role for people's later life physical health, with differences being more pronounced in the actual data. There are steeper and more pronounced father's (rather than mother's) occupational gradients in physical health. The counterfactual analysis shows that having a father in a high-skilled occupation (when respondent aged 14) results in a higher PCS-12 score of about 2.49 points (better physical health functioning) compared to non-working/low skilled occupations; the corresponding gap in physical health score is a little lower (2.27 PCS-12 units) with the actual data.

Results for mental health functioning are presented in Table 5. Men and those of white origin experience better mental health in the actual and the counterfactual analysis; the effects are lower in the actual as opposed to the counterfactual analysis. Mother's education at the age of 14, but not father's, plays a systematic role on individuals mental health functioning later in their adult life; there is a strong association between mother's education and better mental health functioning for both actual and counterfactual estimates. Father's occupation at respondent's age of 14 and to lesser extent mother's occupation have systematic gradients in mental health functioning (Table 5).

Table 3. Household income regression models: actual and counterfactual scenarios

	Actual	Counterfactual
Male	134.8***	186.1***
	(15.5)	(20.0)
White	75.8	94.1
	(62.6)	(104.4)
Mother's education		
Some qualification	175.5***	142.9***
	(21.2)	(30.5)
Post school quals/certs	202.0***	204.2***
	(27.8)	(41.2)
University/higher education degree	280.3***	228.0***
	(52.3)	(84.9)
Father's education		
Some qualification	80.8***	98.9***
	(23.5)	(32.9)
Post school quals/certs	83.2***	80.7***
	(21.4)	(28.6)
University/higher education degree	252.2***	201.0***
	(41.4)	(58.6)
Mother's occupation		
Skill level 2	129.7***	76.5***
	(18.1)	(23.7)
Skill level 3	124.4***	91.8**
	(28.3)	(37.1)
Skill level 4 (high-skilled)	241.5***	129.1**
	(35.9)	(62.2)
Father's occupation		
Skill level 2	122.2***	99.5***
	(22.4)	(25.2)
Skill level 3	197.4***	183.5***
	(21.6)	(24.5)
Skill level 4 (high-skilled)	425.3***	396.9***
	(31.6)	(39.3)
Constant	1343.2***	1178.8***
	(63.2)	(102.0)
Sample size	99,409	

Notes: Birth cohort and age fixed effects are accounted for in both models. Robust standard errors clustered at the individual level are presented in parentheses.

*Statistical significance = 10%. **Statistical significance = 5%. ***Statistical significance = 1%.

Table 4. Physical Component Summary Score (PCS-12) regression models: actual and counterfactual scenarios.

	Actual	**Counterfactual**
Male	0.74***	1.138***
	(0.15)	(0.27)
White	0.33	0.67
	(0.45)	(0.78)
Mother's education		
Some qualification	1.04***	0.98***
	(0.21)	(0.36)
Post school quals/certs	1.41***	2.08***
	(0.25)	(0.44)
University/higher education degree	1.40***	1.61*
	(0.40)	(0.84)
Father's education		
Some qualification	0.75***	0.55
	(0.22)	(0.39)
Post school quals/certs	0.33	0.41
	(0.22)	(0.39)
University/higher education degree	1.50***	0.089
	(0.32)	(0.62)
Mother's occupation		
Skill level 2	0.55***	0.36
	(0.18)	(0.32)
Skill level 3	0.19	-0.32
	(0.30)	(0.54)
Skill level 4 (high-skilled)	0.43	-0.74
	(0.28)	(0.62)
Father's occupation		
Skill level 2	0.87***	0.96**
	(0.27)	(0.44)
Skill level 3	1.43***	1.43***
	(0.25)	(0.41)
Skill level 4 (high-skilled)	2.27***	2.49***
	(0.30)	(0.51)
Constant	46.80***	44.56***
	(0.48)	(0.83)
Sample size	99,409	

Notes: Birth cohort and age fixed effects are accounted for in both model estimations. Robust standard errors clustered at the individual level are presented in parentheses.

