College education, intelligence, and disadvantage: policy lessons from the UK in 1960-2004*

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Abstract

University access has greatly expanded during the past decades and further growth figures prominently in political agendas. We study possible consequences of historical and future expansions in a stochastic, general equilibrium Roy model where tertiary educational attainment is determined by *intelligence* and *disadvantage* from low socioeconomic status or poor non-cognitive skills. The enlargement of university access enacted in the UK following the 1963 Robbins Report provides an ideal case study to draw lessons for the future. We find that this expansion led to the selection into college of progressively less intelligent students from advantaged backgrounds and to a declining college wage premium across cohorts. Our structural estimates indicate that the implemented policy was unfit to reach high-ability, disadvantaged individuals as Robbins had instead advocated. We show that counterfactual meritocratic selection policies would have attained that goal and so would have also been progressive.

JEL Classification: I23, I28, J24, O33

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1 Introduction

Enrollment in tertiary education increased by a factor of 3.4 in OECD countries since 1970 (UNESCO Statistics, 2021)[1] and further expansion figures prominently in political agendas. For example, the European Union's goal for 2030 is that "The share of 25-34 year-olds with tertiary educational attainment should be at least 45%" (Council of the EU, 2021). We investigate the consequences of such historical and planned expansion processes on the selection of college students in terms of *intelligence* and *disadvantage* from low socioeconomic status or poor non-cognitive skills. In our stochastic, general equilibrium Roy (1951) model, these traits determine the graduation probability, and their correlation is crucial to understand how technological progress and higher education policy alter incentives to pursue tertiary education. The model is used to study how actual policies shaped the evolution of students' sorting into college in terms of their intelligence and disadvantage, and to simulate counterfactual policies.

We estimate the model using UK data that span four decades (1960-2004) of expansion: the share of 17-30 year-olds in higher education rose from 5% in 1960 to 43% in 2007 (Chowdry et al., 2013),[2] an increase observed previously in the US (Goldin and Katz, 2008) and subsequently in other OECD countries (Schofer and Meyer, 2005; Meyer and Schofer, 2007). The UK experience offers an ideal case study. We illustrate its nature and consequences, drawing lessons to judge the ambitious target currently set in Europe and elsewhere.

The UK expansion originates in the Robbins (1963) Report, which claimed the existence of large "reserves of untapped *ability* [that] may be greatest in the *poorer* sections of the community" (p. 53, the added italics explain our emphasis on *intelligence* and *disadvantage*) and thus recommended that "all young persons qualified by ability and attainment to pursue a full-time course in higher education should have the opportunity to do so." (p. 49). According to the Report, "fears that expansion would lead to a lowering of the average ability of students in higher education [were] unfounded." (p. 53). These claims have not been adequately investigated for lack of data sets containing cognitive ability measures. An upside of our data is that we observe measures of general cognitive ability (g factor), in addition to predetermined individual measures of disadvantage.

[1]This factor was about 1.9 in the US, 3.7 in France and in Japan, 3.9 in Italy, and 4.5 in the UK. Enrollment is to any tertiary education program, of students who have successfully completed secondary education.

[2]Similar evidence can be found in Blackburn and Jarman (1993), Boliver (2011), Blanden and Machin (2004), Walker and Zhu (2008), Riddell et al. (2013), Major and Machin (2018) and Blundell et al. (2022).

We find that: (i) graduates' average intelligence declined by about 13% of a SD between the 1960s and the 1990s; non-graduates' average intelligence also declined, indicating that students who attained a college degree in the 1990s (and who would have not in the 1960s) were more intelligent than the average high school graduate of the 1960s, yet less intelligent than the average college graduate of the same period;[3] (ii) the reason is a non-meritocratic increase in the number of graduates, achieved by reducing non-tuition costs and by lowering qualification barriers at entry; (iii) the wage gap between college graduates and non-graduates declined progressively across cohorts;[4] like the increase in the supply of graduates, this pattern may mimic with a lag the college premium decline of the 1970s in the US, which was only later followed by an increase (e.g., Katz and Murphy, 1992, Fortin, 2006, Goldin and Katz, 2008 and Autor et al., 2020); (iv) although "untapped ability" did exist, the policy that prevailed was unfit to draw this ability into universities and ended up favoring primarily low-intelligence students from advantaged families;[5] (v) meritocratic policies based on the selection of intelligent students from any socioeconomic background (possibly with a subsidy to the study effort of more disadvantaged students) could have achieved the Robbins Report's progressive goals. In our model, such policies would have been more efficient and more egalitarian than the one that was actually implemented.

Although we eschew the difficult question of which social welfare function should be used to determine the decision to expand university access (a question that we postpone to future research), we claim that a lower average intelligence of college graduates can hardly be

[3] Walker and Zhu (2008) and Blundell et al. (2022) consider this hypothesis in their analysis of the evolution of the wage gap between college and high school graduates over years. They cannot test it because their data source (the UK LFS) does not contain an ability measure. Carneiro and Lee (2011) study the increase in college enrollment in the US in 1960-2000 and present evidence consistent with the possibility that the expansion drew into college marginal students of lower quality than average college students.

[4] Bianchi (2020) studies a large expansion of access to STEM majors enacted in Italy in the early 1960s and finds a similar impact on STEM graduates' wages. Our finding is instead in contrast with the weakly increasing wage gap over cohorts between college and high-school graduates in the UK reported by Blundell et al. (2022) in Figure 4 of their Online Appendix, which is puzzling given that we use the same methodology and Labour Force Survey (LFS) data to construct cohort wage ratios net of age effects. Our Online Appendix to Section 4.4 shows that the reason is the different group to which we compare college graduates: *all individuals without a college degree* instead of *high-school graduates* only. Section 3.2 explains why this is the appropriate comparison group to answer our research question.

[5] These results agree with Blanden and Machin (2004), Machin (2007), Sutton Trust (2018), Boliver (2013) and Major and Machin (2018), who show that the expansion of UK higher education since the 1960s predominantly benefited children from high-income families. They also agree with Campbell et al. (2019) and Cooper and Liu (2019), who find evidence of mismatch between ability and educational attainment in the UK and other OECD countries, respectively. We leave in the background other consequences of higher education expansion such as over-education (Freeman, 1976), i.e., the mismatch between educational attainment and occupation. Cervantes and Cooper (2022) study both margins of mismatch in OECD countries.

characterized as a desirable outcome. In our model the reason is that a higher intelligence is associated (*ceteris paribus*) with a lower study effort cost, which implies a social welfare gain from a more intelligent graduate workforce relative to a less intelligent one of the same size. Other reasons may be considered in a richer model. For example, universities have a double role in society: providing higher education but also supporting basic research at an advanced level in all fields, a task that is facilitated by higher cognitive ability. Thus, the consequences of a decline in the average intelligence of graduates are going to be far reaching, particularly if there is reluctance to allow the tertiary education institutions of higher quality to be more selective in their acceptance. The Robbins Report clearly mentions the lack of a depressing effect on graduates' average ability as a condition that justifies an expansion.[6]

Our conceptual framework is a general equilibrium model that extends the partial equilibrium setting of Katz and Murphy (1992) and Autor et al. (2020) to an active labor supply side that makes human capital investment decisions. The labor demand side has the standard features: competitive firms produce output by combining graduate and non-graduate workers, thus affecting the wage gap. Skill-biased technical change increases the productivity of graduate workers and activates a force that increases the demand for college graduates independently of any change in higher education policy.

The labor supply side is more novel. In our model, obtaining a college degree is the outcome of two factors. One is simply the *intelligence* of the individual. The other is the combination of non-cognitive traits like individual characteristics pertaining to family background (e.g., parents' education, their presence in the household, and their employment status at the time a respondent was young) and personality (e.g., Neuroticism or Conscientiousness). For brevity, we refer to this variable as *disadvantage*. In the model, intelligence and disadvantage affect the cost of study effort that a student must exert to attain a college degree, thereby altering an individual's graduation probability. The government can shape the parameters that link intelligence and disadvantage to the cost of study effort, thus expanding university access in different ways. To clarify the exposition, at the cost of some simplification, we adopt the following labels for three paradigmatic government interventions: a *Meritocratic expansion* (ME) policy favors more intelligent students; a *Progressive expansion* (PE) policy favors students with a more disadvantaged background; an *Indiscriminate*

[6] Surprisingly, such a concern is absent in Council of the EU (2021), which sets the goal of at least 45% of graduates in the EU by 2030. It is not even clear how this specific threshold has been chosen.

expansion (IE) policy enlarges university access independently of intelligence and disadvantage. The combination of intelligence and disadvantage with the effort cost parameters as shaped by policy generates *isoprobability curves* in the corresponding space (i.e., alternative combinations of intelligence and disadvantage such that the graduation probability is constant). These curves mark the boundary between higher and lower graduation probability regions, a stochastic generalization of the classical Roy (1951) model. A higher education policy is a way to change the position and slope of these curves.

Given a policy, the evolution of the characteristics of students selected into college depends on the correlation between intelligence and disadvantage in the society where the policy is implemented. The reforms advocated by the Robbins Report were motivated by the belief that the UK was a stratified society where access to a university was facilitated more by an advantaged background than by high intelligence. In this society, if the correlation between intelligence and disadvantage is positive, even an indiscriminate or progressive expansion policy may increase the fraction of college graduates without reducing their average intelligence, as the Report claimed. Our evidence suggests that the UK society was indeed stratified, but was characterized by a *negative* correlation between intelligence and disadvantage – a finding with different possible explanations that we discuss below and that we take as given. The key lesson that we learn from the UK experience is that, in such contexts, only a shift towards meritocratic policies aimed at increasing the graduation probability more strongly for more intelligent students (possibly with a twist in favor of those sufficiently intelligent but disadvantaged) could achieve the desiderata of the Robbins Report.

Our analysis has of course some limitations. Three of them must be highlighted upfront so that the reader can calibrate expectations. The first one relates to the interaction between intelligence and the educational process. To maintain tractability, we assume that higher intelligence reduces the effort cost of acquiring a college degree, and this is the reason why it is desirable, *ceteris paribus*, that the intelligence of college attendants is higher. However, we abstract from other implications of higher intelligence, like in particular the possibility of a direct effect on productivity for a given education level. Likewise, we abstract from the possible consumption value of a college education. The second one is that we aggregate the other socioeconomic and personality determinants of educational attainment in a single factor that captures a student's non-cognitive disadvantage. This way, we can contrast traditional disadvantage factors in attaining a college degree with the role of intelligence, which is the novel contribution of our analysis. The third one is that, again for tractability, the educational policies modeled in this paper are parameterized in an abstract manner, although hypothetical and historical examples are provided.

The rest of the paper proceeds as follows. Section 2 presents the theoretical model. Section 3 describes the data, in particular our measures of intelligence and disadvantage. Section 4 illustrates the key facts. Section 5 estimates the model and uses it in counterfactual quantitative analysis. Section 6 concludes.

2 Model

We adopt a Becker-style human capital model in which education increases productivity. An innovation is the introduction of a study effort cost that depends on intelligence and on socioeconomic and psychological disadvantage, in a way that is affected by policy.

2.1 Workers

There is a unit mass population of economic agents who are fully employed at equilibrium. Each individual is characterized by a given pair $(\theta, \eta) \in \mathbf{\Theta} \times \mathbf{H} \subset \mathbb{R}_+ \times \mathbb{R}_+$.[7] Θ denotes *intelligence* and its support $\mathbf{\Theta}$ is ordered by the order on the real numbers; H summarizes non-cognitive *disadvantage*, i.e., a set of socioeconomic factors and personality traits that increase study effort cost, and its support $\mathbf{H}$ is similarly ordered.[8] The two variables are assumed to be publicly observable, and their joint distribution is denoted by $\mu \in \Delta(\mathbf{\Theta} \times \mathbf{H})$.

Each individual is also characterized by an endogenous human capital level $k \in \mathbf{K}$, where $\mathbf{K}$ is an ordered set of human capital levels. Given our focus on higher education, we consider only two levels, and so $\mathbf{K} = \{0, 1\}$ ($\equiv \{school, college\}$), where school denotes any education level below college.[9] k is determined by an allocation function π that describes the probability on human capital obtained by an individual, for given cognitive skills and

[7]We use bold face to denote a set, capitals to denote random variables, and lower case to denote generic variables and realizations of random variables. Recall that in the Greek alphabet the capital for η is H.

[8]As mentioned in Introduction, the intelligence-disadvantage dichotomy was prominent in the Robbins (1963) Report (e.g., at p. 53).

[9]By adopting this definition, we deviate from the literature that studies the evolution of the wage gap between college and high school graduates, e.g., Machin and McNally (2007), Walker and Zhu (2008), and Blundell et al. (2022). The reason is that we are interested in evaluating whether the UK expansion was successful in drawing into college talented students who were previously likely to drop out of education at any lower level, not just at the high-school level.

study effort level. The set of effort levels $\mathbf{S}$ is the positive real line. We assume that the human capital level "college", once achieved, cannot be lost, so the only transition in human capital is from 0 to 1. In sum, we let $\pi : \mathbf{S} \times \mathbf{\Theta} \to [0, 1]$, where $\pi(s, \theta)$ is the probability of attaining a college degree for an individual whose intelligence is θ and who exerts effort s.

For an individual of type (θ, η), preferences are defined over lifetime consumption and leisure and are represented by

$$u(c, s; \theta, \eta) = \frac{c^{1-\sigma_c} - 1}{1 - \sigma_c} + \Omega(\eta)\frac{(1 - \Gamma(\theta)s)^{1-\sigma_s} - 1}{1 - \sigma_s}, \tag{1}$$

where c denotes consumption and $\sigma_c > 0$ and $\sigma_s > 0$ are parameters; the functions $\Omega \geq 0$ and $\Gamma \geq 0$ are *effort cost shifts*, hence non-negative. They are influenced by the policy maker and depend on disadvantage and intelligence.[10] Absent policy interventions, it is standard (and reasonable) to assume $\frac{d\Gamma(\theta)}{d\theta} < 0$ (the marginal disutility of study effort decreases with intelligence) and $\frac{d\Omega(\eta)}{d\eta} > 0$ (the marginal disutility increases with disadvantage). Under these assumptions, *ceteris paribus*, it is less costly in terms of leisure utility to admit to college more intelligent and more advantaged students. However, for efficiency or equity reasons, higher education policy can alter the opportunity cost of study effort selectively on the basis of an individual's θ and η. Examples are provided in Section 2.4.

Let $s^*(\theta, \eta)$ be the optimal study effort of a (θ, η)-type individual. Since the model is static, consumption is equal to earnings, which in turn depend *only* on an individual's human capital. That is, an individual's wage is given by $w(k)$.[11] Given a vector of wages $\mathbf{w} \equiv (w(0), w(1))$, an individual solves:

$$\max_{s \geq 0} \left(\pi(s, \theta)\Delta U(\mathbf{w}) + \Omega(\eta)\frac{(1 - \Gamma(\theta)s)^{1-\sigma_s} - 1}{1 - \sigma_s} \right), \tag{2}$$

where we denote

$$\Delta U(\mathbf{w}) \equiv \frac{w(1)^{1-\sigma_c}}{1 - \sigma_c} - \frac{w(0)^{1-\sigma_c}}{1 - \sigma_c}. \tag{3}$$

[10] The two effort cost shifts $\Omega(\eta)$ and $\Gamma(\theta)$ enter the utility function in an asymmetric way because we hypothesize that higher intelligence improves effectiveness of study effort directly, while disadvantage affects only the leisure utility at the given effort.

[11] As mentioned in the Introduction, this is an assumption that we make for tractability. However, note that even if the productivity of college graduates does not depend on intelligence, in this framework it is still desirable – *ceteris paribus* – to select high-intelligence students in college because their study effort cost is lower. A more general model where additional factors (for example intelligence, background, or gender) may affect wages directly is a task for future research.

It is convenient to specify

$$\pi(s,\theta) = \Pi(\theta s), \tag{4}$$

where $\Pi(\cdot) \equiv \min(\max(\cdot,0),1)$ is the cut-off function. The resulting probability of attaining college education is a piece-wise linear probability model. Thus, for a given level of effort, a more intelligent individual is more likely to attain a tertiary degree. Under assumptions (2), (3) and (4), the optimal effort is unique and given by:

$$s^*(\theta,\eta) = \min\left(\max\left(\frac{1}{\Gamma(\theta)}\left(1-\left(\frac{\Omega(\eta)\Gamma(\theta)}{\theta\Delta U(\mathbf{w})}\right)^{\frac{1}{\sigma_s}}\right),0\right),1\right). \tag{5}$$

Note that although an individual can choose any positive effort level, it is never optimal to choose any $s > \frac{1}{\Gamma(\theta)}$, because effort is costly and the probability of college would not change. From equation (5), given a utility gap $\Delta U(\mathbf{w})$, the probability of college graduation for an individual of type (θ,η) is

$$\pi(\theta,\eta) = \Pi\left(\frac{\theta}{\Gamma(\theta)}\left(1-\left(\frac{\Omega(\eta)\Gamma(\theta)}{\theta\Delta U(\mathbf{w})}\right)^{1/\sigma_s}\right)\right). \tag{6}$$

Let $x(k)$ denote the population fraction with educational attainment k. The aggregate supply vector $\mathbf{x}^S \equiv [x^S(0)\ x^S(1)]$ is composed by

$$x^S(1) = \int_{\mathbf{\Theta}\times\mathbf{H}} \pi(s^*(\theta,\eta),\theta)d\mu(\theta,\eta); \qquad x^S(0) = 1 - x^S(1). \tag{7}$$

2.2 Firm

A representative firm has a technology that maps a vector of labor allocation into quantity of output produced. This technology is of the CES type; for every $\mathbf{x} \in \mathbb{R}^2_+$,

$$Q(\mathbf{x}) \equiv A\left(\sum_{k\in\{0,1\}} a(k)x(k)^\rho\right)^{\frac{1}{\rho}}, \tag{8}$$

where A is total factor productivity (TFP), the product of population size and the additional factor that allows us to normalize $\sum_k x^S(k) = 1$ *and* also $\sum_k a(k) = 1$. We assume $\rho \leq 1$, where $\rho \equiv \frac{\varsigma-1}{\varsigma}$, for ς the elasticity of substitution between *school* and *college* labor inputs.

The firm is competitive and solves, for any wage vector $\mathbf{w}$ taken as given, the following problem: $\max_{\mathbf{x}\in\mathbb{R}^2_+}(Q(\mathbf{x}) - \mathbf{wx})$, where $\mathbf{wx}$ is the inner product. Note that while aggregate labor supply is constrained at equilibrium by equation (7) to add up to 1, the competitive firm ignores this constraint. The first-order conditions for an interior solution are:

$$w(k) = A^{\rho} a(k) x(k)^{\rho-1} Q(\mathbf{x})^{1-\rho}, \qquad k \in \{0,1\}, \tag{9}$$

and so labor demand by educational attainment, $x^D(k)$ for $k = 0, 1$ satisfies

$$\frac{w(1)}{w(0)} = \frac{a(1)}{a(0)} \left(\frac{x^D(1)}{x^D(0)} \right)^{\rho-1} \quad \Leftrightarrow \quad r = \alpha (\xi^D)^{\rho-1}, \tag{10}$$

where $\alpha \equiv \frac{a(1)}{a(0)}$ is the technological skill ratio and $r \equiv \frac{w(1)}{w(0)}$ and $\xi^D \equiv \frac{x^D(1)}{x^D(0)}$ are the college-to-school wage and labor demand ratios, respectively. In this model, technical change is represented by any change in A, α, or ρ. A change from $a(k)$ to $a'(k)$ is called *progress* if for all k, $a'(k) \geq a(k)$. A progress *favors college graduates* (i.e., is *skill-biased*) if $\alpha' \geq \alpha$.

2.3 Equilibrium

Definition 1 *An equilibrium in an economy described by the parameters* $(\Omega, \Gamma, \sigma_c, \sigma_s, A, \alpha, \rho)$ *is a vector* $(\boldsymbol{w}^*, s^*, \boldsymbol{x}^*)$ *such that*

1. *Individuals choose effort to maximize utility; that is, for* μ *almost every* (θ, η)*:*

$$s^*(\theta, \eta) \in \arg\max_{s \geq 0} \left(\pi(s, \theta) \Delta U(\boldsymbol{w}^*) + \Omega(\eta) \frac{(1 - \Gamma(\theta)s)^{1-\sigma_s} - 1}{1 - \sigma_s} \right),$$

   and the aggregate labor supply $\boldsymbol{x}^S$ *is determined by equation (7).*

2. *The firm chooses labor to maximize profits:* $\boldsymbol{x}^D \in \arg\max_{\boldsymbol{x} \in \mathbb{R}^2_+} Q(\boldsymbol{x}) - \boldsymbol{w}^* \boldsymbol{x}$*.*

3. *The labor market clears:* $\boldsymbol{x}^S = \boldsymbol{x}^D = \boldsymbol{x}^*$*.*

4. *The good market clears:*

$$Q(\boldsymbol{x}^D) = \sum_k w^*(k) x^S(k). \tag{11}$$

We focus on vectors of labor allocation that satisfy the necessary equilibrium condition (10) and the constraint in (7). The following observation is convenient to establish existence of the equilibrium (and uniqueness in the special case that we consider in the empirical analysis).

Lemma 1 *For every $r > 0$ there is a unique pair $\boldsymbol{x}(r) = (x(0,r), x(1,r))$ and a corresponding pair $\boldsymbol{w}(r) = (w(0,r), w(1,r))$ such that*

$$x(0,r) + x(1,r) = 1, \quad \frac{Q_{x(1)}(\boldsymbol{x}(r))}{Q_{x(0)}(\boldsymbol{x}(r))} = r; \tag{12}$$

$$\forall k : w(k,r) = A^{\rho} Q(\boldsymbol{x}(r))^{1-\rho} a(k) x(k,r)^{\rho-1}. \tag{13}$$

Any pair $(\boldsymbol{x}^*, \boldsymbol{w}^*)$ which is part of an equilibrium is of the form in equations (12) and (13) for some value of the wage ratio r.