*Statistical significance = 10%. **Statistical significance = 5%. ***Statistical significance = 1%.

Table 5. Mental Component Summary Score (MCS-12) regression models: actual and counterfactual scenarios

	Actual	Counterfactual
Male	1.84***	2.20***
	(0.12)	(0.17)
White	1.27***	1.96**
	(0.48)	(0.72)
Mother's education		
Some qualification	0.76***	0.42
	(0.17)	(0.24)
Post school quals/certs	0.52**	0.77***
	(0.21)	(0.27)
University/higher education degree	0.89**	1.34**
	(0.35)	(0.54)
Father's education		
Some qualification	0.24	0.21
	(0.18)	(0.25)
Post school quals/certs	-0.09	0.02
	(0.17)	(0.24)
University/higher education degree	0.22	0.65*
	(0.28)	(0.38)
Mother's occupation		
Skill level 2	0.41***	0.31
	(0.14)	(0.21)
Skill level 3	0.19	0.41
	(0.23)	(0.30)
Skill level 4 (high-skilled)	0.44*	0.14
	(0.24)	(0.36)
Father's occupation		
Skill level 2	0.81***	0.52*
	(0.21)	(0.28)
Skill level 3	1.20***	0.81***
	(0.21)	(0.27)
Skill level 4 (high-skilled)	1.20***	0.85**
	(0.25)	(0.34)
Constant	46.44***	47.34***
	(0.50)	(0.75)
Sample size	99,409	

Notes: Birth cohort and age fixed effects are accounted for in both model estimations. Robust standard errors clustered at the individual level are presented in parentheses.

*Statistical significance = 10%. **Statistical significance = 5%. ***Statistical significance = 1%.

4.3. Inequality of opportunity

Table 6 presents descriptive statistics and inequality measures for the fitted income and health outcomes, based on the models presented in Tables 3-5, for the actual and counterfactual analyses. Turning to the income models (Panel A), as expected given improvement in the university graduation opportunities, the predicted mean values and quantiles of the income distribution attributed to circumstances are lower when graduation rates are fixed at pre-1963 levels (counterfactual) as opposed to allowing them to vary across generations (actual). The inequality measures show that absolute and relative IOp in income are similar between actual and counterfactual analyses. Although we find that the difference in the inequality measures between actual and counterfactual are statistically significant (at the 1% level), the IOp measures do not differ substantially in practice.[8] Our relative IOp measures suggest that the proportion of the total inequality in household income that is attributed to the pre-determined circumstances is comparable in the case of actual (6.57%) and counterfactual (6.52%) scenarios.[9]

Table 6, Panel B presents the results for physical health (PCS-12). As in the case of income, limited differences are observed in the absolute and relative IOp measures for physical health between our actual and counterfactual analyses. We find that IOp in actual outcomes is somewhat lower in magnitude than when the rate of graduation is fixed to the pre-1963 levels, suggesting that IOp in physical health decreased as higher education opportunities actually improved across generations.

The last part of Table 6 (Panel C) shows results for our mental health functioning scores (MCS-12). Unlike physical health, we find that mean and quantiles of the distribution of the predicted MCS-12 scores from our set of circumstances indicate worse mental health (lower MCS-12 scores) in the case of actual as opposed to counterfactual analysis. On the other hand, our IOp analysis suggests that the actual outcomes resulted in lower IOp (both in absolute and relative terms) in mental health functioning compared to freezing graduation rates to pre-1963 levels.

Results from our sensitivity analysis on employing a counterfactual scenario that only freezes the likelihood of university graduation to pre-1963 levels are presented in Table A4 (Appendix) for robustness. Comparisons between these counterfactual results (Table A4) and our actual analysis results (Table 6), lead to similar conclusions both for the case

[8] Employing the Gini coefficient as IOp measure for household income shows comparable results between the actual and counterfactual analysis (0.0825 versus 0.0823 in the actual and counterfactual scenarios). Our results using the Gini coefficient confirm the absence of differences in IOp between the actual and counterfactual analyses.