Proof. See the Online Appendix to Section 2.3. ∎

In our structural estimation we use a characterization of the equilibrium labor allocation that provides a convenient computational algorithm. Using equation (9) to write wages at equilibrium as a function of the labor allocation, the difference in utility of consumption between college and school graduates at equilibrium can be written as

$$\Delta U(\mathbf{w}(\mathbf{x}^*)) = \frac{\left(q(\mathbf{x}^*)a(1)x^*(1)^{\rho-1}\right)^{1-\sigma_c} - \left(q(\mathbf{x}^*)a(0)x^*(0)^{\rho-1}\right)^{1-\sigma_c}}{1-\sigma_c}, \tag{14}$$

where $q(\mathbf{x}) \equiv A^{\rho} Q(\mathbf{x})^{1-\rho}$. Thus, an equilibrium labor allocation vector $\mathbf{x}^*$ is fully characterized by the following equation in the skilled labor fraction $x(1)$,

$$x(1) = \int_{\boldsymbol{\Theta}\times\mathbf{H}} \Pi\left(\frac{\theta}{\Gamma(\theta)}\left(1 - \left(\frac{\Omega(\eta)\Gamma(\theta)}{\theta\Delta U(\mathbf{w}(1-x(1), x(1))}\right)^{\frac{1}{\sigma_s}}\right)\right) d\mu(\theta,\eta), \tag{15}$$

where we use the fact that at equilibrium the wage vector is a function of the pair $(1 - x(1), x(1))$ of labor allocation from equation (9).

2.4 Higher education policy

In order to define higher education policy formally and in a tractable way, we follow the macroeconomic literature and set $\sigma_c = \sigma_s = 1$.[12] Under this assumption,

$$\Delta U(\mathbf{w}) = \ln w(1) - \ln w(0) \equiv \Delta \ln w. \tag{16}$$

[12] For example, Prescott (2004) and Greenwood et al. (2017) set $\sigma_c = \sigma_s = 1$; Olivetti (2006), Guner et al. (2011), and Bick and Fuchs-Schündeln (2018) set $\sigma_c = 1$.

Next, we specify the effort cost shifts as linear functions:[13]

$$\Omega(\eta) = \delta + \beta\eta, \tag{17}$$

$$\Gamma(\theta) = \gamma + \tau\theta, \tag{18}$$

where the four parameters are controlled by the government, either actively (i.e., a purposeful stimulation of college attendance by students with certain characteristics) or passively (i.e., a mere accommodation of changes in students' demand for higher education driven by other factors). Therefore, in what follows we refer to them as to "policy parameters", and a higher education policy is a quadruple $G = (\delta, \beta, \gamma, \tau)$.[14] Combining equations (6) and (16)-(18), the equilibrium probability of attaining a college education for an individual of type (θ, η) at policy G is given by

$$\pi^*(\theta, \eta; G) = \Pi\left(\frac{\theta}{\gamma + \tau\theta} - \frac{\beta}{\Delta \ln w(G)}\eta - \frac{\delta}{\Delta \ln w(G)}\right). \tag{19}$$

Examples of policies that can be well represented in this framework follow. A government that wishes to stimulate college attendance by disadvantaged students can offer means-tested grants, which in the model would be represented by a reduction of β. On the contrary, an active policy that increases β is the design of complex financial aid, tuition, and enrollment systems that disadvantaged households can hardly navigate. A public investment program to build new universities in response to an increased demand for college education across all families, can be represented as a passive policy that allows δ to decrease. A government can also build new universities in the absence of such increased demand; this active policy would aim at increasing the probability of graduation of students living in the affected areas independently of their intelligence or family background, which in the model would again correspond to a reduction of δ. As for the remaining parameters, a policy that grants scholarships based on an intelligence measure not affected by family background (g-factor), or that ranks college applicants according to this same measure would correspond in the model to a reduction of τ. Beyond these hypothetical examples, the Online Appendix to Section 4.1 provides historical evidence of policies that took place after the Robbins (1963) Report, like the construction of universities and polytechnics (a decrease of δ or β) and the

[13] As shown below, linearity allows for tractability while not limiting in any important way the types of higher education policies that we can analyze.

[14] Recall that the logic of the problem requires that we consider values of G ensuring $\Omega(\eta) \geq 0$ and $\Gamma(\theta) \geq 0$ for the values of θ and η in the range of the economy. This restriction is imposed throughout the analysis.

introduction of less stringent admission criteria (an increase of τ).

Given a status quo policy G, it is convenient to classify the possible interventions into three abstract categories of expansionary higher education policies G'.

Definition 2 *Let $\Delta\pi^*(\theta, \eta) = \pi^*(\theta, \eta; G') - \pi^*(\theta, \eta; G)$.*

1. *An Indiscriminate Expansion (IE) policy is a G' that induces a function $\Delta\pi^*(\theta, \eta) > 0$ and equal for all θ and η.*

2. *A Progressive Expansion (PE) policy is a G' that induces a function $\Delta\pi^*(\theta, \eta) > 0$ and increasing in η for all θ.*

3. *A Meritocratic Expansion (ME) policy is a G' that induces a function $\Delta\pi^*(\theta, \eta) > 0$ and increasing in θ for all η.*

We emphasize that these categories are intended to provide a benchmark for the evaluation of real policies that do not necessarily match these requirements exactly. Note also that the intended aim of a policy is not necessarily the same as the actual outcome of the policy, once general equilibrium effects are considered. We return on this point below.

A central question that is relevant to study the consequences of further expanding university access, is precisely the one addressed in the Robbins Report: namely, whether an increase in college participation is possible that would put unexploited ability to good use. To answer this question we need an operational definition of the notion of *untapped ability* that is at center stage in the Robbins Report (but notably absent in Council of the EU, 2021 when setting the EU goal of at least 45% of graduates by 2030). A possible definition is that untapped ability exists if there are two individuals i and j with $\theta_i > \theta_j$ and $k_i < k_j$ (i.e., i is more intelligent than j but j achieves a college degree while i does not). However, because in a free society individuals cannot be forced to go to college, we need a policy-relevant definition of *reachable ability*. To this end, we denote with $\xi(G)$ the college-to-school labor ratio at equilibrium under policy G.

Definition 3 *Reachable ability at a policy G exists if there exists a different policy G' such that* : $\mathbb{E}(\Theta|K = 1; G') \geq \mathbb{E}(\Theta|K = 1; G)$ *and* $\xi(G') > \xi(G)$.

That is, there are skills that can be put to good use via higher education if there exists a policy such that, at equilibrium, the fraction of population with a university degree is higher and mean intelligence of college graduates is not smaller. As remarked in the Introduction, the Robbins Report claimed the existence of reachable ability by ruling out "that expansion would lead to a lowering of the average ability of students in higher education." (p. 53).

In order to establish the conditions for the existence of reachable ability, we assume (departing from the finite set assumption) that intelligence and disadvantage, $[\Theta\ H]$, are joint normal with mean $[m_\Theta\ m_H]$, standard deviation $[\sigma_\Theta\ \sigma_H]$, and correlation λ. Our data show that the empirical distribution of Θ and H is close to normal. The effects of higher education policies of different type on the distribution of intelligence in the college population depends on the relation between the slopes of two functions that link Θ and H.

The first is the tilt of the joint density $\mu(\Theta, H)$. Its inclination can be conveniently characterized by the slope $\lambda\frac{\sigma_H}{\sigma_\Theta}$ of the population linear regression of H on Θ,

$$H - m_H = \lambda\frac{\sigma_H}{\sigma_\Theta}(\Theta - m_\Theta). \tag{20}$$

The second slope is that of the *isoprobability curves* of obtaining a college degree, i.e., the locus of (θ, η) combinations such that the probability of graduating is constant. Using equation (19), it is immediate that this slope is given by

$$\frac{\partial H}{\partial \Theta}(\theta, \eta) = \frac{\gamma\Delta\ln w(G)}{(\gamma + \tau\theta)^2\beta}. \tag{21}$$

When $\tau = 0$, isoprobability curves are straight lines. The comparison between the two slopes is crucial in the following analysis, so it is convenient to label the difference:

$$\psi(\theta, G) \equiv \frac{\gamma\Delta\ln w(G)}{(\gamma + \tau\theta)^2\beta} - \lambda\frac{\sigma_H}{\sigma_\Theta}. \tag{22}$$

2.5 Characterization of the effects of higher education policy

The behavior of mean intelligence in the population of college graduates and so the existence of reachable ability depends on the sign of the derivative of the function D defined as:

$$D(\theta) \equiv \theta\left(\frac{1}{\gamma + \tau\theta} - \frac{\beta\lambda\sigma_H}{\Delta\ln w(G)\sigma_\Theta}\right). \tag{23}$$

To appreciate the role played by this function, consider the simple case in which $\tau = 0$. In this case, the expression in parentheses on the RHS of equation (23) is independent of Θ and (when $\beta > 0$) is positive or negative depending on whether the slope of the isoprobability curves (which in this case is constant and is given by $\frac{\Delta \ln w(G)}{\gamma\beta}$) is larger or smaller than the tilt of the density (which is given by $\lambda\frac{\sigma_H}{\sigma_\Theta}$). When larger, D is an increasing function, and then part (ii) of the following proposition states that the probability of attaining a college degree, conditional on intelligence θ, is increasing in θ.

Proposition 1 *At the equilibrium:*

(i) The probability of attaining a college degree conditional on θ is

$$P(K=1|\theta) = \mathbb{E}_{\phi_\epsilon}\pi\left(D(\theta) - \frac{\beta}{\Delta \ln w(G)}\epsilon + \frac{\beta\lambda\sigma_H}{\Delta \ln w(G)\sigma_\Theta}m_\Theta - \frac{\delta}{\Delta \ln w(G)}\right), \quad (24)$$

with ϵ a normal random variable, independent of Θ; its density ϕ_ϵ has parameters $(m_\epsilon, \sigma_\epsilon^2) = (m_H, (1-\lambda^2)\sigma_H^2)$.

(ii) If π is any increasing function $\mathbb{R}$ to $[0,1]$, then for any θ_1, θ_2:

$$P(K=1|\theta_2) \geq P(K=1|\theta_1) \textit{ if and only if } D(\theta_2) \geq D(\theta_1).$$

(iii) If π is increasing and D is increasing over $\boldsymbol{\Theta}$, for any increasing function g on $\boldsymbol{\Theta}$:

$$\mathbb{E}(g|K=1) \geq \mathbb{E}(g|K=0), \quad (25)$$

with a strict inequality if g is strictly increasing. In particular, when g is the identity function, equation (25) states that the mean intelligence among college graduates is higher than among school graduates.

(iv) The mean intelligence of college graduates has the selection equation form in (28).

Proof. For part (i), consider the linear transform of H that is normal, uncorrelated with, and hence independent, from θ:

$$\epsilon \equiv H - \lambda\frac{\sigma_H}{\sigma_\Theta}(\Theta - m_\Theta). \quad (26)$$

Let $\phi_{\Theta\epsilon}$ denote the density of the joint distribution of (Θ, ϵ), and denote by ϕ_Θ and ϕ_ϵ its marginal densities. ϕ_ϵ is a normal density with parameters $(m_\epsilon, \sigma_\epsilon^2) = (m_H, (1-\lambda^2)\sigma_H^2)$. Expressing the probability of obtaining a college degree as a function of (θ, ϵ) yields (24).

Part (ii) follows from equation (24) and the assumption that π is increasing.

We now consider Part (iii). First recall the definition of likelihood ratio order (e.g., Shaked and Shanthikumar, 2007, definition 1.C.1):

Definition 2 *Given two densities f_1 and f_0 on Θ, we say that f_1 is larger than f_0 in the likelihood ratio order if the function $\theta \to \frac{f_1(\theta)}{f_0(\theta)}$ is increasing.*

Take f_i in Definition 2 to be $P(\cdot|K = i)$ for $i = 0, 1$. To verify the condition in this definition, we consider

$$\begin{aligned}\frac{P(\theta|K=1)}{P(\theta|K=0)} &= \frac{P(K=0)}{P(K=1)}\frac{P(\theta,K=1)}{P(\theta,K=0)} = \frac{P(K=0)}{P(K=1)}\frac{P(K=1|\theta)}{P(K=0|\theta)} \\ &= \frac{P(K=0)}{P(K=1)}\left(\frac{P(K=1|\theta)}{1-P(K=1|\theta)}\right).\end{aligned}$$

Therefore, by part (ii) above, if $D(\theta)$ is increasing then function $\theta \to P(K = 1|\theta)$ is increasing and conditional probability $P(\cdot|K = 1)$ is larger than $P(\cdot|K = 0)$ in the likelihood ratio order, by definition of this order. The conclusion then follows from the fact that the likelihood ratio order implies the stochastic order (Shaked and Shanthikumar (2007), Theorem 1.C.1), and from well-known properties of the stochastic order.

To establish part (iv), define

$$(P\phi)(\theta) \equiv \frac{\phi(\theta; m_\Theta, \sigma_\theta^2)P(K=1|\theta)}{\int_{\mathbb{R}} \phi(\tau; m_\Theta, \sigma_\theta^2)P(K=1|\tau)d\tau} \tag{27}$$

and the moment-generating function $M_{P\phi}(t) \equiv \int_{\mathbb{R}}(P\phi)(\theta)e^{t\theta}d\theta$. The mean intelligence in the population in college is given by $\mathbb{E}(\Theta|K = 1) = \frac{d}{dt}M_{f\phi}(t)|_{t=0}$, which we can compute:

$$\mathbb{E}(\Theta|K=1) = m_\Theta + \sigma_\Theta^2 \int_{\mathbb{R}}\left(\frac{\phi(z;0,1)P'(m_\Theta+\sigma_\Theta z|K=1)}{(\int_{\mathbb{R}}\phi(x;0,1)P(m_\Theta+\sigma_\Theta x|K=1)dx)}dz\right). \tag{28}$$

■

Proposition 1 holds for any increasing function π. Thus, this result is an extension of the standard selection problem in the Roy (1951) model, when selection is determined by a function of Θ between 0 and 1 described in (24) rather than by passing a threshold. In fact equation (28) is a general form of the standard selection equation, which is its special case when the function P is the indicator function of a half line. Following the same steps, a symmetric result can be derived that characterizes $\mathbb{E}(H|K = 1)$.

The comparative statics of interest is how expansive higher education policies of different type alter mean conditional intelligence and disadvantage, $\mathbb{E}(\Theta|K)$ and $\mathbb{E}(H|K)$, of students selected or not selected into college. Such policies induce general equilibrium responses with effects that vary across regions of the policy space G. For this reason, their consequences are cumbersome to characterize analytically and we resort to simulations of the model's equilibrium to illustrate them.

2.6 Numerical simulation

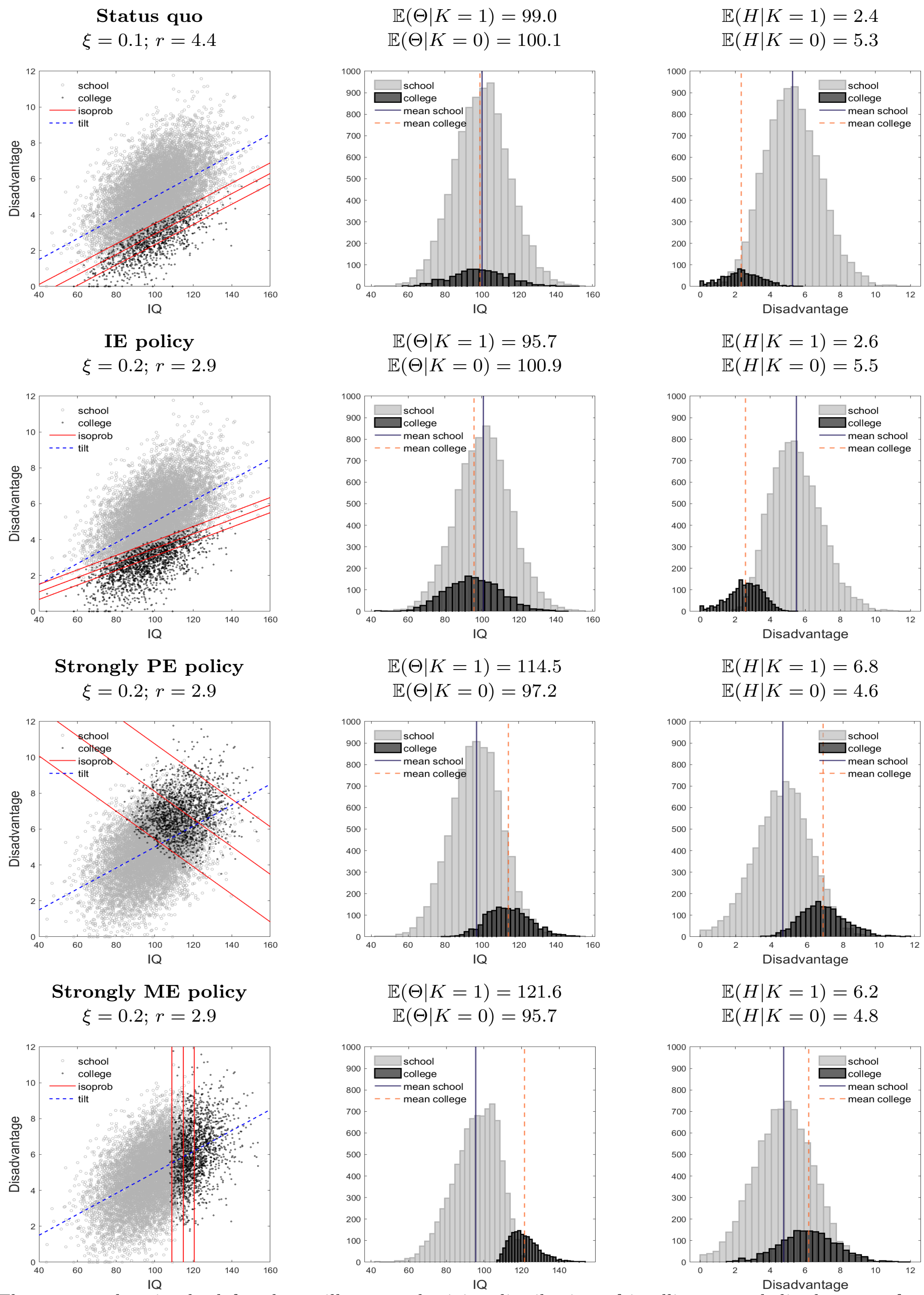
Using simulated data, Figures 1 and 2 describe the effects of the three higher education policies of Definition 2 in two paradigmatic types of society. In Figure 1 (Society 1), $\lambda > 0$ (i.e., intelligence Θ and disadvantage H are positively correlated), but $\psi(\cdot, G) < 0$ (i.e., isoprobability lines are flatter than the line describing the tilt of the joint distribution $\mu(\Theta, H)$). Figure 2 (Society 2) features instead $\lambda < 0$, in which case it is necessarily $\psi(\cdot, G) \geq 0$.[15]

The top rows illustrate the role of ψ and λ in determining the conditional distribution of Θ and H at equilibrium. The scatter plots on the left represent individuals of type (θ, η) in the population and their allocation to school and college attainment at equilibrium wages. The dashed line graphs equation (20), which measures the tilt of $\mu(\Theta, H)$. The three continuous lines are isoprobability curves associated with graduation probability of 0.9 (bottom), 0.5 (middle), and 0.1 (top). For each isoprobability curve, an individual above or below the line has a college graduation probability $\pi^*(\theta, \eta; G)$ smaller or larger than the probability associated with that curve, respectively. Each individual is assigned to college or school attainment if $\pi^*(\theta, \eta; G)$ is above or below a random threshold. In the status quo, it is $\tau = 0$ and so these curves are straight lines. A policy change from G to G' changes the slope of isoprobability curves, which is given by equation (21), or their vertical intercept, which for some probability level π is given by $-\frac{\Delta \ln w(G)}{\beta}\left(\pi + \frac{\delta}{\Delta \ln w(G)}\right)$, or both. The histograms are the resulting conditional distributions of intelligence and disadvantage.

In Society 1, many intelligent students with a disadvantaged background are excluded from higher education (north-eastern region of the scatter plot in the top row of Figure 1), hence the paradoxical outcome that the population in college is on average less intelligent than the population outside college. In this society, university access is easier for students from affluent families even if they are not very talented. As shown below, this is the most favorable case for a government that wishes to expand access without reducing the quality

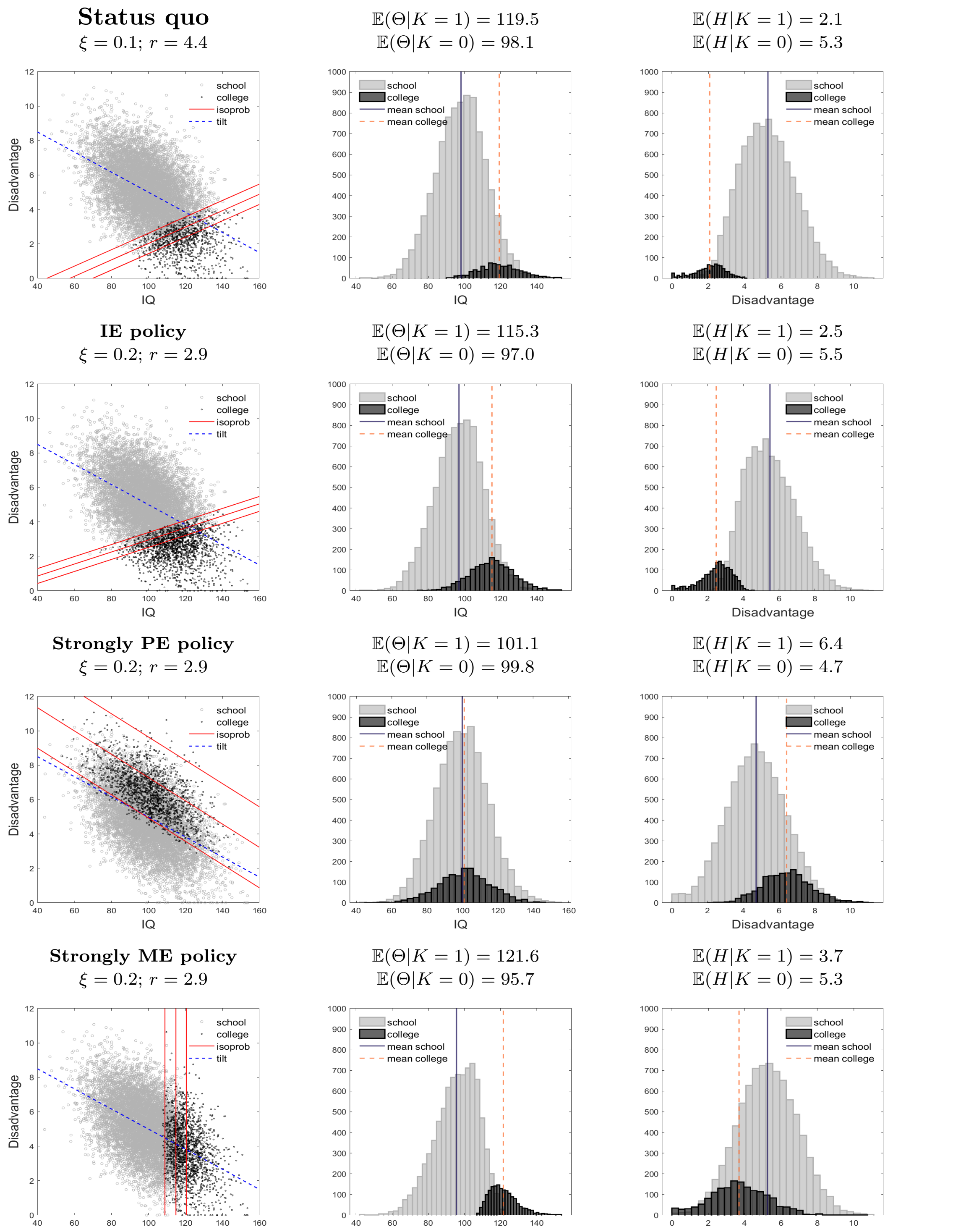
[15]For completeness, the third possible society characterized by $\lambda > 0$ and $\psi(\cdot, G) \geq 0$ is considered in Figure A-1 of the Online Appendix to Section 2.6.

Figure 1: Status quo in Society 1 ($\lambda > 0, \psi < 0$) and effects of three expansion policies: Indiscriminate Expansion (IE), Progressive Expansion (PE), Meritocratic Expansion (ME).



Notes: The scatter-plots in the left column illustrate the joint distribution of intelligence and disadvantage for school and college graduates at equilibrium. The continuous straight lines are the isoprobability curves at values 90%, 50% and 10%, at equilibrium. The dashed lines describe values satisfying equation (20). The histograms in the middle and right columns of panels illustrate the associated marginal distributions. The data consist of a simulated population of 10,000 individuals with type (θ, η) drawn from a jointly normal distribution ($m_\Theta = 100$; $\sigma_\Theta = 15$; $m_H = 5$; $\sigma_H = 1.75$; $\text{corr}(\Theta, E) = \lambda = 0.5$). In the first row (status quo), the policy parameters are set to generate $\xi = 0.1$: $\gamma = 26.1$, $\tau = 0$ (so isoprobability curves are straight lines), $\delta = 2$, $\beta = 1$. The technology parameters are $\alpha = 1.1$ and $\rho = 0.4$. For each policy experiment in the other rows, the parameters are set so as to double the college-to-school labor ratio. The wage ratio adjusts to equilibrium. IE policy: $\delta = 0$. Strongly PE policy: $\beta = -0.16$, $\gamma = 86$. Strongly ME policy: $\tau = -8$, $\beta = 10^{-6}$, $\gamma = 30.1$, $\delta = 5.3$.

Figure 2: Status quo in Society 2 ($\lambda < 0, \psi < 0$) and effects of three expansion policies: Indiscriminate Expansion (IE), Progressive Expansion (PE), Meritocratic Expansion (ME).



Notes: The scatter-plots in the left column illustrate the joint distribution of intelligence and disadvantage for school and college graduates at equilibrium. The continuous straight lines are the isoprobability curves at values 90%, 50% and 10%, at equilibrium. The dashed lines describe values satisfying equation (20). The histograms in the middle and right columns of panels illustrate the associated marginal distributions. The data consist of a simulated population of 10,000 individuals with type (θ, η) drawn from a jointly normal distribution ($m_\Theta = 100$; $\sigma_\Theta = 15$; $m_H = 5$; $\sigma_H = 1.75$; $\text{corr}(\Theta, E) = \lambda = -0.5$). In the first row (status quo), the policy parameters are set to generate $\xi = 0.1$: $\gamma = 31$, $\tau = 0$ (so isoprobability curves are straight lines), $\delta = 2$, $\beta = 1$. The technology parameters are $\alpha = 1.1$ and $\rho = 0.4$. For each policy experiment in the other rows, the parameters are set so as to double the college-to-school labor ratio. The wage ratio adjusts to equilibrium. IE policy: $\delta = 0$. Strongly PE policy: $\beta = -0.18$, $\gamma = 87$. Strongly ME policy: $\tau = -8$, $\beta = 10^{-6}$, $\gamma = 30.1$, $\delta = 5.3$.

of graduates: in Society 1 it is relatively easy to reduce access barriers and draw talented students from any background into college.

In Society 2, graduates are on average more intelligent than non-graduates and have a relatively advantaged background. The pool of intelligent students with a disadvantaged background that are excluded from higher education is evidently smaller than in Society 1. There is still reachable ability in Society 2 but less than in Society 1. Section 4.5 shows that this is the case that best characterizes the UK in the years that we study.

The remaining rows of Figures 1 and 2 illustrate the policy effects. Starting from a college-to-school graduation rate of $\xi = 0.1$, we simulate three policy changes of interest that increase this rate to $\xi = 0.2$. First, an *intended* indiscriminate expansion (IE) policy, which decreases the intercept δ in effort cost shift $\Omega(H) = \delta + \beta H$ (equation 17). By decreasing δ, this policy may appear to shift isoprobability curves upward without affecting their slope and thus, since $\lambda > 0$, to allow high-intelligence and high-disadvantage students to access college. But this conclusion ignores the effect of the policy on the wage gap, which would be reduced due to the higher supply of graduates; this may offset the policy change by making isoprobability curves flatter (see equation 21) and ultimately *reduce* the average intelligence of individuals selected into college. Parameters are chosen to demonstrate that this may be the case even in Society 1 (where students not attaining higher education are on average more intelligent than those who do): although the government intends to shift isoprobability lines up as an easy way of reaching the many talented students outside college, the drop in the wage ratio from $r = 4.4$ to $r = 2.9$ reduces the slope of the lines and the policy ends up favoring primarily the not-so-talented students with a relatively advantaged background in the southwestern portion of the scatter plot. The incidence of graduates with a disadvantaged background increases only marginally relative to the status quo.

A fortiori, also in Society 2 a similarly intended IE policy reduces mean intelligence of graduates while not affecting their average background much. Note that in this society – which is the empirically relevant one in our case study – the expansion decreases mean intelligence both conditional on having attained a college degree *and* conditional on not having attained it. This means that in Society 2 the indiscriminate expansion draws into college students who are more intelligent than the average non-graduate, yet less intelligent than the average graduate. As shown in Section 4.2, this is a pattern that we find in the data.

Consider next an intended progressive expansion (PE) policy that decreases the slope β

of effort cost shift $\Omega(H) = \delta + \beta H$ (equation 17) while increasing the intercept γ of effort cost shift $\Gamma(\Theta) = \gamma + \tau\Theta$ (equation 18). This reform aims at decreasing the importance of a student's background relative to intelligence in determining the graduation probability. In Figures 1 and 2, it takes a strong form because β turns from positive to negative, so that a disadvantaged background (large η) becomes an advantage in college access, as indicated by the fact that isoprobability curves become negatively sloped. This policy induces a large increase in the incidence of graduates with a disadvantaged background in both societies. However, its effect on their average intelligence is positive and large in Society 1 but *negative* in Society 2. Expanding university access without lowering the average ability of college students is not easy when the correlation λ between intelligence and disadvantage is negative.

This dilemma is resolved by the strongly meritocratic (ME) policy illustrated in the bottom row of the two figures. Here the parameters of the effort cost shifts $\Omega(H)$ and $\Gamma(\Theta)$ are adjusted to make $\tau < 0$ (so there is a cost shift in favor of intelligent students), while β approaches zero (so that one's background becomes irrelevant) and γ and δ both increase to obtain the desired college-to-school rate ξ. The result is that isoprobability curves become nearly vertical. This strongly ME raises the incidence of high-intelligence *and* high-disadvantage individuals in the college population of the two societies. Such a policy not only increases the average ability of students in higher education; it is also an egalitarian one, in the sense that it draws into college talented students with a disadvantaged background. In Society 2, this is the *only* one among the three classes of expansion strategies that achieves these goals. In Society 1 they can be obtained with a wider range of policies.[16]

3 Data

We next describe our data sources and the measurement of the four variables that are at center stage in the model: college attainment, intelligence, disadvantage, and earnings.

3.1 Data sources

Our main data source is Understanding Society (USoc), a representative longitudinal survey of UK households. Wave 3 (2011-2013) contains information on respondents' intelligence and

[16] We emphasize that these conclusions are fairly general. The reader can use the Matlab files available in our replication package to experiment with different parameter values.

consists of 49,692 observations that compose our core sample. We restrict this sample to: (i) observations with non-zero cross-sectional response weights (38,223); (ii) white respondents born in the UK (31,132), so as to work with homogeneous cohorts; (iii) observations with non-missing education information (31,072); (iv) individuals born between 1940 and 1984 (23,288). Table 1 reports descriptive statistics. Since 1,113 observations have missing information on intelligence, we distinguish between individuals with and without intelligence test scores to show that the intelligence measure is missing quasi at random. Our final USoc sample consists of 22,175 individuals with non-missing intelligence scores.

Table 1: The UK Understanding Society sample

	White UK born in 1940-1984					White UK born in 1940-1984 with non-missing intelligence score				
	N	mean	sd	min	max	*N*	mean	sd	min	max
Individual characteristics										
Age	23,288	49.40	12.32	24	72	22,175	49.25	12.29	24	72
Female	23,288	0.52	0.50	0	1	22,175	0.52	0.50	0	1
Any tertiary degree	23,288	0.24	0.43	0	1	22,175	0.25	0.43	0	1
Age left school	22,896	16.26	1.11	7	21	21,794	16.29	1.12	7	21
Age left FT edu	11,450	22.08	6.18	15	67	11,146	22.10	6.17	15	67
Born in England	22,990	0.81	0.39	0	1	21,892	0.81	0.39	0	1
Health status	23,287	2.57	1.11	1	5	22,174	2.54	1.10	1	5
Number of marriages	20,475	1.01	0.61	0	4	19,469	1.01	0.61	0	4
N. of children < 18	23,288	0.36	0.81	0	8	22,175	0.36	0.81	0	8
Religious belonging	22,051	0.48	0.50	0	1	20,986	0.48	0.50	0	1
Real monthly income	23,288	2.00	1.71	-8	26	22,175	2.03	1.73	-8	26
Family characteristics at age 14-16										
Father's yrs school	19,207	11.93	2.81	0	18	18,353	11.98	2.82	0	18
Mother's yrs school	19,846	11.47	2.44	0	18	18,950	11.51	2.44	0	18
Father employed	22,905	0.88	0.32	0	1	21,818	0.89	0.32	0	1
Mother employed	23,020	0.62	0.48	0	1	21,930	0.63	0.48	0	1

Notes: We start from the third wave (2011-2013) of the UK Understanding Society survey (USoc). This wave contains information on respondents' intelligence and consists of 49,692 observations. We apply four selection criteria: first, we keep observations with non-zero cross-sectional response weights (38,223); second, we restrict to white respondents born in the UK (31,132); third, we keep observations with non-missing education information (31,072); finally, we restrict the sample to individuals who were born between 1940 and 1984 (23,288). The left panel of the table reports descriptive statistics for this sample. The right panel reports the same descriptive statistics for our final USoc sample consisting of 22,175 individuals with non-missing intelligence scores. The similarity of the statistics in the two panels suggests that information on intelligence is missing quasi at random. Real monthly income is expressed in thousands of 2015 GBP.

In order to corroborate some of the evidence produced using USoc, we also use data from the UK Biobank (UKB). Sample size is considerably larger than USoc, but the UKB is not a random sample of the UK population because subjects are adult volunteers who are older and more educated than average. Like USoc, the UKB contains information on educational attainment and intelligence. Starting from 502,412 UKB subjects who did not later withdraw from the survey, we retain white respondents born in the UK (434,123) between 1940 and 1969 (417,242), with non-missing information on education (411,681). Information on intelligence is missing for 199,034 observations. Descriptive statistics are reported in Table 2 for the four variables that can be directly compared with USoc. This table suggests that also in the UKB the intelligence measure is missing quasi at random. Our final UKB sample consists of 212,647 observations with non-missing intelligence score.

Table 2: The UK Biobank sample

	White UK born in 1940-1984					White UK born in 1940-1984 with non-missing intelligence score				
	N	mean	sd	min	max	*N*	mean	sd	min	max
Age	411,681	56.40	7.78	39	70	212,647	56.56	7.78	39	70
Female	411,681	0.54	0.50	0	1	212,647	0.54	0.50	0	1
Any tertiary degree	411,681	0.31	0.46	0	1	212,647	0.36	0.48	0	1
Age left school	279,293	16.64	2.21	0	35	134,529	16.82	2.22	0	35

Notes: Starting from about 502,412 UK Biobank subjects who did not later withdraw from the survey, we retain white respondents born in the UK (434,123) between 1940 and 1969 (417,242), with non-missing information on education (411,681). Information on intelligence is missing for 199,034 of these observations. The left panel of the table reports descriptive statistics for the four UKB variables that can be directly compared with USoc. The right panel reports the same statistics for our final UKB sample consisting of 212,647 observations with non-missing intelligence score. The similarity of the statistics in the two panels suggests that information on intelligence is missing quasi at random.

Our third data source is the University Statistical Record (USR), which contains administrative information on the universe of students enrolled at UK universities between 1972 and 1993. These data are described and used in the Online Appendix to Section 4.1 to provide evidence on how the UK expansion was enacted.

Finally, following Blundell et al. (2022), we use the UK Labour Force Survey (LFS) for the analysis of the evolution of the wage gap between college graduates and non-graduates. Our sample is 1993:Q1–2019:Q4. The LFS is a quarterly survey of about 100,000 adults who, after applying the appropriate weights, are representative of the UK population in terms of individual characteristics and earnings. Respondents are asked about earnings during the first and fifth quarters in the survey. We discard those with missing information on age, gender, education, earnings, and hours worked, missing or zero weights for earnings and personal characteristics, or a foreign educational attainment.

Real hourly wages are constructed for each respondent as the ratio between the weekly wage in the main job and the actual weekly hours. Nominal values are deflated using the 2022 edition of the OECD GDP deflator (base year: 2015). While Blundell et al. (2022) study *median* wages by education group, the relevant variable in our model is the *average* wage, at a given age, of college graduates and non-graduates.[17] To neutralize the effect of outliers on average wages, we also drop the top and bottom 0.1% of the real wage distribution.

Our final sample are 936,135 subjects observed during at least one year between 1993 and 2019, with observations in each year ranging between about 25,000 and 50,000. Table 3 presents descriptive statistics for the relevant variables. Section 4.4 explains how we use this information to measure the evolution of the college-to-school wage ratio over cohorts.

Table 3: The UK Labour Force sample (1993–2019)

	UK employees born in 1940-1984				
	N	mean	sd	min	max
Age	936,135	41.35	11.41	16	79
Female	936,135	0.50	0.50	0	1
Any tertiary degree	936,135	0.25	0.43	0	1
Real hourly wage, college graduates	213,632	19.53	12.87	0.80	149.00
Real hourly wage, non-graduates	722,503	11.96	8.61	0.80	148.89

Notes: Starting from the UK Labour Force Survey (LFS) 1993:Q1–2019:Q4, we keep only the first and fifth quarters for each respondent, i.e., the instances that contain earnings. Respondents with missing information on age, gender, education, weakly earnings, and weekly hours worked, or with missing or zero weights for earnings and personal characteristics, or with a foreign education attainment are discarded. We also drop the top and bottom 0.1% outliers of the real wage distribution. Nominal values are deflated using the 2022 edition of the OECD GDP deflator. Yearly observations range between 25,000 and 50,000.

3.2 College graduation rate and college cohorts

Before 1992, high school graduates wishing to pursue higher education in the UK had two options: enrolling in a traditional university or attending a polytechnic.[18] As illustrated in Pratt (1997), Willet (2017) and Jandarova and Reuter (2021), these two types of institutions differed in many ways, e.g., funding, target populations, teaching organization, subjects, and admission criteria. The *Further and Higher Education Act* of 1992 allowed polytechnics to

[17]The Online Appendix to Section 4.4 shows that the use of mean wages instead of median wages is essentially irrelevant.

[18]There was also the option of attending professionally-oriented public colleges, such as teacher training and nursing colleges. This group was relatively small and so we consider it as part of “polytechnics”.

obtain university status and so eliminated this "binary divide". Such innovation was a follow-up on the Robbins Report, which had recommended the unification of the UK higher education system in consideration of the similarities between universities and polytechnics.

In line with the literature on the evolution of the wage gap between college and high school graduates in the UK (for example: Machin and McNally, 2007; Walker and Zhu, 2008; Blundell et al., 2022), in the present paper a "college graduate" is defined as a person who obtained a higher education degree of any kind. This is not a limitation given that we are studying the expansion of the UK higher education system and that ending the "binary divide" was in fact part of this policy.

We instead depart from this literature in the definition of the comparison group (see also Section 2.1). We are interested in evaluating whether the UK expansion was successful in drawing into college those talented students who were previously likely to drop out of education at *any* lower level, not just at the high school level. Therefore, our comparison group is composed by individuals with any educational attainment below a tertiary degree in the population that we study.[19]

To facilitate the interpretation of our results in relation to historical information on policy and technology trends, we aggregate individuals into "college cohorts". These are groups of individuals in actual (for graduates) or potential (for non-graduates) college attendance age. For such age, we use as a label the year of birth plus 20. The large sample size available in the UKB allows us to construct college cohorts using 5-year windows. For the smaller USoc sample that we use for inference, we construct three 15-year periods in order to increase sample size and thereby statistical power. These three periods are: 1960-1974 for individuals born between 1940 and 1954 (7,103 individuals in the final sample), 1975-1989 for those born between 1955 and 1969 (8,329 individuals), and 1990-2004 for subjects born between 1970 and 1984 (6,743 individuals). Labeling these groups as "college cohorts" avoids possible confusion with birth cohorts. In light of evidence suggesting that the time of entry in the labor market has long-term consequences on wages and employment along the life cycle,[20] it is reasonable to assume the absence of first-order substitutability between college graduates across these cohorts, and similarly for non-college graduates.

[19]To quantify the difference in the definition of the comparison groups, out of the 936,135 observations in our LFS sample, 146,565 (15.7% of the total) are not high school graduates according to the definition of Blundell et al. (2022) and so are not included in their comparison group, while they are included in ours.

[20]See, among others, Kahn (2010), Oreopoulos et al. (2012), Giuliano and Spilimbergo (2014), Schwandt and von Wachter (2019), von Wachter (2020) and Jandarova (2022).

3.3 Intelligence

In Wave 3 of USoc, respondents aged 16 or older were eligible for a cognitive ability test, which was composed of six sub-tests: immediate word recall (episodic memory), delayed word recall (episodic memory), subtraction (working memory), number series (fluid reasoning), verbal ability (semantic fluency), and numeric ability (problem solving/numeracy).[21] We observe the fraction of correct answers given by each subject as well as whether help was received during the test – either specific help in answering a question or generic material aid during the test. This information results into 14 cognitive ability variables: the six fractions of correct answers in the sub-tests and eight dummies for whether help was received.

A possible problem in our analysis is that these cognitive variables are measured after potential or actual college attendance and so may be endogenous to university studies. However, while Brinch and Galloway (2012) provide evidence that pre-college education may affect intelligence, Kremen et al. (2019) and Arum and Roksa (2011) show that this is not the case for college.[22] Moreover, consistent with evidence that general cognitive ability (g factor) is unlikely to be malleable beyond infancy (Heckman and Mosso, 2014; Protzko, 2015), Ritchie et al. (2015) show that any effect of schooling on specific cognitive skills is not mediated by the g factor which instead seems to be largely unaffected by education.[23]

In light of this evidence and following the psychometric literature (Fawns-Ritchie and Deary, 2020), we capture the g factor underlying the 14 cognitive ability variables available in USoc by aggregating them into a single intelligence score via Principal Component Analysis (PCA). The First Principal Component, which we label "IQ" and which is the empirical counterpart of the intelligence construct Θ in the model, has an eigenvalue of 2.55 and explains 18.2% of the data variability. The corresponding eigenvector features positive values for the fractions of correct answers, negative values for 6 of the 8 help dummies, and positive but near-zero values for the remaining two help dummies (see Table A-1 in the Online Appendix to Section 3.3 for additional details). We therefore conclude that IQ summarizes the cognitive ability of USoc respondents in a satisfactory way.

The UKB provides instead a Fluid Intelligence Score (FIS), which is the sum of the cor-

[21] See McFall (2013) for a detailed description of these cognitive tests.

[22] Conditioning on intelligence measured in adolescence, Clouston et al. (2012) find that higher education is correlated with cognitive ability measured during midlife, but this evidence cannot be regarded as causal.

[23] This conclusion is consistent with Ritchie and Tucker-Drob (2018), since "the vast majority of the studies in [their] meta-analysis considered specific tests and not a latent g factor" (p. 1367).

rect answers to 13 cognitive questions: numeric addition, identification of the largest number, word interpolation, positional arithmetic, family relationship calculation, conditional arithmetic, synonim, chained arithmetic, concept interpolation, arithmetic sequence recognition, antonym, square sequence recognition, and subset inclusion logic.[24] There is no reason to aggregate the results of the sub-tests in a way different from the one adopted by the UKB, and so we use FIS as the intelligence measure in this data set, despite its discrete nature. Fawns-Ritchie and Deary (2020) validate the presence of a g component in FIS and conclude that "despite the brief and non-standard nature of the UK Biobank cognitive assessment, a measure of general cognitive ability can be created using these tests" (p. 19).

The intelligence scores produced by PCA in USoc (IQ) or by the UKB aggregation (FIS) are taken to be cardinal measures of the underlying intelligence construct, so any monotonic linear transformation (MLT) of these measures is admissible and we must pick one. It is convenient to choose a MLT such that variable Θ has mean 100 and standard deviation 15, so as to make the comparison with the widely used measures of intelligence. This choice implies that we can identify γ and τ as policy parameters determining the cost of effort *relative to that scale* of the intelligence measure, as is evident in equation (19). Since we are interested in policy *changes*, the particular scale that we choose is irrelevant.