[9] The corresponding results from individual's own income are available in the Appendix (Table A3). Overall, the predicted mean values and quantiles of the personal income distribution attributed to circumstances are lower when graduation rates are fixed at pre-1963 levels (counterfactual) as opposed to the actual scenario; IOp in own income is modestly higher in the case of freezing the society to pre-1963 levels as opposed to the actual, current case.

of levels and IOp measures; the new counterfactual results (Table A4) are very close to those when the likelihood of being a university graduate and the joint distribution of graduation and circumstances to the levels prior to 1963 are held constant. The only difference observed is a slightly larger reduction (about 12%) in the observed IOp (both in absolute and relative terms) when moving from the new counterfactuals to actual analysis as opposed to the almost identical actual-counterfactual IOp measures in our base case analysis (Table 6).

Table 6. Summary statistics and IOp measures based on actual and counterfactual predictions from the wellbeing models

	Actual	Counterfactual
Panel A: Income models		
Mean‡	1894.2	1710.9
q25	1676.0	1532.9
q50	1872.6	1687.8
q75	2059.8	1876.8
q90	2272.0	2056.9
Inequality measures: absolute IOp		
MLD Index‡	0.0105*** (0.0001)	0.0104*** (0.0001)
Inequality measures: relative IOp		
% of the total inequality explained (MLD Index)	6.57	6.52
Panel B: PCS-12		
Mean‡	49.86	48.00
q25	48.74	46.76
q50	49.79	47.90
q75	50.89	49.14
q90	51.74	49.96
Inequality measures: absolute IOp		
Variance‡	2.10*** (0.008)	2.20*** (0.009)
Inequality measures: relative IOp		
% of the total inequality explained (Variance)	1.73	1.82
Panel C: MCS-12		
Mean‡	49.99	51.39
q25	49.04	50.26
q50	49.91	51.21
q75	50.78	52.45
q90	51.70	53.10
Inequality measures: absolute IOp		
Variance‡	1.39*** (0.005)	1.70*** (0.006)
Inequality measures: relative IOp		
Variance share (%)	1.50	1.83

Note: Bootstrapped (500 replications) standard errors in parenthesis (were relevant).
‡ Mean predictions and inequality measures differ systematically (at least at the 1% level) between actual and counterfactual cases.
***P-value<0.01.

We are not making any causal inferences about the effect of the Robbins reform in this study as well as we have explicitly mentioned that we study the expansion of higher education in the UK, since the landmark Robbins Report in 1963, rather than the reform itself. However, one may be interested to explore how our results may vary if we focus only on those cohorts that are affected by the new universities or fees reforms. As a sensitivity analysis, we re-estimated our results presented in Table 6 when restricting our working sample to have the youngest birth cohort aged 21 years old in 1992 (when the new universities reform took place) and, thus, they are not affected by both the fees and new universities reforms as they are likely to have their first degree completed by the age of 21 years old in the UK. Thus, these additional results are estimated in a sub-sample with those born at 1971 (and thus aged 21 in 1992) being the youngest cohort (Table A5, Appendix). Overall, we found that the results presented in Table A5 and our base case results in Table 6 are qualitatively identical (and very similar quantitively too).

Contribution of circumstances to IOp

Shapley decomposition analysis is used here to quantify the contribution of each of the circumstances to IOp and to assess the relative role of each of the circumstances in comparison to the counterfactual scenario. In Table 7, Panel A, the Shapley decomposition of the MLD index for IOp in income shows that relative (percentage) contribution of father's occupation is lower for the actual outcomes and is higher for mother's education and occupation. This indicates that, as university participation expanded across generations, differences in mother's socioeconomic status became more relevant, while the socioeconomic status of the father became less important (although still the dominant source) for explaining IOp in income.[10]

Shapley decomposition results for the physical health functioning score (Table 7, Panel B) show a higher relative contribution of father's education and a lower contribution of mother's education in the actual outcomes compared to the counterfactual. On the other hand, there are different patterns in the relative contribution of our circumstance variables between the actual and counterfactual analysis for IOp in the mental health functioning score (MCS-12, Table 7, Panel C). Specifically, the relative contribution of ethnicity, mother's and father's education is smaller for the actual outcomes. However, the relative contribution of father's occupation is 13% for the counterfactual and 53% for the actual outcomes.