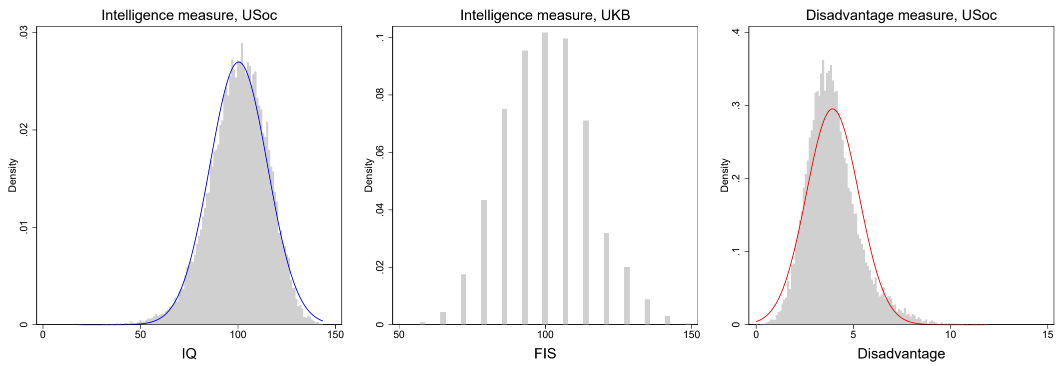
Like all variables in econometric analysis, our intelligence indicators contain measurement error. For example, it is has been argued that intelligence varies over time for a given age and over age for a given cohort. The first variation is known as the "Flynn effect" because Flynn (1987) measured an apparent improvement in IQ scores in 14 nations during the 20th century (an effect that reversed itself in recent years). The second has been documented by Salthouse (2012, 2019), who observed that different types of cognitive skills evolve in different ways during the life cycle. By analogy, we label this as the "Salthouse effect". Since we want a measure of intelligence that does not reflect the average age of a cohort, the Salthouse effect must be removed by normalizing both IQ and FIS within birth years.[25] This comes at the cost of removing also the Flynn effect, which is less of a concern because this finding is more questionable. For example, using high-quality data from Norway that enable a within-family analysis of IQ, Bratsberg and Rogeberg (2018) argue that the Flynn effect and its reversal in recent years are explained by environmental factors.

[24]See the UK Biobank data show case for a detailed description of these cognitive tests.

[25]The comparison between Figure A-2 and Figure A-3 in the Online Appendix to Section 3.3 illustrates the effect of this normalization on the two measures.

Notice that the within-birth year normalization implies that the policy parameters γ and τ that we will estimate incorporate any residual measurement error and therefore must be interpreted with a grain of salt. The distribution of the resulting intelligence measures in USoc and the UKB are illustrated in the left and middle panels of Figure 3, respectively.

Figure 3: Distribution of intelligence and disadvantage measures



Notes: The figure illustrates the empirical distribution of our measures of intelligence (left and middle) and disadvantage (right). The continuous line in the left and right panels is the normal density that has the same mean and standard deviation as the data. The UKB measure is the Fluid Intelligence Score, resulting from the sum of correct answers in 13 cognitive questions. The USoc measures are: for intelligence, the FPC of 14 cognitive ability variables; for disadvantage, the FPC of 8 socioeconomic variables at age 14 and the Big Five traits, rescaled so that the minimum is zero.

3.4 Disadvantage

Recall that we are interested in the intelligence-disadvantage dichotomy that was emphasized in the Robbins (1963) Report. There are two relevant, non-cognitive dimensions of disadvantage that reduce the probability of college enrollment and graduation. The first has a socioeconomic nature. For example, for given intelligence, students from low-income, low-education, or single-parent families are less likely to enroll and graduate (Bailey and Dynarski, 2011; Hoxby and Avery, 2012). The second, instead, is in the personality domain. For example, keeping again cognitive ability constant, a student who is characterized by low conscientiousness and openness or high neuroticism is less likely to succeed in tertiary education (see Corazzini et al., 2021). These two dimensions of disadvantage can be measured in USoc as follows.

For *socioeconomic disadvantage*, we aggregate via PCA eight relevant variables: mother's and father's years of schooling, and six dummies referring retrospectively to when the respondent was 14, namely whether a respondent's father or mother were employed, whether a respondent was living with only one parent, and whether a respondent's parent was deceased. The First Principal Component (FPC) explains 22% of the variability in these eight variables. The corresponding eigenvector contains negative values for whether either parent was absent or dead, and positive values for the other variables (see Table A-2 in the Online Appendix to Section 3.4). We therefore conclude that this FPC summarizes a socioeconomic *advantage*. Since we want a measure of disadvantage in college enrollment and graduation of USoc respondents, we simply invert the sign of this FPC.

For *personality disadvantage*, we proceed in a similar way by aggregating via PCA the Big Five personality traits (Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism). The FPC explains 35% of the variability in the five personality variables. The corresponding eigenvector contains a negative value for neuroticism and positive values for the remaining four traits (see Table A-3 in the Online Appendix to Section 3.4). We therefore conclude that also the FPC of the Big Five variables summarizes a personality *advantage*, and we invert its sign to obtain a measure of disadvantage.

For tractability, the model of Section 2 features a single disadvantage variable H in contrast with intelligence Θ. We can safely employ a single measure of socioeconomic *and* personality disadvantage because both PCA disadvantage measures are negatively correlated with the intelligence measure (see Table A-4 in the Online Appendix to Section 3.4). The single measure of H that we use is produced by a single PCA of the 13 pooled socioeconomic and Big Five variables. The FPC explains 12.6% of their variability and the resulting eigenvector preserves the signs of the eigenvectors from the distinct PCAs (see Table A-5 in the Online Appendix to Section 3.4), so that the negative of the FPC provides a satisfactory measure of overall disadvantage in college enrollment and graduation of USoc respondents. The sign of the correlation between our measures of H and Θ is also preserved, as discussed in detail in Section 4.5. Finally, we shift the support of the FPC distribution so that disadvantage has a minimum of zero.

Like for IQ, we take the disadvantage measure produced by PCA as a cardinal measure of the underlying concept and any MLT is admissible. Since there is no scale in the psychometric tradition for variable H, we simply use the translation of the PCA measure that we have described above. As is again evident in equation (19), the scale of parameter β adapts to this particular scale, which is immaterial as we only need to identify changes in β across cohorts. However, like for γ and τ in the case of intelligence, our estimates of policy parameters δ and β will contain some measurement error due to our inability to include in the PCA all the factors that are relevant determinants of variable H in the model. The distribution of our disadvantage measure is illustrated in the right panel of Figure 3.

Finally, note that while we normalize IQ within birth year, we do not do the same for disadvantage. The reason is that there has been an unquestionable improvement of socioeconomic standards in the UK during the period that we study, which is part of the reason why the demand for college education has increased. We therefore do not want to remove by construction the effects of this force from our empirical analysis, contrary to the removal of the Salthouse effect which is instead desirable for the reasons discussed in Section 3.3.

4 Key empirical facts

In this section we document four key facts that the model is required to reproduce empirically: the increase in the fraction of college graduates; the decrease in the average intelligence of both college and non-college graduates; the decrease in average disadvantage, for the entire population and by graduation status; and the decline of the wage ratio between college graduates and non-graduates (college-to-school wage ratio, for brevity). We also document a fifth key fact that is relevant for interpreting the consequences of the UK expansion: the correlation between intelligence and disadvantage is negative; this means that, in the period that we consider, the UK resembles Society 2 of Figure 2.

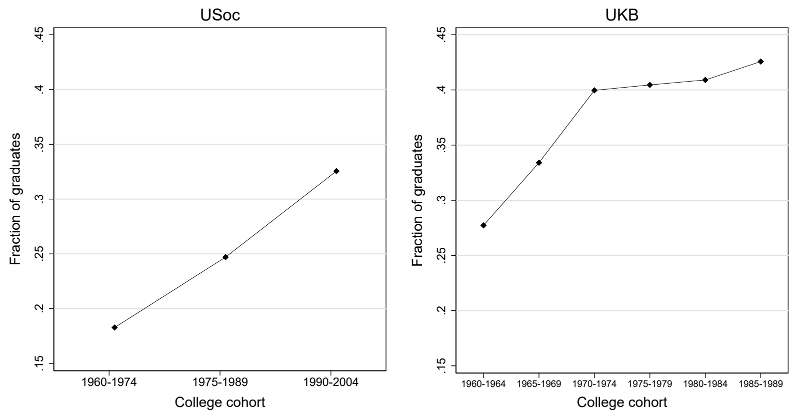
4.1 The fraction of college graduates increased steeply

Figure 4 shows that in the USoc sample (left panel) the fraction of graduates increased from about 17% in college cohort 1960-1974 to about 32% in cohort 1990-2004. A similar trend is observed in our UKB data sample (right panel). Since UKB respondents are on average more educated than the UK population, their college graduation rate is higher than in USoc; yet we observe a similar increase in college graduation rates: from about 28% to about 43%.[26] In the Online Appendix to Section 4.1, we summarize the literature documenting that this expansion was enacted in a mostly non-meritocratic way, by ending the binary divide between

[26] Figure 4 plots model variable $x(1)$, i.e., the fraction of graduates. The structural analysis is in terms of ξ, i.e., the college-to-school labor ratio. Of course there is a 1:1 mapping between the two, because $\xi = \frac{x(1)}{1-x(1)}$.

traditional universities and polytechnics, by increasing the number of academic institutions, and by reducing ability requirements at entry.

Figure 4: Fraction of college graduates by college cohort



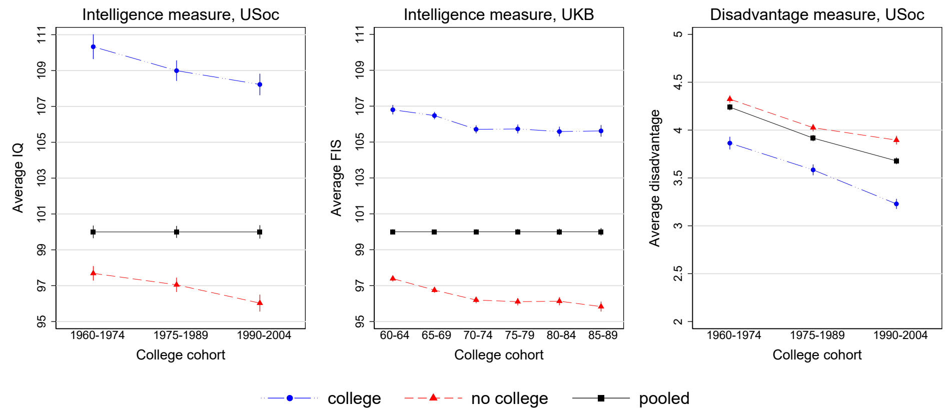
Notes: The left panel displays the fraction of graduates – model variable $x(1)$ – in three Usoc college cohorts (sample: 22,175 white respondents born in the UK between 1940 and 1984, with non-missing education and intelligence score; see Table 1). The right panel displays the same variable in six UKB college cohorts (sample: 212,659 white respondents born in the UK between 1940 and 1969, with non-missing education and intelligence score; see Table 2).

4.2 Graduates' average intelligence declined

The left and middle panels in Figure 5 report the average of the intelligence score (model variable Θ) in our samples across the different college cohorts, by college graduation status. In USoc, the average IQ of the population is constant by construction (see Section 3.3), at a value of 100. However, for college graduates (left panel) it declined by about two points (13% of a standard deviation), from 110.3 in the 1960-1974 college cohort to 108.2 in the 1990–2004 cohort. Interestingly, during the same period, also the average IQ of non-graduates declined by about two points, from 97.7 to 96.0. Similar dynamics are observed in the UKB sample, where graduates' average FIS (middle panel) declined from 106.8 in the 1960-1964 cohort to 105.6 in the 1985-1989 cohort; for non-graduates the decline was from 97.4 to 95.8. The declining average intelligence of both graduates and non-graduates suggests that the expansion of higher education that was enacted in the UK brought into college students who were more intelligent than average in the group of those previously excluded, yet less intelligent than the average student who was previously admitted to college, as conjectured by Walker and Zhu (2008) and Blundell et al. (2022).[27]

[27] Additional evidence supporting this interpretation is offered in Table A-7 of the Online Appendix to Section 5.2, which shows that the bottom percentiles of the intelligence distribution of graduates declined

Figure 5: Dynamics of intelligence and disadvantage measures by college attainment



Notes: The left and right panels display, respectively, the dynamics of average IQ and average disadvantage in the population and by college graduation status across the three USoc college cohorts (sample: 22,175 white respondents born in the UK between 1940 and 1984, with non-missing education and intelligence score; see Table 1). The middle panel shows the dynamics of average FIS in the population and by college graduation status across the UKB college cohorts (sample: 212,659 white respondents born in the UK between 1940 and 1969, with non-missing education and intelligence score, see Table 2).

4.3 Graduates' average disadvantage declined

The right panel in Figure 5 reports the average disadvantage (model variable H) in the USoc sample, for the entire population and by college attainment status. This variable is not constrained to be constant on average in the population (see Section 3.4). In fact it exhibits a declining trend that reflects the improving socioeconomic status of the UK population during the period that we consider.[28] Between the 1960-1974 and the 1975-1990 college cohorts, the decline was 7.6% in the population, 7.2% among college graduates, and 6.9% among non-graduates. The similarity between these numbers indicates that, initially, the expansionary higher education policy affected the average background of college and non-college students only marginally.

The outcome of the sorting process departs more substantially from mere population changes for the 1990-2004 college cohort: relative to the 1975-1990 cohort, average disadvantage declined by 6.1% in the population, 9.9% among college graduates, and 3.2% among non-graduates. These figures suggest that the more recent stage of the expansion process brought students into college who were relatively advantaged in the group of those previously excluded, and also more advantaged than the average student who was previously admit-

significantly while the top remained almost unchanged. The opposite happened for non-graduates.

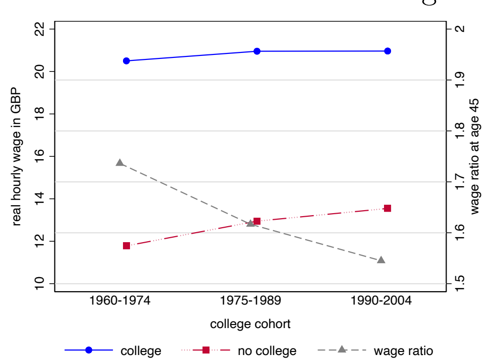
[28]The standard deviation does not change and is about 1.35 in all cohorts. A declining mean and a constant SD imply a declining coefficient of variation, i.e., widening relative inequality along the disadvantage dimension, in line with evidence in, e.g., Machin (1996) and Office for National Statistics (2021).

ted to college. This fact is in line with existing evidence that the enlargement of higher education in the UK has predominantly benefited children from high-income families (e.g., Blanden and Machin, 2004; Machin, 2007; Sutton Trust, 2018; Boliver, 2013; and Major and Machin, 2018, among others), and confirms that our disadvantage measure is (also) a reliable proxy for socioeconomic status.

4.4 The college-to-school wage ratio declined

The evolution of the college-to-school wage ratio over cohorts is illustrated in Figure 6, using the LFS data described in Table 3. Since the college cohorts that we study are observed over different age ranges in the 1993–2019 period covered by our LFS sample, we adopt the methodology of Blundell et al. (2022) to remove age effects. Specifically, we aggregate the data in cells defined by the combination of college cohort and age. Using these cells as observations, we regress the average real hourly wage of college graduates on dummies for each age and for each cohort. The three dots connected by a continuous line in Figure 6 represent this average real hourly wage at age 45 in each cohort, net of age effects. The three squares connected by a dotted–dashed line represent the analogous average real hourly wage of non-graduates. Finally, we compute the college-to-school wage ratio in each cell and we regress it on dummies for each age and cohort. The triangles connected by a dashed line describe the evolution of this wage ratio.

Figure 6: Evolution over cohorts of the wage ratio at age 45



Notes: Evolution over college cohorts of real hourly wages at age 45 for graduates and non-graduates, and of the corresponding ratio; Left scale: real monetary values obtained using the 2022 edition of the OECD GDP deflator; right scale: ratio between the two wage levels. Sample: 936,135 LFS respondents surveyed between 1993 and 2019, born in 1940-1984 (see Table 3).

The real hourly wage at age 45 of students who obtained a college degree between 1990 and 2004 increased by about 0.5 GBP with respect to those who graduated thirty years earlier (from 20.5 to 21.0 GBP). For non-graduates, the real hourly wage increased instead by more than 1.5 GBP (from 11.8 to 13.5 GBP). As a result, the wage ratio declined by about 11 percent, from 1.74 to 1.55. This finding contrasts with the evidence of a weakly increasing wage gap between *college and high-school graduates* reported in the literature for UK post-WW2 cohorts, particularly by Blundell et al. (2022).[29] The Online Appendix to Section 4.4 shows that this discrepancy is essentially due to our different definition of the comparison groups (college graduates vs non-graduates; see Section 3.2 for the rationale of this choice in our analysis). In fact there is no contrast between our evidence and the literature when we compare the Blundell et al. (2022) groups (college graduates vs high-school graduates), given that we use their same data and methodology to remove age effects. Other differences, namely the range of the LFS sample (1993–2019 instead of 1993–2016), the use of mean instead of median wages by education group, the use of age dummies instead of age polynomials in the regressions to remove age effects, or the focus on only three cohorts of 15 birth years between 1940 and 1984 instead of eight cohorts of 5 birth years between 1950 and 1989 are less, if at all, relevant.

4.5 Intelligence and disadvantage are negatively correlated

Our measures of intelligence (Θ) and disadvantage (H) are *negatively* correlated in the USoc sample. This correlation, which is labeled λ in Section 2, is reported in Table 4 for the three different college cohorts, alongside its standard error. It is about -0.2, and varies over time by a statistically insignificant amount. Thus, as far as the correlation between intelligence and disadvantage in the population is concerned, in the period that we consider the UK society is represented by Society 2 of Figure 2.

Table 4: Correlation between IQ and disadvantage in USoc

	College cohort		
	1960-1974	1975-1989	1990-2004
$\lambda = \text{Corr}(\Theta, H)$	-0.163	-0.198	-0.199
	(0.013)	(0.012)	(0.014)
N	7,103	8,329	6,743

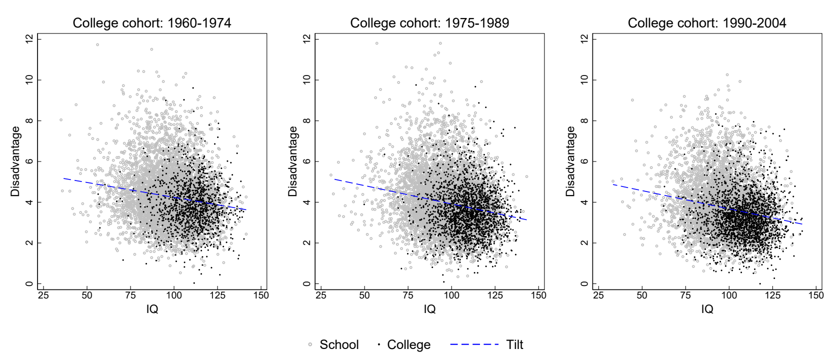
Notes: The table reports the correlation between our measures of intelligence (Θ) and disadvantage (H). The standard error is produced via the delta method. Cross-sectional response weights are applied. Sample: USoc, 22,175 white respondents born in the UK in 1940-1984 with non-missing education and intelligence information (see Table 1).

[29] Other studies include Blanden and Machin (2004), O'Leary and Sloane (2005), Walker and Zhu (2008), Devereux and Fan (2011), and Chowdry et al. (2013).

We conjecture that such negative correlation is the outcome of two forces that work in the same direction. First, since cognitive ability increases education and income, if there is a sufficiently large heritability of intelligence, more intelligent parents transmit to their children both higher cognitive ability via genes and higher socioeconomic status via social forces. Second, advantaged families offer children an early childhood environment that favors cognitive development via nurture. Note that the underlying mechanism has no consequences for our conclusions, because the correlation λ determines only the effects of higher education policy on the sorting process. It is conceivable that early childhood interventions can compensate the relative disadvantage reflected in this correlation, turning λ into a positive value. Therefore, λ reflects a particular social equilibrium and not a deep relation between intelligence and disadvantage. But from the viewpoint of this paper, if λ is negative, our model suggests that it would be very costly for society to change this social equilibrium with a non-meritocratic expansion of tertiary education, because of the ensuing decline of the cognitive ability of college graduates. Moreover, it would also be hopeless because, as discussed in Section 3.3, the g factor is not affected by college attendance. To put it differently, it would be a mistake to ask tertiary education to correct for the lack of adequate early education policies.

Figure 7 displays the empirical counterpart of the scatter plot in the top row of Figure 2, for the three cohorts. The negative correlation between IQ and disadvantage is reflected in the negative tilt of the underlying distribution (dashed line). Note that although the separation between graduates and non-graduates is less sharp in USoc data than in the simulated data, graduates still concentrate among the high-IQ, low-disadvantage individuals.

Figure 7: Empirical joint distribution of IQ and disadvantage in the three college cohorts



Notes: The figure displays the empirical counterpart of the scatter plot in the top row of Figure 2, for the three USoc college cohorts. Each point is an individual in our sample. The dashed line represents the tilt of the underlying joint distribution of intelligence and disadvantage (see equation 20). Sample: USoc, 22,175 white respondents born in the UK in 1940-1984 with non-missing education and intelligence information (see Table 1).

5 The UK higher education policy and its consequences

In this section we estimate the model presented in Section 2. The goal is to: (i) infer the type of higher education policy that prevailed in the UK after the Robbins Report; (ii) study how the actual policy affected sorting into college in terms of students' intelligence and disadvantage; (iii) contrast the realized policy with the one that should have been implemented to achieve the Report's aim of drawing into higher education talented children from disadvantaged backgrounds; (iv) draw lessons for the planned expansion of university access in Europe and elsewhere.

5.1 Identification and estimation

There are three technology parameters in the model: α (the technological skill ratio), ρ (one minus the inverse of the elasticity of substitution between school and college labor inputs), and A (TFP). Equation (16) implies that TFP does not affect the consumption utility gap $\Delta U(\mathbf{w})$, equation (3), and so parameter A can be ignored. Still, it is clear that without further assumptions, α and ρ are not separately identified in our model – only the locus given by equation (10) is identified. Using US data, Katz and Murphy (1992) and more recently Autor, Goldin, and Katz (2020) produce estimates of ρ around 0.3 and 0.4, respectively, in a partial equilibrium model where technology follows a linear trend. The implicit assumption is that the relative supply of college graduates is exogenous, and specifically does not respond to unobserved (to the econometrician) wage shocks originating from the demand side. Such an assumption cannot hold in our general equilibrium framework. However, since we do not need to identify the technology parameters separately, we can estimate the model for three alternative values of ρ in the range that is typically found in the literature: 0.3, 0.4, and 0.5. It follows that technical change is represented only by changes in α. An increase in α represents skill-biased technical change (see Section 2.2).

On the contrary, the policy parameters that control the effort cost shifts $\Omega(H) = \delta + \beta H$ (equation 17) and $\Gamma(\Theta) = \gamma + \tau\Theta$ (equation 18), are identified – a fact that follows immediately from equation (19) – and so we are left with parameters $(\gamma, \tau, \delta, \beta, \alpha)$ to estimate. For a given value of ρ, the empirical counterpart of the joint distribution $\mu(\Theta, H)$, and a target set of empirical moments, we estimate these parameters by minimum distance (MD) in each college cohort. Specifically, for each point in the discretized parameter space (the "grid"), we solve numerically for the equilibrium supply of graduates, $x(1)$, by finding the unique fixed point of the following equation, which combines equations (14) and (15),

$$x(1) = \sum_{\theta,\eta} \omega(\theta,\eta)\Pi\left(\frac{\theta}{\gamma+\tau\theta} - \frac{\delta+\beta\eta}{\ln\alpha + (\rho-1)(\ln x(1) - \ln(1-x(1)))}\right)\mu(\theta,\eta), \tag{29}$$

where $\omega(\theta,\eta)$ denote USoc cross-sectional response weights, adding up to 1. Given the equilibrium college-to-school workforce ratio $\xi = \frac{x(1)}{1-x(1)}$, we obtain the equilibrium college-to-school wage ratio r. The equilibrium individual graduation probabilities are then used to classify each individual in the sample as a college graduate if that individual's probability is above an individual-specific random threshold. Finally, we pick the parameters that minimize the distance between six informative theoretical moments and their empirical analogs: the college-to-school workforce ratio, the college-to-school wage ratio, and the average intelligence and disadvantage of graduates and non-graduates. These six moments are the most informative for estimating our four policy parameters and the residual technology parameter because in our model it is precisely the change in higher education policy or technical progress that alter the labor market equilibrium and the sorting process into college. Additional, untargeted moments are set aside to check how well we match facts not used in our minimum distance estimation. In consideration of the importance of intelligence and disadvantage in our analysis, we select – among the many possible untargeted moments – the 25^{th} and 75^{th} percentiles of the conditional (to educational attainment K) distributions of Θ and H, i.e., eight moments.

All of the targeted and untargeted moments are estimated using USoc, except for the college-to-school wage ratio which is based on the LFS, applying the appropriate weights in all cases. Denoting by

$$\widehat{T} = \left[\widehat{\xi}\ \ \widehat{r}\ \ \widehat{\mathbb{E}}(\Theta|K=1)\ \ \widehat{\mathbb{E}}(\Theta|K=0)\ \ \widehat{\mathbb{E}}(H|K=1)\ \ \widehat{\mathbb{E}}(H|K=0)\right] \tag{30}$$

the target vector of empirical quantities and by

$$T(\gamma,\tau,\delta,\beta,\alpha;\rho) = [\xi\ \ r\ \ \mathbb{E}(\Theta|K=1)\ \ \mathbb{E}(\Theta|K=0)\ \ \mathbb{E}(H|K=1)\ \ \mathbb{E}(H|K=0)] \tag{31}$$

its theoretical counterpart at equilibrium, the criterion function is

$$J(\gamma,\tau,\delta,\beta,\alpha;\rho) = (T(\gamma,\tau,\delta,\beta,\alpha;\rho) - \widehat{T})\Upsilon W \Upsilon (T(\gamma,\tau,\delta,\beta,\alpha;\rho) - \widehat{T})', \tag{32}$$

where Υ is a diagonal matrix whose elements are the inverse of the elements of $\widehat{T}$ and W is a weighting matrix. Thus, the criterion function is a weighted sum of *percentage* squared deviations of the theoretical moments from the empirical ones. We set $W = I$ and we find the minimum of $J(\cdot;\rho)$ over the grid. To produce standard errors, we repeat this MD estimation 10,000 times in bootstrap samples obtained from random draws with replacement. The bootstrap standard errors are given by the standard deviation of each parameter's estimate across the 10,000 replications.[30]

A crucial question about our identification is whether the criterion function $J(\cdot;\rho)$ attains a *global* minimum at the estimated parameters. It is plausible that this function has local minima, and given that the grid is finite, the "wrong" starting point for the search process may yield estimates that correspond to one of them. This is particularly worrisome as there is no reference scale for policy parameters γ, τ, δ, and β – while for technology parameter α a natural reference point is 1, i.e., $a(1) = a(0)$ in equation 8 – and so one does not know where the grid should be centered in $\mathbb{R}^5$ in order not to get stuck into a local minimum. We solve this problem by noting that a researcher not interested in disentangling the impact of higher education policy $G = (\gamma, \tau, \delta, \beta)$ from changing technology and socioeconomic characteristics or not interested in using the model for equilibrium policy analysis, can obtain a partial set of estimates by Nonlinear Least Squares (NLS) from the supply-side equation (19), after replacing $\Delta \ln w(G)$ with its empirical analog, $\ln \widehat{w}(1) - \ln \widehat{w}(0)$. The NLS estimates provide a guess that should be close to the actual policy parameters, i.e., the "right" starting values, even if it ignores the equilibrium effects of higher education policy. Such initial estimates are reported in Table A-6 of the Online Appendix to Section 5.1. Anchoring the grid search process to these NLS estimates of $G = (\gamma, \tau, \delta, \beta)$ and the natural reference value for α increases our confidence that the MD algorithm – which instead takes into account that $\Delta \ln w(G)$ depends on the parameters to be estimated – does not end up at a local minimum.

The Online Appendix to Section 5.1 provides more computational details, including a visual analysis of two- and three-dimensional sections of the criterion function $J(\cdot;\rho)$. The figures show that local minima do exist and suggest that our MD estimates correspond in fact to a global minimum.[31]

[30] This procedure is not necessarily efficient because we are not employing the optimal weighting matrix This is not an issue given that, as reported below, our standard errors turn out to be quite small anyway.

[31] Our replication files include a Matlab code that can be used to inspect the criterion function over any subset of $\mathbb{R}^5$.

5.2 Estimates

Our MD estimates of the structural parameters are reported in panel [A] of Table 5 for $\rho = 0.4$, which is the value estimated for the US by Autor, Goldin, and Katz (2020). The Online Appendix to Section 5.2 reports estimates for $\rho = 0.3$ (Katz and Murphy, 1992) and $\rho = 0.5$. The remaining panels of Table 5 compare the model-predicted values of the six targets to the empirical values computed from the data. The six target moments are matched remarkably well. Table A-7 in the Online Appendix to Section 5.2 shows that the eight untargeted moments are also well matched. The MD estimates of the policy parameters are very close to the NLS estimates, which are reported in Table A-6 of the Online Appendix to Section 5.1. This is unsurprising given that we search for a minimum around these values, but is also reassuring in consideration of (i) the different objective functions that the two estimators optimize; and (ii) the fact that our MD estimator involves five, not necessarily independent parameters while the NLS estimator involves four parameters only.

According to our estimates, policy parameter γ declines by about 38% between the 1960-1974 and the 1990-2004 college cohorts; similarly, τ declines, in absolute value, by about 42%. Parameter δ also declines substantially between the two periods, by about 84%, while β is approximately constant between the first and second college cohorts and nearly doubles for the third cohort. The implied variations in the effort cost shifts $\Gamma(\theta) = \gamma + \tau\theta$ (equation 18) and $\Omega(\eta) = \delta + \beta\eta$ (equation 17), which we analyze in greater detail in Section 5.4, indicate: (i) a large reduction in the cost of attending college that is more pronounced for the relatively less intelligent students; (ii) a lower cost of attending college for the relatively advantaged ones; and (iii) an increased cost for the relatively disadvantaged ones.

As for technology parameter α, we estimate a significant increase of about 41% during the same period, which indicates skill-biased technological progress.[32]

5.3 Anatomy of the policy mechanism

The next step in our analysis is the characterization of the policy that was actually implemented and of policies that could have been implemented instead to improve the quality of graduates while also reaching disadvantaged students more widely as advocated in the Rob-

[32] Our estimates of α are all below 1, which implies $a(0) > a(1)$ in the production function, equation (8). This inequality does *not* imply that non-graduates are more productive than graduates because marginal productivity depends on $a(k)$ but also, inversely, on the fraction of the workforce in education group k.

Table 5: Minimum-distance estimates of model parameters for $\rho = 0.4$

[A] Parameter estimates

	College cohort 1960-1974	College cohort 1975-1989	College cohort 1990-2004
γ	6.173	5.431	3.832
	(0.023)	(0.022)	(0.017)
τ	-3.430	-3.054	-1.981
	(0.028)	(0.025)	(0.021)
δ	0.055	0.048	0.009
	(0.002)	(0.002)	(0.002)
β	0.015	0.013	0.027
	(0.001)	(0.001)	(0.002)
α	0.707	0.829	0.998
	(0.013)	(0.013)	(0.015)
N	7,103	8,329	6,743

[B] Labor market targets

	College cohort 1960-1974	College cohort 1975-1989	College cohort 1990-2004
1. College-to-school workforce ratio, ξ			
model	0.224	0.328	0.483
	(0.007)	(0.009)	(0.013)
data	0.224	0.328	0.483
	(0.007)	(0.009)	(0.014)
2. College-to-school earnings ratio, r			
model	1.737	1.617	1.546
	(0.008)	(0.006)	(0.007)
data	1.736	1.617	1.545
	(n/a)	(n/a)	(n/a)

[C] Intelligence targets

	College cohort 1960-1974	College cohort 1975-1989	College cohort 1990-2004
3. Graduates' IQ, $\mathbb{E}(\Theta\|K = 1)$			
model	110.2	109.2	108.2
	(0.4)	(0.4)	(0.4)
data	110.3	109.0	108.2
	(0.4)	(0.3)	(0.3)
4. Non-graduates' IQ, $\mathbb{E}(\Theta\|K = 0)$			
model	97.7	97.0	96.0
	(0.2)	(0.2)	(0.3)
data	97.7	97.0	96.0
	(0.2)	(0.2)	(0.)

[D] Disadvantage targets

	College cohort 1960-1974	College cohort 1975-1989	College cohort 1990-2004
5. Graduates' disadvantage, $\mathbb{E}(H\|K = 1)$			
model	3.87	3.58	3.24
	(0.03)	(0.03)	(0.03)
data	3.86	3.58	3.23
	(0.03)	(0.03)	(0.03)
6. Non-graduates' disadvantage, $\mathbb{E}(H\|K = 0)$			
model	4.32	4.03	3.89
	(0.02)	(0.02)	(0.02)
data	4.32	4.02	3.90
	(0.02)	(0.02)	(0.02)

Notes: The table reports the mean and standard deviation of minimum-distance (MD) estimates of model parameters over 10,000 bootstrap samples, setting $\rho = 0.4$, and of model-predicted vs empirical values of the six targets. The MD criterion function is given by equation (32), and the weighting matrix is the identity matrix. The Online Appendix to Section 5.1 provides more computational details. The intelligence score is expressed in IQ units in the table but in hundreds IQ units in the estimation, so as to reduce the order of magnitude of the estimated γ and τ. A college cohort is defined by the period of actual of potential college attendance, which is an individual's age plus 20. Cross-sectional response weights are applied. Sample: USoc, 22,175 white respondents born in the UK in 1940-1984 with non-missing education and intelligence information (see Table 1).

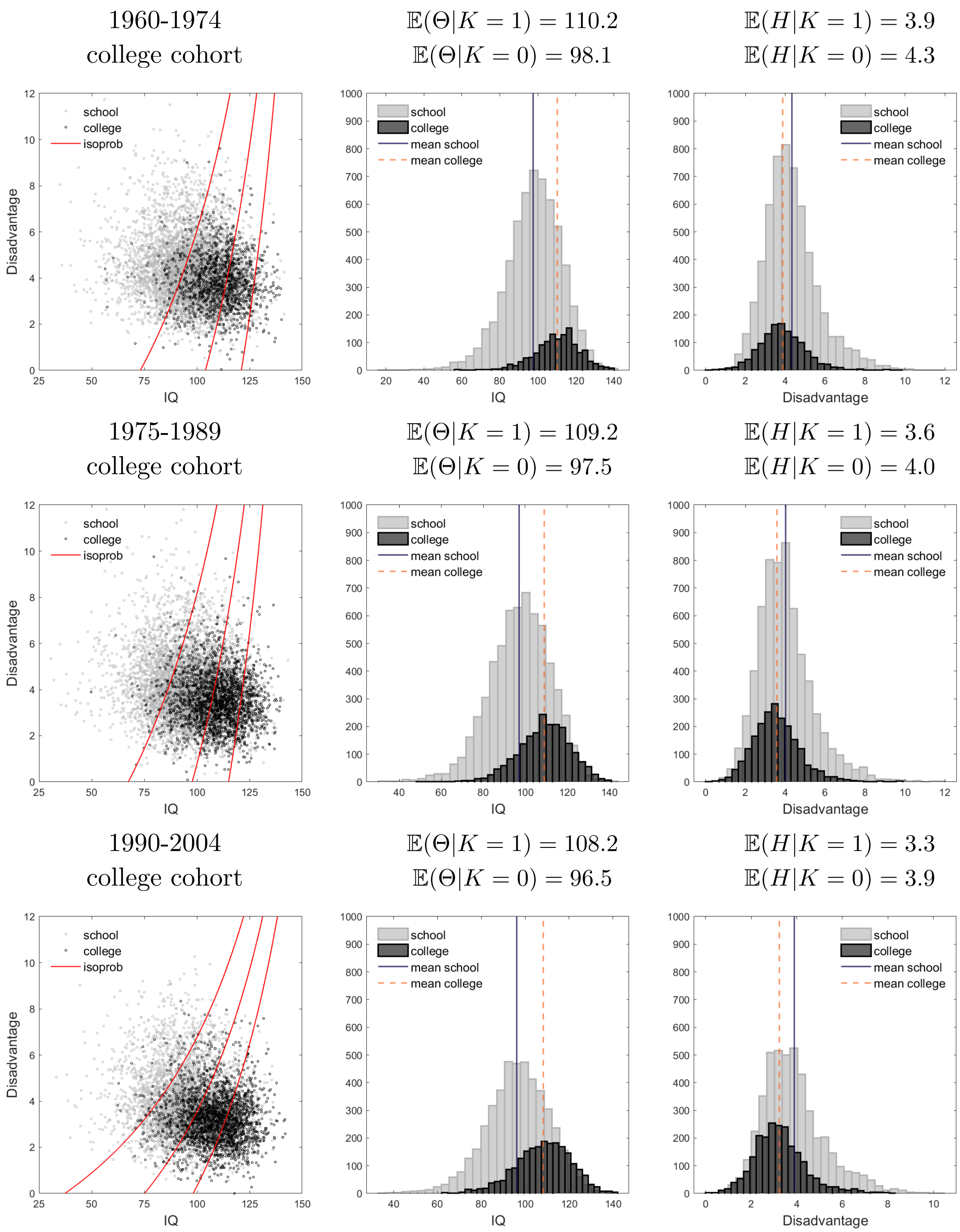
bins (1963) Report. For the first task, we use the estimates in Table 5 to construct empirical isoprobability curves to be superimposed to the empirical joint distribution of intelligence and disadvantage illustrated in Figure 7. The result is shown in Figure 8, which also reports the empirical conditional distributions of IQ and disadvantage in the three college cohorts. The isoprobability curves represented in the fgure are those associated with probabilities of graduating from college equal to 0.1, 0.3, and 0.5.

Moving from the 1960–1974 (top row) to the 1990–2004 (bottom row) college cohorts, we observe a clockwise rotation of the isoprobability curves, which results from a higher vertical intercept $-\frac{\Delta \ln w(G)}{\beta}\left(\pi + \frac{\delta}{\Delta \ln w(G)}\right)$ and a reduced slope $\frac{\gamma \Delta \ln w(G)}{(\gamma+\tau\theta)^2 \beta}$. This change becomes particularly evident in the comparison between the 1975–1989 and the 1990–2004 cohorts. Considering the estimates in panel [A] of Table 5, the main drivers of the increase in the intercept are the decline of δ and the increase of β in the effort cost shift $\Omega(\eta)$. The ensuing increase in the number of graduates reduced the wage ratio $\Delta \ln w(G)$, which further contributes to increasing the intercept. As for the slope, its decline is the result of the reduced wage gap in the numerator and the larger β in the denominator that were not compensated by a sufficiently large decline of τ in the effort cost shift $\Gamma(\theta)$. Actually, the slope τ of this shift increased towards zero during the period that we consider, particularly between the last two cohorts, which contributes to flattening out isoprobability curves.

Therefore, we conclude that the UK higher education policy that followed the Robbins Report was characterized by a weak meritocratic content and by a "regressive" component for the more recent cohort. As is evident in the scatter plots of Figure 8, this policy brought into college a large number of less disadvantaged and less intelligent students (i.e., individuals with low η and low θ). The more disadvantaged and more intelligent students in the northeastern portion of the scatter plot, actually ended up with *reduced* opportunities to access higher education.

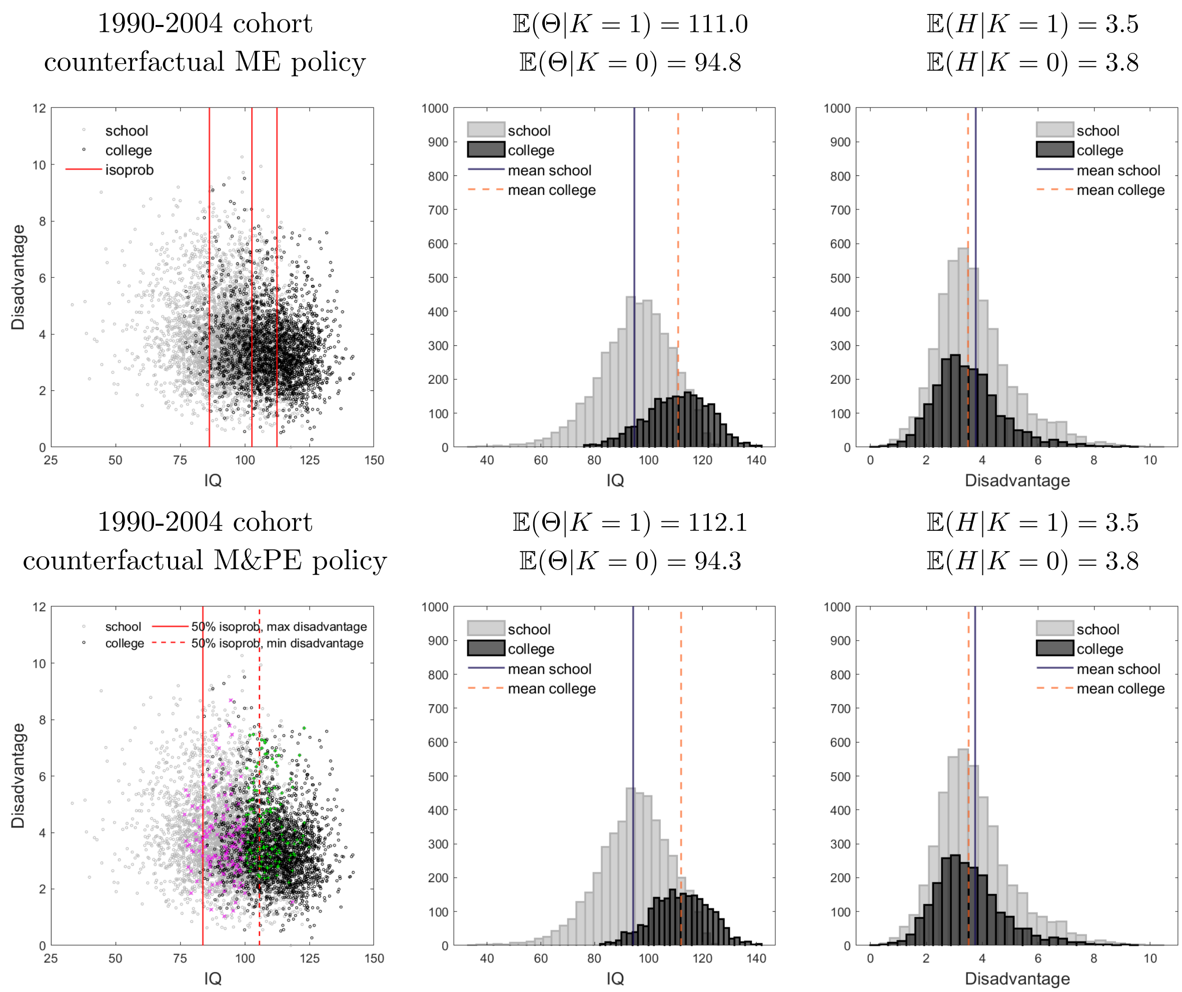
Policies with a strong meritocratic component, instead, could have reached the "reserves of untapped ability [...] in the poorer sections of the community" (p. 53) that were a central concern in the Robbins Report. This claim is illustrated by two counterfactual policy experiments presented in Figure 9. This figure shows what would have happened in the UK at the end of our period of observation (i.e., the 1990-2004 college cohort) if the government had adopted two policies that would have achieved the observed graduate-to-school workforce ratio of $\xi = 0.48$ in a more meritocratic way than in the bottom row of Figure 8.

Figure 8: Status quo in the UK and effects of actual expansion policies



Notes: The figure displays the empirical counterpart of the scatter plots and histograms in Figure 2, for the three USoc college cohorts. In the scatter plots, each point is an individual in our sample. The continuous lines are the 10%, 30%, and 50% isoprobability lines (see equation 19). Sample: USoc, 22,175 white respondents born in the UK in 1940-1984 with non-missing education and intelligence information (see Table 1).

Figure 9: Effects of two counterfactual expansion policies in the UK



Notes: The figure displays the effects on the USoc college cohort 1990-2004 of two counterfactual expansion policies that would have achieved the observed graduate-to-school workforce ratio $\xi = 0.48$. First (top row), a strongly Meritocratic Expansion (ME) policy that – relative to the 1960-1974 status quo – decreases τ to -4.1 and β to 10^{-6}, adjusting γ and δ to values of 6.15 and 0.1, respectively. This policy turns isoprobability curves into essentially vertical lines. Second (bottom row), a ME policy with a Progressive Expansion (PE) component that, relative to the ME policy in the top row, sets δ to 0.123 for students whose intelligence is below average and to to $0.123 - 0.12\eta$ for the above-average ones. This policy makes isoprobability curves individual-specific, shifting them to the left for more disadvantaged students. Students marked with a "×" graduate from college under the counterfactual ME policy but not under the counterfactual M&PE policy; for students marked with a "+" the opposite happens. The policy that was actually implemented is represented in the bottom panel of Figure 8. In the scatter plots, each point is an individual in the 1990-2004 college cohort in our sample, and the lines are the 10%, 30%, and 50% isoprobability lines (see equation 19) for the top row, and the 50% isoprobability lines of the most disadvantaged (continuous) and least disadvantaged (dashed) students in the sample for the bottom row. Sample: USoc, 22,175 white respondents born in the UK in 1940-1984 with non-missing education and intelligence information (see Table 1).