[10] Similar patterns are observed in the case of the Shapley decomposition results for individual's own income (Table A6, Appendix).

Table 7. Shapley decomposition of IOp measures for actual and counterfactual predictions

	Actual % contribution	Counterfactual % contribution
Panel A: Income models		
MLD-Index		
Gender	0.22%	0.42%
Ethnicity	0.22%	0.57%
Mother education	16.30%	11.82%
Father education	30.60%	28.88%
Mother occupation	14.84%	7.93%
Father occupation	37.81%	50.37%
Total	**100.0%**	**100.0%**
Panel B: PCS-12		
Variance		
Gender	0.06%	0.24%
Ethnicity	0.11%	0.71%
Mother education	9.35%	21.67%
Father education	43.64%	18.07%
Mother occupation	4.03%	2.23%
Father occupation	42.80%	57.07%
Total	**100.0%**	**100.0%**
Panel C: MCS-12		
Variance		
Gender	14.65%	14.22%
Ethnicity	23.75%	47.72%
Mother education	3.59%	10.51%
Father education	4.23%	13.16%
Mother occupation	0.90%	1.43%
Father occupation	52.88%	12.96%
Total	**100.0%**	**100.0%**

5. Conclusions

Education plays a central role in human development and reforms to educational systems have been considered as one of the most significant social transformations of the second half of the 20th Century (Shavit et al., 2007). Education, especially access to university, is also considered as a powerful tool to promote social mobility and reduce the gap in later life attainments between individuals from different socioeconomic backgrounds. In this paper, using nine waves of data from the longitudinal survey *Understanding Society* (UKHLS), we study the university expansion in the UK and its consequences for inequalities and wellbeing across generations for three outcomes: income, physical and mental health functioning. Using longitudinal models, with age and birth-year fixed effects, we estimate the role of the role of pre-determined circumstances for later life outcomes net of potential confounding by lifecycle and birth-cohort effects. Using entropy balancing weights, we assess the contribution of university expansion to overall wellbeing and inequality of opportunity (IOp) by comparing analysis using the actual data and counterfactual projections. Shapley decomposition quantifies the contribution of each of the circumstances to IOp and assesses how the relative role of each of the circumstances has changed as society has evolved in comparison to the hypothetical counterfactual scenario that fixes the opportunity set.

Our analysis leads to several findings that are relevant for the IOp literature in which the set of opportunities are usually considered as fixed. There is a scarcity of studies that look at the evolution of IOp across generations and at how IOp varies when the set of opportunities changes as society evolves. We find that university expansion triggered a large increase in the proportion of graduates in the UK. Compared to the counterfactual scenario, we find an increase of around the 180% in the proportion of graduates in our youngest birth cohort (1980 birth cohort). At the same time, we find that while this holds irrespective of the individual's parental background, our results show that the increase in the likelihood of holding a degree is more pronounced in absolute terms for those having parents with a higher socioeconomic background; providing further evidence of the persistent socioeconomic gradient in participation in higher education (e.g., Blanden and Machin, 2004; Machin and Vignoles, 2004; Chowdry et al., 2013; Crawford et al., 2016).

Comparison of the actual and counterfactual projections reveals a difference in household income of around £224 for the youngest birth cohort (1980), which is equivalent to 20% of the standard deviation of average income across waves and generations. We also find positive and significant differences for physical health (equivalent to a 6% change in average physical health) and a negative difference for mental health.

However, we find that IOp does not differ substantially between actual and counterfactual scenarios for household income, while we observe a small reduction in IOp in both physical and mental health functioning. This indicates that university expansion has barely affected IOp in income, since the absolute increase in university graduates has been more concentrated among individuals with more advantaged socioeconomic backgrounds (e.g., Blanden and Machin, 2004; Machin and Vignoles, 2004; Chowdry et al., 2013; Crawford et al., 2016). Shapley decomposition analysis reveals differences in the relative role of our set of circumstances. For example, we find that the socioeconomic status of the father is the dominant source of IOp in income, however, as university participation expanded across generations, differences in mother's socioeconomic status became increasingly relevant (although father background remained the dominant source).

Our findings are broadly consistent with a recent study by Hechman and Landersø (2021) that compares educational inequalities in the US with the generous Danish welfare model. A striking finding of their analysis is that while welfare policies have diverged during the latest decades, with educational reforms in Denmark such as the substantial expansion of lower secondary schooling, equal access to public services, and no tuition costs for education, the two countries have converged in terms of educational levels. The main reason behind this result is that, despite equalized access to education policies, more advantaged families are better able to access and utilize educational programmes.

Interestingly, while Hechman and Landersø (2021) compare inequalities across two countries with different welfare models, our analysis leads to similar conclusions.

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Appendix

Table A1. Description and mean values of variables used in the analysis

	Mean
Household income (equivalised and deflated)	1894.2
PCS-12	49.9
MCS-12	50.0
Age (in years)	52.3
University Degree	
Degree	0.29
No degree (reference)	0.71
Gender	
Male	0.43
Female (reference)	0.57
Ethnicity	
White	0.98
Non-white (reference)	0.02
Mother's occupation	
1 (Low-skilled) or not working (reference)	0.53
2	0.29
3	0.08
4(high-skilled)	0.10
Father's occupation	
1(low-skilled) or not working(reference)	0.14
2	0.26
3	0.43
4(high-skilled)	0.17
Mother's education	
No qualification (reference)	0.48
Some qualification	0.31
Post school quals/certs	0.16
University/higher education degree	0.05
Father's education	
No qualification (reference)	0.45
Some qualification	0.20
Post school quals or certs	0.27
University/higher education degree	0.08
Sample size	99,409

Table A2. Summary statistics for holding a university degree and for our circumstance variables: using entropy balancing weights and unweighted analysis.

	Using entropy balancing weights	Unweighted
Variables	**Mean**	**Mean**
University degree		
Degree	0.158	0.287
Non-degree	0.841	0.712
Gender		
Male	0.472	0.430
Female	0.528	0.570
Ethnicity		
White	0.990	0.980
Non-white	0.010	0.020
Mother's education		
No qualification	0.650	0.484
Some qualification	0.221	0.309
Post school quals/certs	0.108	0.159
University/higher education degree	0.022	0.047
Father's education		
No qualification	0.567	0.449
Some qualification	0.155	0.201
Post school quals/certs	0.232	0.268
University/higher education degree	0.046	0.083
Mother's occupation		
Not working/skill level 1	0.634	0.532
Skill level 2	0.232	0.290
Skill level 3	0.084	0.083
Skill level 4 (high-skilled)	0.050	0.095
Father's occupation		
Not working/skill level 1	0.154	0.144
Skill level 2	0.283	0.257
Skill level 3	0.441	0.426
Skill level 4 (high-skilled)	0.123	0.172

Notes: UKHLS waves 1-9. Details on the working sample are available in the data sub-section.

Table A3. Summary statistics and IOp measures of individual's total income based on actual and counterfactual predictions.

	Actual	Counterfactual
Mean‡	1693.5	1430.0
q25	1293.7	1048.9
q50	1705.1	1353.5
q75	2051.3	1772.1
q90	2265.2	1964.8
Inequality measures: absolute IOp		
MLD Index‡	0.035*** (0.0001)	0.043*** (0.0001)
Inequality measures: relative IOp		
% of the total inequality explained (MLD Index)	11.9%	14.5%

Note: Bootstrapped (500 replications) standard errors in parenthesis (were relevant).
‡ Mean predictions and inequality measures differ systematically (at least at the 1% level) between actual and counterfactual cases.
***P-value<0.01.

Table A4. Summary statistics and IOp measures on counterfactual predictions from the wellbeing models that only freeze the likelihood of university graduation to the pre-1963 levels.