The first policy experiment (top row of Figure 9) is the strongly ME policy described in the bottom row of Figure 2, which would have reduced τ towards larger, negative values and reduced β to essentially zero. The result is that isoprobability curves would have become nearly vertical. Relative to the observed status quo (1960-1974 college cohort, top row of Figure 8), the average intelligence of college graduates would have *increased* by about one point, instead of decreasing by two points. Their average disadvantage would have been still lower than in the 1960s – which partly reflects the declining average disadvantage of the British population during this period depicted in the right panel of Figure 5 – but higher than the actual average in the 1990s. Therefore, this counterfactual strongly ME policy would have brought into college more high-talent disadvantaged students and fewer low-talent advantaged ones than the policy that was actually implemented.[33]

The second policy experiment (bottom row of Figure 9) is a variant of this counterfactual strongly ME policy that reduces parameter δ in proportion to a student's disadvantage, provided that the student is above average in terms of intelligence. This policy, which we label meritocratic *and* progressive expansion (M&PE) policy results in individual-specific isoprobability curves that shift leftward as disadvantage increases, as indicated by the two 50% isoprobability lines represented in the figure and associated with the least (dashed line) and most (continuous line) disadvantaged students, respectively, in our sample. In the figure, we mark with a "$\times$" students who would have graduated from college under the counterfactual ME policy but not under the counterfactual M&PE policy, and with a "+" those students for whom the opposite holds. Clearly, this M&PE policy raises enrollment and graduation barriers for low-intelligence, more advantaged students while correspondingly lowering such barriers for high-intelligent, more disadvantaged ones, on average.[34] An example of such a policy is an increase in tuition fees combined with scholarships for sufficiently high-intelligent students and whose amount increases with a student's disadvantage.

Relative to the counterfactual ME policy, the M&PE policy selects into college students whose average intelligence is one point higher (four points above the actual average for the 1990-2004 college cohort, and two points above the 1960-1974 cohort level) and whose average disadvantage is also (marginally) higher. This is the outcome that was envisioned by Robbins (1963), which is the exact opposite of what happened in the UK since the 1960s.

[33] Note that this counterfactual meritocratic expansion of tertiary education would have been more effective if complemented by secondary education policies aimed at improving the attainment of talented teenagers from disadvantaged families. As pointed out by Chowdry et al. (2013), "poor achievement in secondary schools is more important in explaining lower [Tertiary Education] participation rates among pupils from low socio-economic backgrounds than barriers arising at the point of entry to [Tertiary Education]" (p. 431).

[34] The 133 "$\times$" students in the bottom row of Figure 9 have an average intelligence of 90.5 and an average disadvantage of 3.8, while the 125 "+" students in the bottom row of Figure 9 have an average intelligence of 109.2 and an average disadvantage of 4.3. The size of the two groups is different due to the stochastic nature of the model.

5.4 Welfare implications of alternative expansion policies

Although we do not engage here in a comprehensive social welfare analysis, we show that, under three assumptions and relative to the policy that was actually implemented, in our model there is no welfare loss from adopting the counterfactual ME policy, and a welfare gain from adopting the counterfactual M&PE policy. The reason is that both counterfactual policies select into college a larger fraction of intelligent and disadvantaged students, which in the model has contrasting effects on welfare: higher intelligence reduces the cost of each unit of study effort, higher disadvantaged increases it, and total study effort changes. While in the ME policy that we simulate these forces compensate each other and so welfare remains approximately constant, in the counterfactual M&PE policy the negative effect of higher intelligence on study effort cost dominates and so welfare increases.

The three assumptions are that, following a higher education policy change, (i) total output does not change; (ii) income distribution does not change; and that (iii) the cost of alternative higher education policies is the same for a given variation in the number of graduates. Assumptions (i) and (ii) hold in our model because output and the income distribution depend only on the fraction of graduates and not on the distribution of intelligence and disadvantage conditional on educational attainment, $\mu(\theta, \eta|K)$. Assumption (iii) can be regarded as an approximation to reality in a setting in which we do not model explicitly the government sector; it implies that the aggregate consumption cost of a given expansion $\Delta\xi$ (such as from 0.22 in 1960-1974 to 0.48 in 1990-2004) is approximately invariant to the type of higher education policy that implements it.

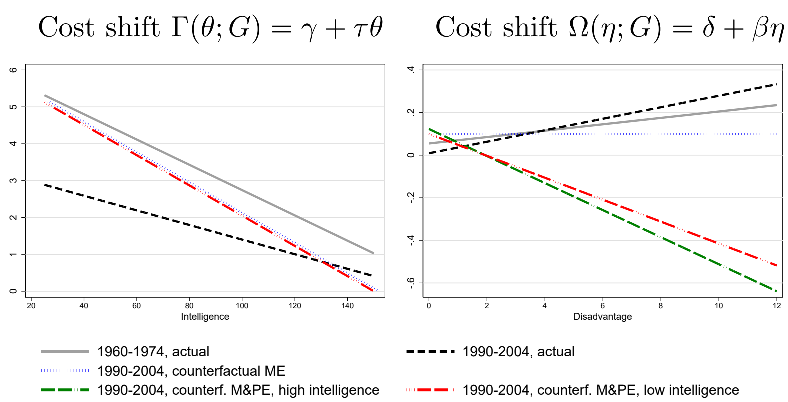
Under these assumptions, we can separate the expansion process in two stages, conceptually: first, increase the number of available places in higher education; second, choose how to allocate those places. Then the aggregate utility cost of study effort in equilibrium is a welfare measure for the purposes of comparing alternative higher education policies $G = (\gamma, \tau, \delta, \beta)$ at this second stage:

$$\mathcal{W}(G) = \int_{\mathbf{\Theta}\times\mathbf{H}} \Omega(\eta|G) \ln(1 - \Gamma(\theta|G)s^*(\cdot|G))d\mu(\theta, \eta). \tag{33}$$

The conditioning on G on the RHS of (33) is meant to clarify that different policies have different welfare properties because they induce different study effort cost shifts $\Gamma(\cdot)$ and $\Omega(\cdot)$ and, as a consequence, different study efforts s^* in equilibrium.

Figure 10 shows how $\Gamma(\cdot)$ and $\Omega(\cdot)$ vary across the 1960-1974 status quo, the actual policy implemented in 1990-2004 and the two counterfactual ME and M&PE policies. In either panel, the actual policy change is described by the shift from the continuous line to the short-dashed line. In the left panel, the shift of $\Gamma(\cdot)$ implies a reduction of effort cost that is larger at lower levels of intelligence. In the right panel, the shift of $\Omega(\cdot)$ implies a reduction of effort cost for more advantaged students and an increase for disadvantaged ones. Thus, the actual policy favored primarily low-intelligence children from advantaged families. This policy is associated with an aggregate utility cost of study effort $\mathcal{W}(G_{\text{actual}}) = -0.0792$, which we normalize to 100 for the comparison that follows.

Figure 10: Actual and counterfactual study effort cost shifts



Notes: The figure shows the different study effort cost shifts $\Gamma(\cdot)$ and $\Omega(\cdot)$ implied by different actual (for the 1960-1974 or 1990-2004 college cohorts) or counterfactual (for the 1990-2004 college cohorts) higher education policies, as a function of intelligence (left panel) or disadvantage (right panel). The shifts implied by the actual policies are computed using the estimated policy parameters. The shifts implied by the two counterfactual strongly meritocratic expansion (ME) and meritocratic&progressive expansion (M&PE) policies are computed using the policy parameters underlying the experiments illustrated in Figure 9.

The counterfactual ME policy is described in either panel by the shift from the continuous line to the dotted line. In the left panel, the shift of $\Gamma(\cdot)$ implies a cost reduction that is more pronounced for more intelligent students. In the right panel, $\Omega(\cdot)$ becomes flat because the ME policy makes effort cost independent of disadvantage. The resulting aggregate utility cost of effort is $\mathcal{W}(G_{\text{ME}}) = -0.0790$, or 100.3 on the normalized scale, and therefore equivalent to the cost of the actual policy, but with a larger fraction of intelligent and disadvantaged students obtaining a college degree.

Finally, the counterfactual M&PE policy is described in either panel by the shift from the continuous line to the dashed-dotted lines. On the left, the meritocratic component is the same as in the ME policy and so the M&PE dashed-dotted line coincides with the ME dotted line. The progressive component is evident in the right panel, where the slope of $\Omega(\cdot)$ becomes negative (indicating that the policy turns disadvantage into an advantage) and higher in absolute value for the more intelligent students (four-dashes-dots line versus two-dashes-dot line). The net result for welfare is $\mathcal{W}(G_{\text{M\&PE}}) = -0.0709$, or 111.7 on the normalized scale, making the M&PE policy welfare-maximizing and most egalitarian among the actual and the counterfactual policies that we consider.

6 Conclusions

We have introduced into the analysis of higher education policy the systematic consideration of the intelligence of individuals (g factor), in addition to more conventional measures of disadvantage. The notion of intelligence as a scarce resource to be allocated across different levels of education was an important consideration in the rich analysis that led to the Robbins (1963) Report. Such consideration and analysis are conspicuously absent in the current debate, and notably in the statement of the European Union's goal for 2030 (Council of the EU, 2021). In this document, the target of 45% of 25-34 year-olds with tertiary educational attainment is set with no mention of any cognitive skill which might be desirable for these individuals. Ignoring the role of intelligence in higher education may be a laudable criterion inspired by equity considerations, but it will not alter the importance of students' ability at the university level. Most important, it ignores that considerations of intelligence and equity can be fully reconciled by considering appropriate policy options. This is a key message that emerges from our analysis.

Our framework is based on a stochastic general equilibrium Roy model where two traits, intelligence and disadvantage from socioeconomic and psychological factors, determine the probability of success in acquiring tertiary education. A general equilibrium approach is essential, because the unintended consequences of policies on the equilibrium outcome may differ substantially from the intended ones. The latter are usually conceived and evaluated from the point of view of the partial equilibrium analysis of how students' choices would be affected by the education policy, keeping important variables fixed at current values. As we have seen, when doing so the errors in evaluations of the consequences may be serious.

A crucial conclusion of our analysis is that the effects of higher education policy on the allocation of ability and on the socioeconomic characteristics of students depend on the sign of the correlation between intelligence and disadvantage in a population. Although there is no consensus on the mechanisms producing such association, it is reasonable to conjecture that heritability of factors producing economic success or higher-quality nurture from advantaged parents are likely to produce a negative rather than a positive correlation. We have shown that when the sign is negative, policies that expand university access tend to reduce the level of intelligence in the college population while not improving the chances of less advantaged students, unless some kind of strongly meritocratic expansion policy is adopted.

To be clear, this conclusion does not imply that university admission should be made even more dependent on test scores at the end of high school (e.g., A-level grades in the UK). Indeed, whether a student has obtained these qualifications and how high he or she scored may reflect selection based on family's socioeconomic status occurring earlier in life. This is precisely why we have defined the "no college" group broadly to include any student without a college degree, not only those who left education at the end of high-school. It follows that secondary education policies aimed at improving the attainment of talented teenagers from disadvantaged families should support a meritocratic expansion of university. This is also why our analysis emphasizes the role of intelligence. We think about a meritocratic policy in terms of low-variance (e.g., repeated over time) and g-loaded intelligence measures (like the ones constructed in this study and based on Usoc and UKB) that reflect students' talent independently of their socioeconomic advantage or disadvantage. A detailed discussion of such measures is beyond the scope of this paper (and should be left to experts), but our evidence clearly indicates that this is the way to go if one wishes to increase the number of graduates and their quality while also providing equality of opportunities.

Is this also the case for European and other advanced countries that are planning to further expand university access? If yes, then the key lesson conveyed by the UK experience is that an appropriate meritocratic expansion is *the* policy that combines graduate workforce quality with more opportunities for the disadvantaged.

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College education, intelligence, and disadvantage: policy lessons from the UK in 1960-2004

Online Appendix

(Not meant to be part of the journal publication)

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October 9, 2022

Appendix to Section 2.3

Proof of Lemma 1

Proof. For given technological skill ratio α and equilibrium graduate-to-school labor ratio $\xi(r)$, we obtain from equation (9) that

$$\xi(r) = \left(\frac{\alpha}{r}\right)^{\frac{1}{1-\rho}}, \tag{A-1}$$

and we obtain from the aggregate constraint on labor supply that

$$x(1,r) = \frac{\xi(r)}{1+\xi(r)}; \quad x(0,r) = \frac{1}{1+\xi(r)}. \tag{A-2}$$

Replacing (A-2) into (9) and using (A-1) yields the skilled and unskilled wages as functions of r, at the demand of the firm. In particular:

$$w(0,r) = Aa(0)^{\frac{1}{\rho}} \left(1 + \alpha^{\frac{1}{1-\rho}} r^{\frac{\rho}{\rho-1}}\right)^{\frac{1-\rho}{\rho}}. \tag{A-3}$$

We can replace equation (A-3) into (3) to express the difference in utility of consumption between a graduate and a non-graduate worker as

$$\Delta U(\mathbf{w}) = w(0,r)^{1-\sigma_c} \left(\frac{r^{1-\sigma_c} - 1}{1-\sigma_c}\right). \tag{A-4}$$

Using equations (A-1) and (A-2), we see that the demand for skilled labor is a decreasing function of r. If we consider the supply of skilled labor, it is clear from equation (5) that effort, and thus supply of skilled labor, is increasing in ΔU, for every pair of individuals characteristics (θ, η), and any value of σ_s. We can consider ΔU as a function of r, using the expression in (A-4), so that the supply of skilled labor is in turn a function of r, written as $\Delta U(r)$. When $\sigma_c = 1$ it is immediate that $\Delta U(r) = \ln r$, increasing in r. Thus the equilibrium exists and is unique in this case. ■

Appendix to Section 2.6

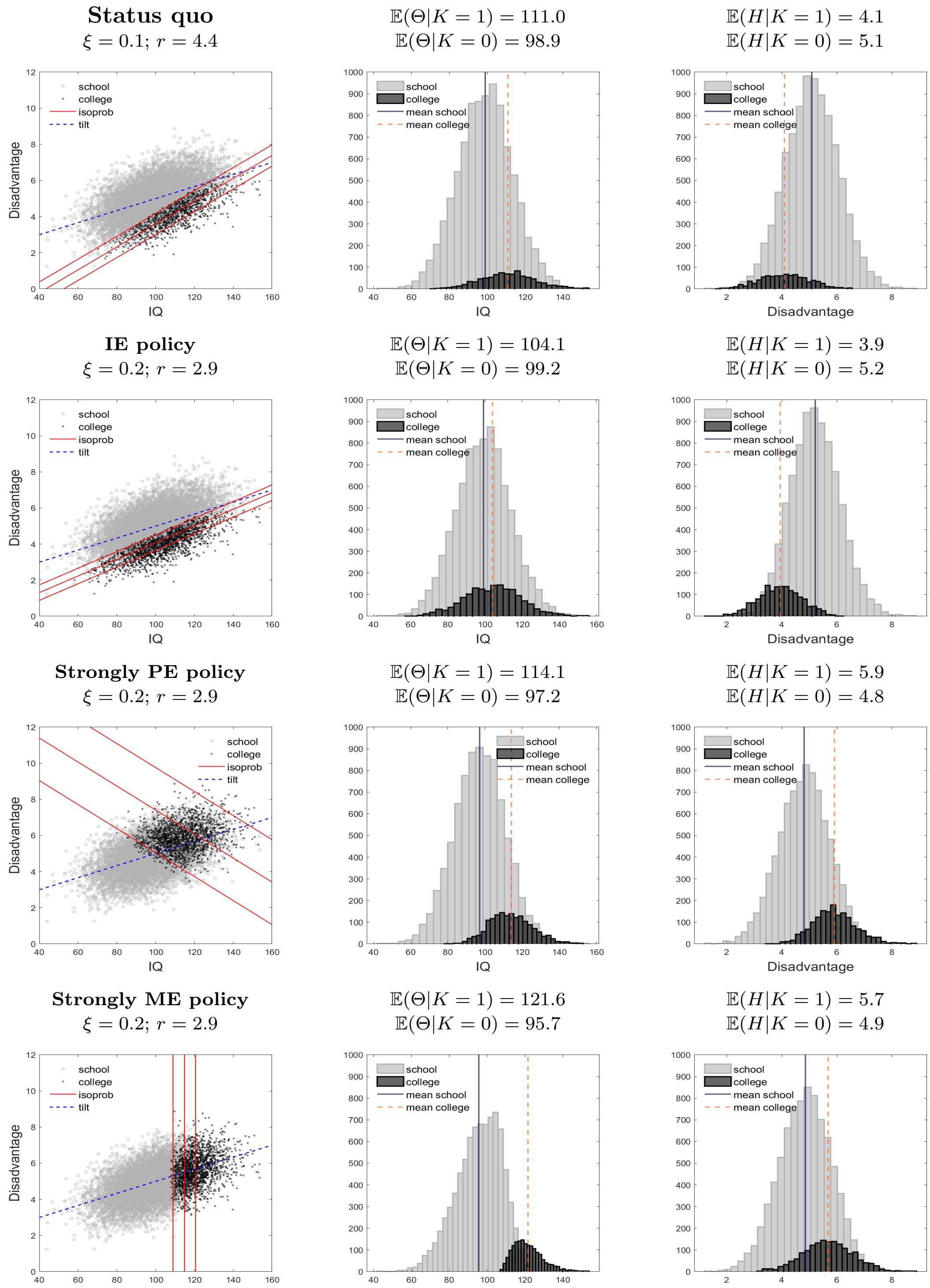
Figure A-1 describes a third type of society, characterized by $\lambda > 0$ (like in Society 1 and different from Society 2) and $\psi(\cdot, G) > 0$ (like in Society 2 and different from Society 1), and the effects that the policies characterized by Definition 2 in the main text would have in this society. In contrast to Society 1 described in Section 2.6 of the paper, the average intelligence of the population in college is now higher than outside college. There are still intelligent students from disadvantaged families who are outside college, but fewer than in Society 1. This fact can be appreciated by drawing in each status-quo scatter plot (first row of the figure) horizontal and vertical lines at, say, $H = 8$ and $\Theta = 120$, and noting how many observations fall in the resulting northeastern quadrants. Thus there is reachable ability also in this third society but, again, less than in Society 1. This third is type society is meant to illustrate precisely this fact, i.e., that a positive correlation λ between intelligence Θ and disadvantage H is necessary but not sufficient for large "reserves of untapped ability [...] in the poorer sections of the community" (Robbins, 1963).

As the figure illustrates, in this third society the indiscriminate expansion (IE) policy, implemented by decreasing the intercept δ in effort cost shift $\Omega(H) = \delta + \beta H$ (Eq. 17) as described in second row of the figure, reduces the mean intelligence of graduates while not affecting their average social background much. As for Society 1, the reason is the equilibrium response of the wage ratio, which drops from $r = 4.4$ to $r = 2.9$, with a flattening effects on the isoprobability lines.

The progressive expansion (PE) policy turns a disadvantaged socioeconomic and psychological background into an advantage in college access by inverting the sign of slope β in effort cost shift $\Omega(H) = \delta + \beta H$ (i.e., the isoprobability lines become negatively sloped as described in the third row of the figure). Like in Society 1 or 2, this policy induces a large increase in the incidence of graduates with a disadvantaged background also in this third society. However, in this case the effect on their average intelligence is not as large as in Society 1 although it remains positive.

Finally, the effect of the strongly meritocratic expansion (ME) policy mix, illustrated in the bottom row of the figure, changes the policy parameters in effort cost shifts $\Omega(H) = \delta + \beta H$ (Eq. 17) and in effort cost shift $\Gamma(\Theta) = \gamma + \tau\Theta$ (Eq. 18) so that the isoprobability lines become vertical. In this case, only students whose intelligence is above a certain threshold experience an increase in graduation probability. Like in Society 1 or 2, this strongly ME raises the incidence of high-intelligence *and* high-disadvantage individuals also in this third society.

Figure A-1: Status quo in Society 3 ($\lambda > 0, \psi > 0$) and effects of three expansion policies: Indiscriminate Expansion (IE), Progressive Expansion (PE), Meritocratic Expansion (ME).



Notes: The scatter-plots in the left column illustrate the joint distribution of intelligence and disadvantage for school and college graduates at equilibrium. The continuous straight lines are the isoprobability curves at values 90%, 50% and 10%, at equilibrium. The dashed lines describe values satisfying equation (20). The histograms in the middle and right columns of panels illustrate the associated marginal distributions. The data consist of a simulated population of 10,000 individuals with type (θ, η) drawn from a jointly normal distribution ($m_\Theta = 100$; $\sigma_\Theta = 15$; $m_H = 5$; $\sigma_H = 1$; $\text{corr}(\Theta, E) = \lambda = 0.5$). In the first row (status quo), the policy parameters are set to generate $\xi = 0.1$: $\gamma = 23.3$, $\tau = 0$ (so isoprobability curves are straight lines), $\delta = 2$, $\beta = 1$. The technology parameters are $\alpha = 1.1$ and $\rho = 0.4$. For each policy experiment in the other rows, the parameters are set so as to double the college-to-school labor ratio. The wage ratio adjusts to equilibrium. IE policy: $\delta = 0$. Strongly PE policy: $\beta = -0.18$, $\gamma = 88.5$. Strongly ME policy: $\tau = -8$, $\beta = 10^{-6}$, $\gamma = 30.1$, $\delta = 5.3$.