Panel A: Income models	
Mean	1721.6
q25	1513.5
q50	1695.0
q75	1891.6
q90	2083.8
Inequality measures: absolute IOp	
MLD Index	0.012*** (0.0001)
Inequality measures: relative IOp	
% of the total inequality explained (MLD Index)	7.36%
Panel B: PCS-12	
Mean	48.1
q25	46.9
q50	48.0
q75	49.2
q90	50.2
Inequality measures: absolute IOp	
Variance	2.34*** (0.008)
Inequality measures: relative IOp	
% of the total inequality explained (Variance)	1.93%
Panel C: MCS-12	
Mean	51.4
q25	50.3
q50	51.2
q75	52.4
q90	53.1
Inequality measures: absolute IOp	
Variance	1.66*** (0.006)
Inequality measures: relative IOp	
Variance share (%)	1.80%
Sample size	

Note: Bootstrapped (500 replications) standard errors in parenthesis (were relevant).
***P-value<0.01.

Table A5. Summary statistics and IOp measures based on actual and counterfactual predictions from the wellbeing models: Sensitivity analysis restricting our working sample so that those born at 1971 (and, thus, aged 21 in 1992) being the youngest cohort.

	Actual	Counterfactual
Panel A: Income models		
Mean	1877.0	1691.2
q25	1680.3	1525.3
q50	1846.2	1659.7
q75	2038.2	1854.0
q90	2251.9	2023.2
Inequality measures: absolute IOp		
MLD Index	0.009*** (0.0001)	0.010*** (0.0001)
Inequality measures: relative IOp		
% of the total inequality explained (MLD Index)	5.73	6.15
Panel B: PCS-12		
Mean‡	49.0	47.4
q25	47.8	46.1
q50	48.8	47.3
q75	50.0	48.5
q90	51.0	49.5
Inequality measures: absolute IOp		
Variance	2.326*** (0.010)	2.378*** (0.011)
Inequality measures: relative IOp		
% of the total inequality explained (Variance)	1.81	1.84
Panel C: MCS-12		
Mean	50.4	51.7
q25	49.4	50.5
q50	50.4	51.5
q75	51.2	52.7
q90	52.1	53.4
Inequality measures: absolute IOp		
Variance	1.404*** (0.006)	1.737*** (0.007)
Inequality measures: relative IOp		
Variance share (%)	1.52	1.88
Sample size	**80,167**	

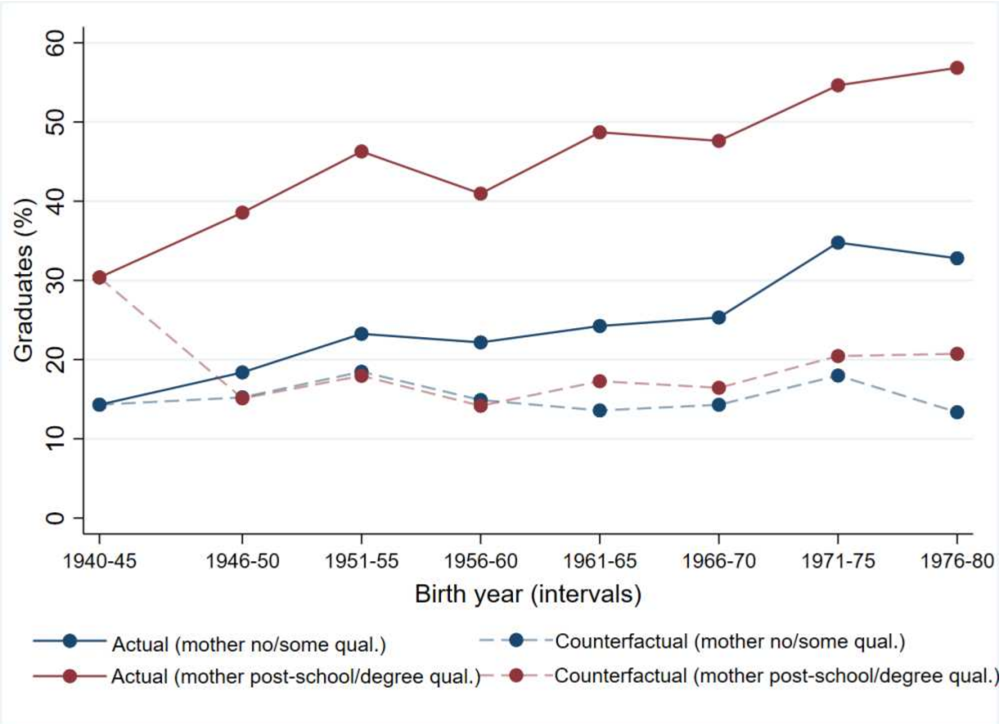
Note: Bootstrapped (500 replications) standard errors in parenthesis (were relevant). ***P-value<0.01.