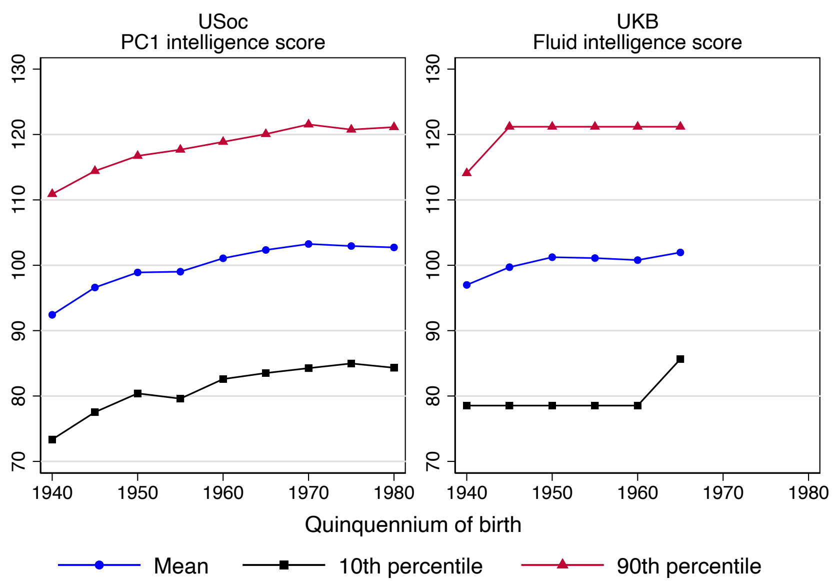
Appendix to Section 3.3

Table A-1: Eigenvector of the PCA of cognitive ability measures in USoc

Immediate word recall	0.457	Help in immediate word recall	–0.011
Delayed word recall	0.449	Help in delayed word recall	0.004
Correct subtractions	0.318	Help in substractions test	–0.050
Number series	0.413	Help in number series test	–0.034
Verbal ability	0.365	Help in verbal ability test	–0.015
Numeric ability	0.423	Help in numeric ability test	–0.004
		Material aid in recall test	0.011
		Material aid in subtraction test	–0.040

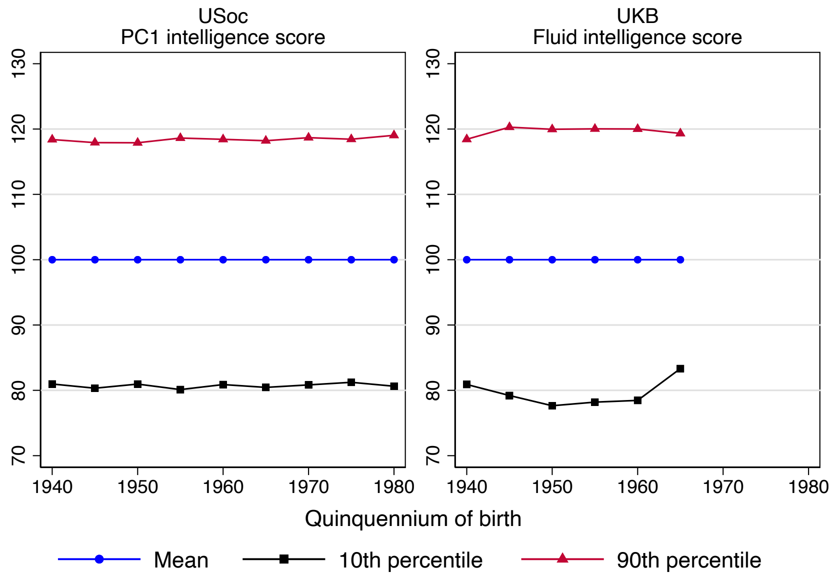
Notes: The table reports the eigenvector of the Principal Components Analysis of the 14 cognitive ability measures contained in Usoc. The First Principal Components (FPC), which we label IQ, is the measure of intelligence that we use in our analysis. It has an eigenvalue of 2.55 and explains 18.2% of the data variability. The left panel of the table displays the positive values of the eigenvector terms for the fractions of correct answers in the 6 cognitive questions. The right panel, shows instead that the eigenvector values are negative for 6 out of 8 help dummies. For the the two remaining help dummies the values are positive but close to zero.

Figure A-2: Evolution of intelligence scores standardized over all birth years



Notes: The left panel of the figure displays the mean, the 10th and the 90th percentiles of the average intelligence score standardized over all birth years in our USoc sample of 22,175 white respondents born in the UK between 1940 and 1984, with non-missing education and intelligence score (see Table 1). The right panel displays the same statistics for the Average intelligence score (FIS) in our UKB sample of 212,659 white respondents born in the UK between 1940 and 1969, with non-missing education and intelligence score (see Table 2).

Figure A-3: Evolution of intelligence scores standardized in each birth year



Notes: The left panel of the figure displays the mean, the 10th and the 90th percentiles of the average intelligence score (IQ) standardized within each birth year in our USoc sample of 22,175 white respondents born in the UK between 1940 and 1984, with non-missing education and intelligence score (see Table 1). The right panel displays the same statistics for the Average intelligence score (FIS) in our UKB sample of 212,659 white respondents born in the UK between 1940 and 1969, with non-missing education and intelligence score (see Table 2).

Appendix to Section 3.4

Table A-2: Eigenvector of the PCA of socioeconomic factors generating advantage in college enrollment and graduation in USoc

Father education	0.277
Mother education	0.290
Mother work	0.191
Mother dead	–0.125
Mother absent	–0.224
Father work	0.617
Father dead	–0.416
Father absent	–0.428

Notes: The table reports the eigenvector of the Principal Components Analysis of the 8 socioeconomic background variables in Usoc (referring retrospectively to when the respondent was 14 years of age) on which we base our measure of socioeconomic disadvantage. The First Principal Component (FPC) has an eigenvalue of 1.76 and explains 22% of the data variability. The table displays negative values for the variables that, as expected, reduce the FPC and increase disadvantage: whether either parent was dead or absent when the respondent was 14 years of age.

Table A-3: Eigenvector of the PCA of personality factors generating advantage in college enrollment and graduation in USoc

Big 5: Agreableness	0.432
Big 5: Consciensciousness	0.500
Big 5: Extroversion	0.489
Big 5: Neuroticism	–0.352
Big 5: Openness	0.449

Notes: The table reports the eigenvector of the Principal Components Analysis of the Big 5 variables in Usoc on which we base our measure of personality disadvantage. The First Principal Component (FPC) has an eigenvalue of 1.75 and explains 35% of the data variability. The table displays negative values for the variable that, as expected, reduce the FPC and increase disadvantage: neuroticism.

Table A-4: Correlation matrix between intelligence, socioeconomic disadvantage, and personality disadvantage measures in USoc

	Intelligence	Socioeconomic disadvantage	Personality disadvantage
Intelligence	1		
Socioeconomic disadvantage	−0.154	1	
Personality disadvantage	−0.073	0.035	1

Notes: The table reports the eigenvector of the Principal Components Analysis of the Big 5 variables in Usoc on which we base our measure of personality disadvantage. The First Principal Component (FPC) has an eigenvalue of 1.75 and explains 35% of the data variability. The table displays negative values for the variable that, as expected, reduce the FPC and increase disadvantage: neuroticism.

Table A-5: Eigenvector of the PCA of pooled socioeconomic and personality factors generating advantage in college enrollment and graduation in USoc

Big 5: Agreableness	0.249	Mother work	0.176
Big 5: Consciensciousness	0.315	Mother dead	–0.087
Big 5: Extroversion	0.320	Mother absent	–0.179
Big 5: Neuroticism	–0.216	Father work	0.424
Big 5: Openness	0.367	Father dead	–0.280
Father education	0.258	Father absent	–0.293
Mother education	0.272		

Notes: The table reports the eigenvector of the Principal Components Analysis of the 13 pooled socioeconomic background (referring retrospectively to when the respondent was 14 years of age) and personality variables in Usoc on which we base our measure of disadvantage (variable H in the theoretical model). The First Principal Component (FPC) has an eigenvalue of 1.82 and explains 12.6% of the data variability. The table displays negative values for the variables that, as expected, reduce the FPC and increase disadvantage: whether either parent was dead or absent when the respondent was 14 years of age.

Appendix to Section 4.1

We provide here some evidence on how the UK expansion policy was enacted, using data from the University Statistical Record (USR). This source provides administrative information on the universe of students enrolled at UK universities between 1972 and 1993. USR was initiated following the Robbins Report, which had stressed the need for better data for the proper design of higher education policies. It was subsequently discontinued and replaced by the Higher Education Statistics Agency (HESA) in 1993. Unfortunately, pre-1993 USR information was not merged into HESA.

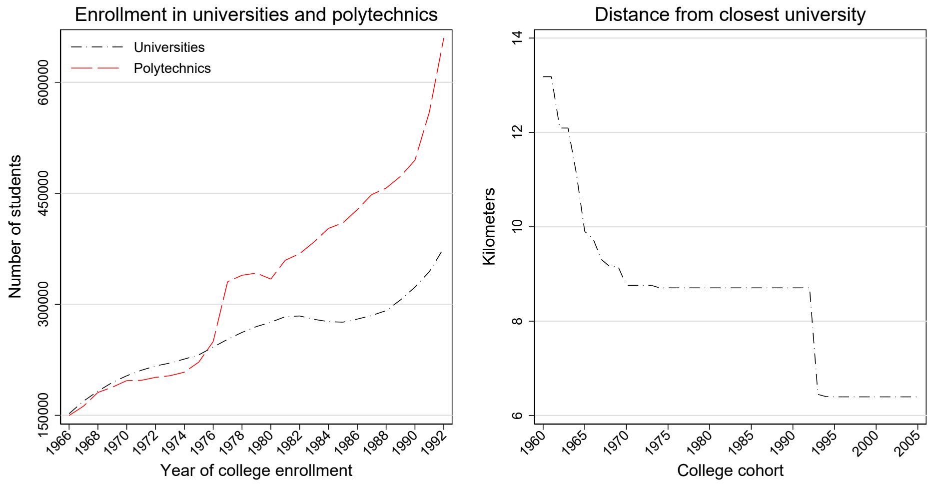
Out of the initial 8,103,977 person/year records of students enrolled in a UK higher education institution in this period, we keep the 6,889,425 records of white individuals born in the UK, so as to match the final USoc and UKB samples. These records correspond, after some minor data cleaning, to 1,523,192 students born between 1948 and 1976. USR provides us with information about the evolution of higher education enrollment and entry criteria (e.g., A-level scores), which we use to characterize the UK expansion. The latter was not just a consequence of the creation and expansion of Polytechnics.[A-1] The left panel of Figure A-4 plots data from Table 3.3 and Figure 3.2 in Pratt (1997), which show that the stock of students enrolled in universities more than doubled (from 152,227 to 376,074) between 1966 and 1992. This increase is smaller than for Polytechnics (where numbers more than quadrupled in the same period, from 149,720 to 659,790), but is still substantial. While the growth of Polytechnics is an obvious consequence of an explicit expansion policy, the increase in the number of students enrolled in traditional universities is the result of more subtle policy changes.

A first piece of evidence is provided in the right panel of Figure A-4, which shows that the cost of accessing a university was reduced by increasing the number of academic institutions and bringing their departments closer to potential students.[A-2] In the USoc sample, the *average* distance from the closest university dropped by about 6km between 1960 and 2005. It is plausible that the goal of this expansion was to reduce enrollment costs. In this period most of these institutions did not impose tuition fees, and so mobility costs were an important component of the total cost of attaining a college degree. As summarized by Willet (2017), the 1962 Education Act introduced tuition and maintenance grants for all UK students, which in the 1980s were tied to family income in order to provide stronger support for more

[A-1] According to Pratt (1997), about thirty institutions of this kind were created between 1966 and 1973. In 1988, the Education Reform Act reduced funding per student granted to Polytechnics, inducing them to expand students' enrolment in order to keep constant the total amount of available resources.

[A-2] According to Blundell et al. (2022), more than twenty new universities were created in the 1960s. See also the evidence in Blackburn and Jarman (1993).

Figure A-4: Higher education enrollment and distance to the closest college



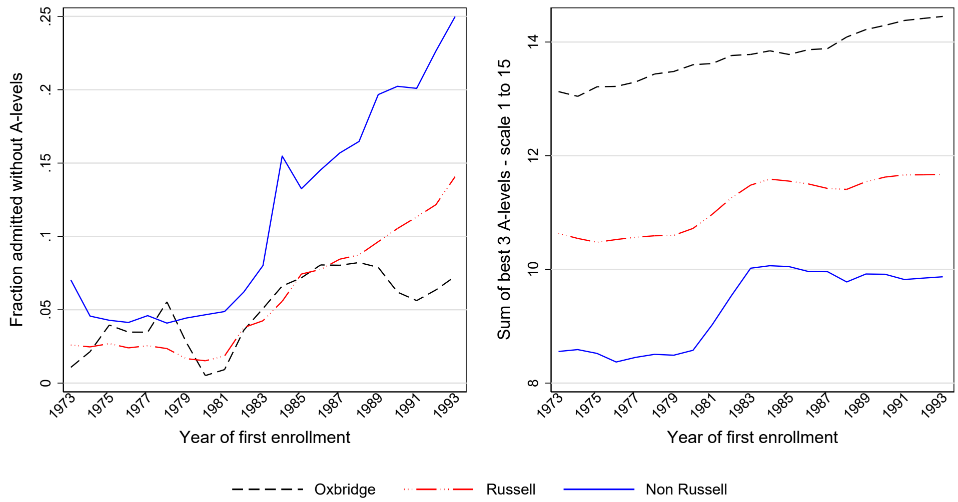
Notes: The left panel uses the data in Table 3.3, page 29, of Pratt (1997) to reproduce a modified version of Figure 3.2, page 31, of the same book. The modification is that we aggregate "Polytechnichs" and "Other colleges", which in Figure 3.2 of Pratt (1997) are displayed separately. For the right panel, we use a list of all Royal Charters granted in the UK ever since the 13th century (the list can be found at https://privycouncil.independent.gov.uk/royal-charters/list-of-charters-granted/), and we selected entries corresponding to universities and colleges. Each entry has a legal address, which we use as a location point to count the number of universities active over time in each area. For each year we then count, how many active universities were located in each county. If this step returns a positive number, we set the distance to zero; if it returns a zero, we compute the distance (in km) to the nearest university from the county boundary. For each year, the figure plots the average distance over counties from the closest university.

disadvantaged students. Only in 1998, with the Teaching and Higher Education Act, fees of 1,000 GBP per year were introduced. And only after the period that we study, with the 2004 Higher Education Act, fees raised to 3,000 GBP per year and then again to 9,000 GBP following the 2010 Independent Review of Higher Education Funding and Student Finance (the "Browne Review").

A second piece of evidence is that the criteria for admission to a university became less stringent. Using USR data, the left panel of Figure A-5 shows the fraction of students admitted without A-levels to three groups of UK universities: Oxbridge, the Russell group, and the remaining, less prestigious institutions. In all groups, the fraction of students admitted without A-levels increased between 1973 and 1993. The increase is particularly evident in the residual group, but it is visible also for the Russell group and even for Oxbridge. The USR documentation explains that this is an indicator of less demanding admission criteria because it refers to two main categories of students: those who had less than 3 A-Level scores (i.e., the regular mininum requirement for admission) and those admitted on the basis of HNC/HND/ONC/OND qualifications, which have a more vocational or technical nature.

The right panel reports instead the average sum of the best 3 A-Level scores for students admitted to the three groups during the period covered by USR data. As expected, in all years students admitted at Oxbridge have higher best A-level scores than students admitted

Figure A-5: Criteria for admission to a university



Notes: The left panel displays the fraction of students admitted without A-level scores to three groups of UK universities: Oxbridge, the Russell group, and remaining institutions. The right panel reports instead the average sum of the best 3 A-Level scores for students admitted to the three groups of universities during the period covered by USR data. Source: USR.

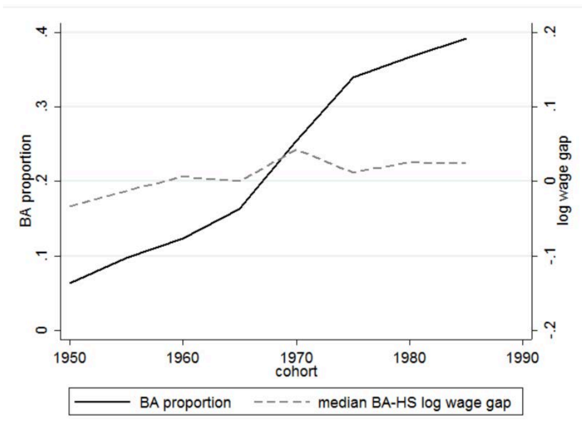
at the Russell group, which in turn dominate students in the remaining institutions. What is more striking is that in all the three groups this indicator increases significantly over the period of observation. This increase has two possible interpretations. First, there was grade inflation in high schools so as to facilitate college admission. Second, universities became more selective in admitting students or high school students improved over time their performance in A-Level exams. We are unable to establish which scenario is the correct one. However, the evidence in Figure 5 of the main text (that the average intelligence of graduates has declined over time) reduces the plausibility of the second explanation. If universities had become more selective, the average intelligence of graduates would have increased.

Another important policy change took place in 1988, when the GCSEs replaced the CSEs and O-Levels as the exams that UK students take at age 16. According to Blundell et al. (2022), this "reform led to an increase in educational attainment at the secondary level and hence an increase in the proportion of the young with sufficient academic credentials for potential admission to universities".

Appendix to Section 4.4

The evolution of the wage gap between college and high school graduates in the UK has been studied by Blanden and Machin (2004), O'Leary and Sloane (2005), Walker and Zhu (2008), Devereux and Fan (2011), Chowdry et al. (2013), and Blundell et al. (2022), among others. Our finding in Section 4.4 of a declining wage ratio between college graduates and less educated individuals over consecutive cohorts is apparently in contrast with the evidence of a weakly increasing gap reported in this literature, particularly by Blundell, Green, and Jin (2022) – BGJ, henceforth. In this appendix we show that the discrepancy is essentially due to the different definition of the comparison groups: college graduates vs high school graduates in BGJ, college graduates vs non-graduates in our paper.[A-3] We have explained in Section 3.2 the rationale of this choice in our analysis. In fact there is no contrast when we use BGJ's comparison groups, given that we use their same data source (LFS) and their methodology to remove age effects. Other differences between the two studies are less relevant.

Figure A-6: College-to-high school wage ratio across birth cohorts in Blundell et al. (2022)



Notes: This figure a screenshot of the right panel of Figure 4 in Section 5 of the Online Appendix of Blundell et al. (2022). Their note to this panel reads: "We aggregate LFS data 1992-2016 up to the level of 5-year-birth-cohorts and age, where age is restricted to 20-59. We look at cohorts 1950-1985 only, so that each cohort appears many years in the data. ... For the right sub-figure, we regress the BA proportion" (proportion of college graduates) "on cohort dummies and an age polynomial of order 5. For the BA proportion, the cohort effects are scaled to the observed proportion for 1965 cohort at 30 year old. For the wage gap, the cohort effects are normalized to 0 for the 1965 cohort."

Figure A-6 reproduces the right panel of Figure 4 in Appendix 5 of BGJ. The dashed line describes the evolution of the college-to-high school wage gap across 5-year birth cohorts, from 1950-54 until 1985-89. The methodology followed by the authors is to aggregate ob-

[A-3]Specifically, we compare college graduates defined as individuals who have obtained a university degree or any other tertiary education diploma to all other subjects with a lower educational attainment. They compare college graduates (defined in the same way) to high-school graduates only (i.e., individuals with a secondary or some tertiary education below a university degree level, where the bottom line of secondary education is Grade C in the GCSE exam).

servations in cells defined by these 5-years cohorts and age in years. The difference between the log of median wages by education group in each cell is then regressed on cohort dummies and on a fifth-order polynomial in age. The dashed line plots the coefficients of the cohort dummies from this regression, normalized to zero in 1965, and suggests a weakly *increasing* pattern of the wage gap across successive cohorts. According to BGJ, the wage ratio was about 4% higher for the 1985-89 birth cohort relative to the 1950-54 cohort.

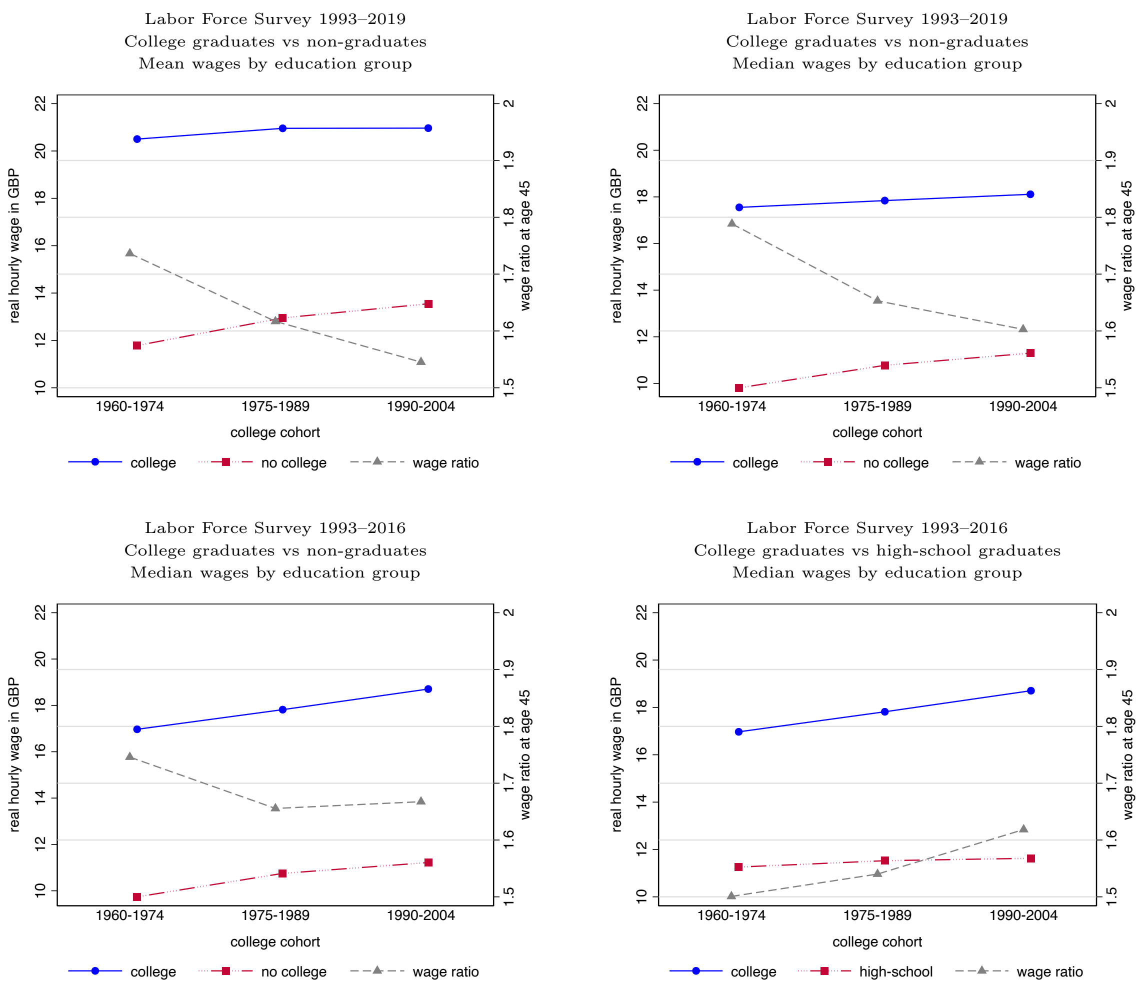
The top-left panel of Figure A-7 reproduces Figure 6 of the main tex, which shows a *decreasing* wage ratio across the three college cohorts that we consider, in contrast with BGJ. A first possible reason of this discrepancy is the fact that (for the reasons explained in Section 3.1) we compare *mean* wages by education group while BGJ compare *median* wages. The top-right panel of Figure A-7 shows that if we use median wages while sticking to all our other specifications, the wage ratio between college graduates and non-graduates exhibits a similar decrease, so using the mean or the median is actually irrelevant for the dynamics of the wage ratio across consecutive cohorts.