Table A6. Shapley decomposition of IOp measures for actual and counterfactual predictions of individual's total income.

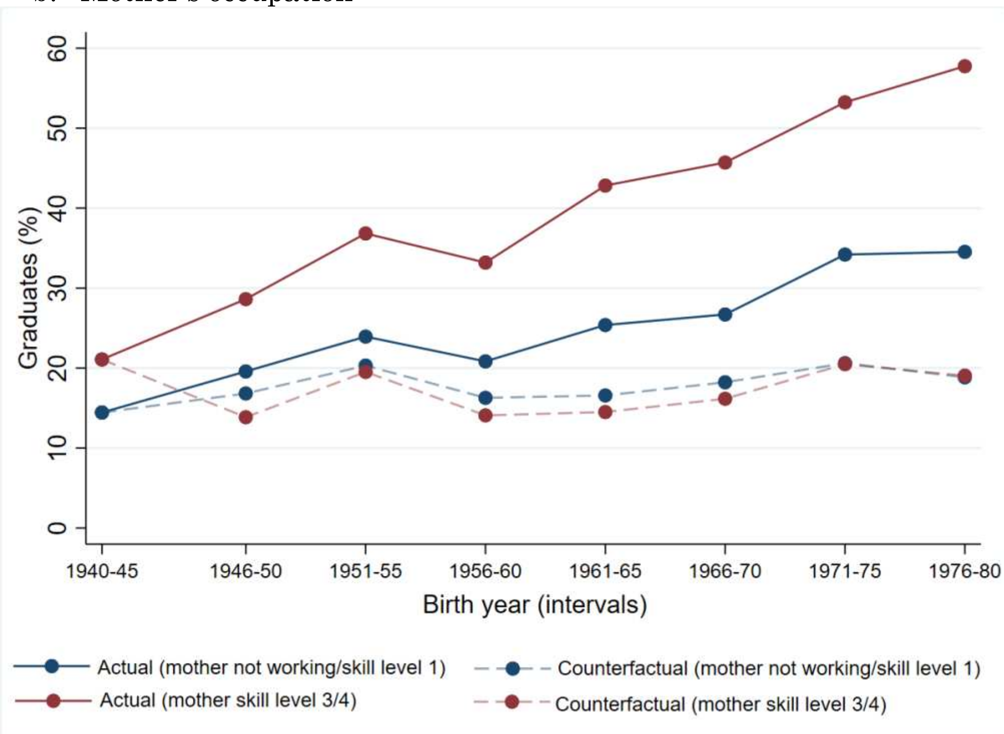
	Actual % contribution	Counterfactual % contribution
Panel A: Income models		
MLD-Index		
Gender	1.81%	1.47%
Ethnicity	0.05%	0.74%
Mother education	15.55%	12.65%
Father education	35.14%	29.41%
Mother occupation	13.48%	6.98%
Father occupation	33.98%	48.74%
Total	**100.0%**	**100.0%**

Figure A1. Actual and counterfactual university graduation rates (%) by birth cohort: analysis by mother's education and occupation

a. Mother's education



b. Mother's occupation



Notes: UKHLS waves 1-9. Details on the working sample are available in the data sub-section. The predicted proportion of graduates is based on linear probability models of the probability of holding a degree on birth cohorts separately by mother education and occupation categories for the case of actual and counterfactual analysis.