The bottom-left panel of Figure A-7, in addition to using medians, makes another step towards the BGJ specification by using 1993-2016 LFS data instead of 1993-2019. All our other specifications are preserved. As expected, this change affects mainly the wage ratio of the most recent cohort, which is now observed for fewer years, and results in a slightly flatter pattern. Finally, in the right-bottom pattern we change the comparison groups to those used by BGJ, while still using the median and the 1993-2016 sample: college graduates vs high-school graduates (see footnote A-3 for the exact definitions). Now the discrepancy between BGJ and us disappears: the wage ratio over consecutive cohorts increases as in BGJ, from 1.50 to 1.62, i.e., by about 8 percent.[A-4]

We conclude from this analysis that the discrepancy between the decreasing wage ratio that we find and the weakly increasing wage ratio found by BGJ is essentially due to the different educational groups considered in the two papers. As explained in Section 3.2, our broader definition of non-college graduates is justified by the fact that we study policies aimed at expanding university access so as to bring into higher education untapped ability from *any* less educated group that was previously excluded from college, not only from the pool of high school graduates. To quantify the difference in the definition of the comparison groups, out of the 936,135 observations in our LFS sample, 146,565 (15.7% of the total) are not high school graduates according to the definition of BGJ and so are not included in their comparison group, while they are included in ours.

[A-4]We do not report here analogous figures showing that the remaining differences are practically irrelevant, namely: the consideration of only three cohorts, each one spanning 15 birth years between 1940 and 1984 (instead of BGJ's eight birth cohorts of 5 years from 1950 until 1989) and the use of age dummies (instead of BGJ's age polynomials) in the regressions that removes age effects.

Figure A-7: Wage levels and ratios for different specifications



Notes: The top-left panel reproduces Fig. 6 in the main text, based on our specifications and definitions. The top-right panel shows how this figure changes when median wages by education are used instead of mean wages. The bottom-left panel is like the top-right, except that the 1993-2016 LFS sample is used (like in BGJ) instead of the 1993-2019 LFS sample. Finally, the bottom-right panel shows how the figure in the bottom-left panel changes when education groups are defined as in BGJ: college graduates vs high school graduates, instead of college graduates vs non-graduates as in the three other panels (see footnote A-3 for the exact definitions).

Appendix to Section 5.1

Our MD estimates and standard errors are obtained as follows. Starting from the initial NLS estimates of the policy parameters (see Table A-6) and considering the reference value $\alpha = 1$ for the technology parameter, we set up a grid to locate the global minimum of criterion function $J(\gamma, \tau, \delta, \beta, \alpha; \rho)$ defined by equation (32) in the main text, for a given value of ρ.

Table A-6: Initial NLS estimates of policy parameters

	College cohort		
	1960-1974	1975-1989	1990-2004
γ	6.193	5.433	3.852
	(1.031)	(0.707)	(0.564)
τ	-3.417	-3.017	-1.963
	(0.770)	(0.524)	(0.408)
δ	0.056	0.049	0.009
	(0.019)	(0.016)	(0.020)
β	0.013	0.011	0.025
	(0.002)	(0.002)	(0.002)
N	7,103	8,329	6,743

Notes: The table reports Nonlinear Least Squares (NLS) estimates of parameters in equation (19), after replacing $\Delta \ln w(G)$ with its empirical value, i.e., $\ln w(1) - \ln w(0)$. The intelligence score is expressed in hundreds IQ units in the estimation, so as to reduce the order of magnitude of the estimated γ and τ. A college cohort is defined by the period of actual of potential college attendance, which is an individual's age plus 20. Cross-sectional response weights are applied. Sample: USoc, 22,175 white respondents born in the UK in 1940-1984 with non-missing education and intelligence information (see Table 1).

In order to mitigate the consequences of the curse of dimensionality, we design an algorithm that starts from a small grid composed by 40,500 points: 3 for each of the four policy parameters (the NLS estimate and two neighboring points, at distance 0.01 for γ and τ and distance 0.001 for δ and β) and 500 for α (from 0.01 to 5, in steps of 0.01). We then solve numerically for the model's equilibrium at each point of this grid by finding the unique fixed point of equation (29) for that particular combination of $(\gamma, \tau, \delta, \beta, \alpha)$, and we obtain a MD estimate by locating the minimum of $J(\cdot; \rho)$ over the grid. If this MD estimate hits a grid boundary (for example, if the estimate for γ is the minimum or the maximum in the vector of values for γ that is used to build the grid), then a point is added to enlarge that boundary and estimation is repeated with the expanded grid.

This process is iterated until the MD estimates are at an interior point of the grid. When calibrating $\rho = 0.4$, in the initial, actual sample ("one-shot" estimates) this occurs in final grids of: 96,000 points for college cohort 1960-1974 (the minimum value of the criterion function is min $= 0.0000128$); 720,000 points for cohort 1975-1989 (min $= 0.0000213$); and

96,000 points for cohort 1990-2004 (min = 0.0000140). Thus, the advantage of anchoring the MD starting values to the partial equilibrium NLS estimates is that we can greatly reduce the grid size. Despite this computational gain, we needed a further expedient in order to complete the 10,000 bootstrap replication in no more than 10 hours (on a fast computer) for each cohort. The expedient is that the initial grid for each bootstrap sample consists of only $3^5 = 243$ points, resulting from vectors of 3 points for each parameter (the MD, one-shot estimates and 2 neighboring points); estimation is iterated according to the "no boundary estimates" rule described above, and repeated in the 10,000 bootstrap samples. The distribution of the resulting 10,000 bootstrap estimates of each parameter (conditional on $\rho = 0.4$) is illustrated in Figure A-8 for three three college cohorts. The vertical lines mark the averages that we report as our point estimates in Table 5 of the main text, and the standard deviations are our bootstrap standard errors in that table.

As discussed in the main text, a crucial question is whether our MD algorithm produces estimates corresponding to a global minimum or not. To increase our confidence that it does, we inspect two- and three-dimensional sections of the criterion function over a much wider grid than the one employed in our computational algorithm. The two-dimensional sections are shown in Figure A-9 for each cohort and for $\rho = 0.4$. A panel plots the value of the log of the MD criterion as a function of a parameters, keeping the remaining 4 parameters fixed at the one-shot MD estimates. The global minimum as well as local minima are clearly visible in each panel. Note that despite the appearance of a cusp, the function is smooth around the minimum. This appearance is produced by the log scale, which is convenient but produces a large negative value at the minimum because it is very close to zero. The associated three-dimensional sections are shown in Figure A-10 for college cohort 1960-1974. Here we fix 3 parameters at the one-shot MD estimates and we plot the contour lines of the MD criterion as a function of the 10 possible combinations of the remaining 2 parameters. The minimum is marked by the intersection of the two dashed lines. It is again clear that the NLS estimates provide a guess that helps us locating the global minimum in the presence of several local minima. Our replication package can be used to produce the analogous figures for college cohorts 1975-1989 and 1990-2004.

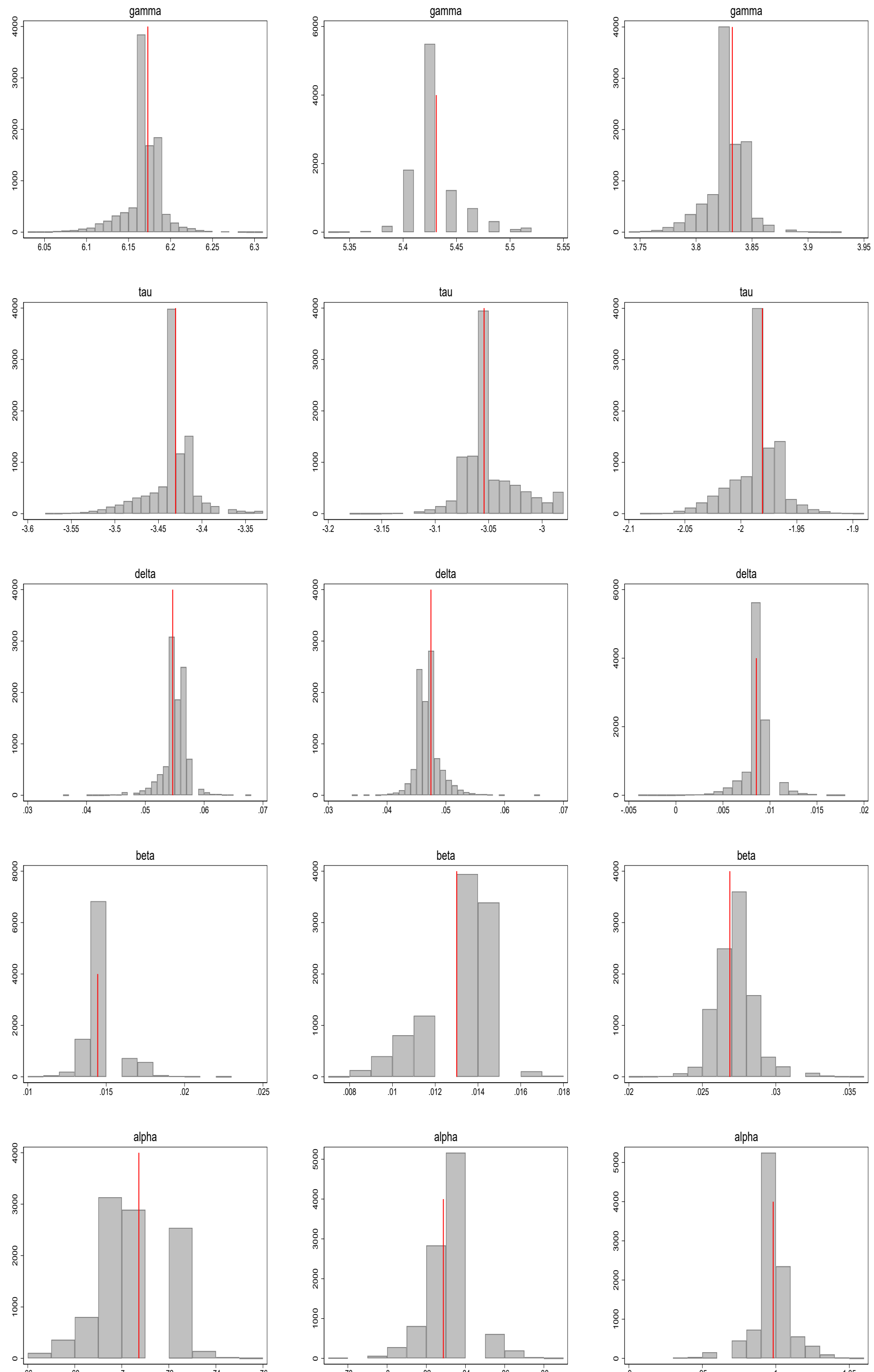
Appendix to Section 5.2

This Appendix shows how well we match eight untargeted moments not used for estimation (namely, the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles of the conditional – to educational attainment K – distributions of Θ and H, Table A-7) and replicates the results in Table 5 of the main text and Table A-7 in this Appendix for the cases in which ρ is assumed to be equal to 0.3

Figure A-8: Distribution of MD estimates across 10,000 bootstrap samples, for $\rho = 0.4$

College cohort

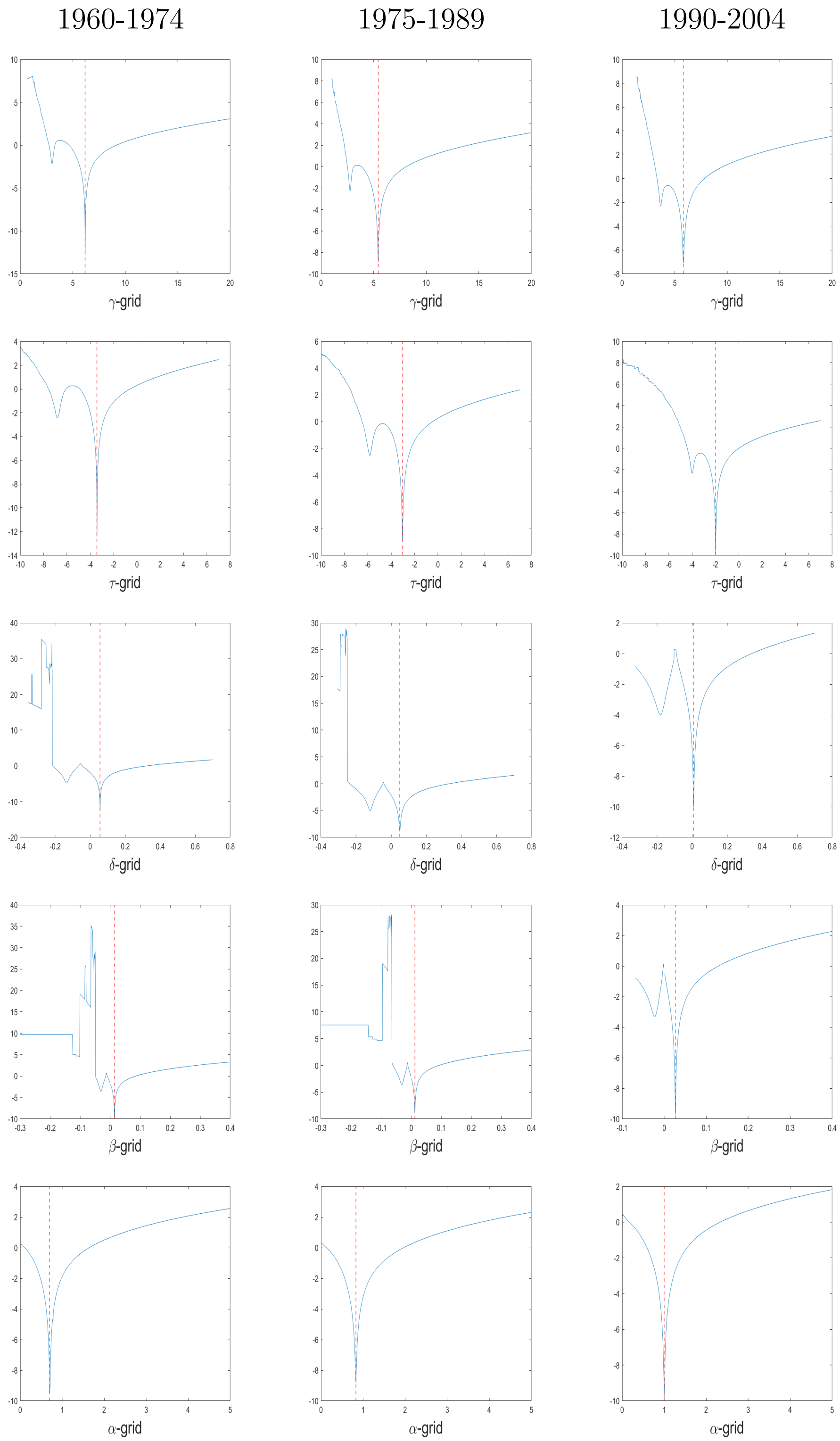
1960-1974 | 1975-1989 | 1990-2004



Notes: The figure illustrates the distribution of MD estimates of the five structural parameters of interest across 10,000 bootstrap samples, conditional on $\rho = 0.4$. The vertical line is the mean of the distribution. The point estimates and standard errors reported in Table 5 of the main text are the means and standard deviations, respectively, of these distributions.

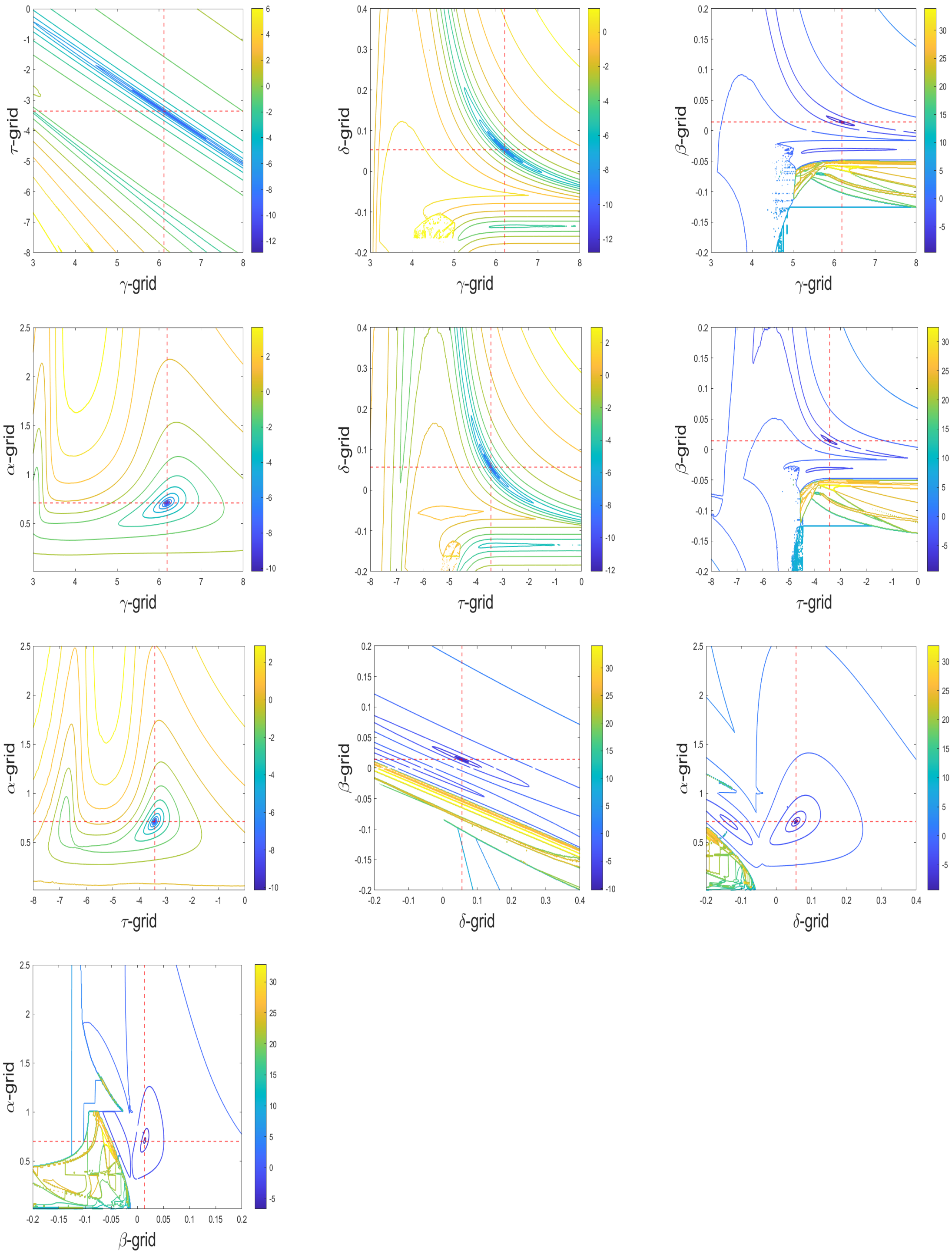
Figure A-9: 2D sections of criterion function for $\rho = 0.4$, log scale

College cohort



Notes: Each panel plots the value of the log of the MD criterion as a function of one parameter, keeping the remaining four parameters fixed at the MD estimates obtained in the actual (as opposed to bootstrap) sample. The dashed line marks the global minimum, which corresponds to our MD estimates. Local minima are clearly visible, and anchoring the grid to the initial NLS estimates of the policy parameters (see Table A-6) helps avoiding them. Note that despite the appearance of a cusp, the function is smooth around the global minimum, which takes a large negative value on the log scale because it is very close to zero.

Figure A-10: 3D sections of criterion function for $\rho = 0.4$ and cohort 1960-1974, log scale



Notes: Each panel plots the contour lines of the log of the MD criterion as a function of two parameters, keeping the remaining three parameters fixed at the MD estimates obtained in the actual (as opposed to bootstrap) sample. The possible $\binom{5}{2} = 10$ combinations are represented. The intersection of the two dashed lines marks the global minimum, which corresponds to our MD estimates. Local minima are clearly visible, and anchoring the grid to the initial NLS estimates of the policy parameters (see Table A-6) helps avoiding them.

(Table A-8 and Table A-9) or 0.5 (Table A-10 and Table A-11). Our replication package can be used to replicate also for these alternative values of ρ the visual analysis of the criterion function performed in the previous Appendix to Section 5.1.

Table A-7: Quality of match for eight untargeted moments at minimum-distance estimates of model parameters for $\rho = 0.4$

	Intelligence distribution			**Disadvantage distribution**		
	College cohort			College cohort		
	1960-1974	1975-1989	1990-2004	1960-1974	1975-1989	1990-2004
	Graduates' IQ, 25^{th} percentile			*Graduates' disadvantage, 25^{th} percentile*		
model	102.1	101.2	99.8	3.14	2.80	2.54
	(0.5)	(0.4)	(0.4)	(0.04)	(0.03)	(0.03)
data	103.0	101.6	100.3	3.12	2.79	2.51
	(0.5)	(0.3)	(0.4)	(0.04)	(0.03)	(0.03)
	Graduates' IQ, 75^{th} percentile			*Graduates' disadvantage, 75^{th} percentile*		
model	118.1	118.0	117.3	4.52	4.20	3.86
	(0.5)	(0.3)	(0.3)	(0.04)	(0.04)	(0.03)
data	117.7	117.6	117.0	4.53	4.23	3.85
	(0.4)	(0.3)	(0.3)	(0.05)	(0.04)	(0.04)
	Non-graduates' IQ, 25^{th} percentile			*Non-graduates' disadvantage, 25^{th} percentile*		
model	89.2	88.2	87.5	3.42	3.08	2.92
	(0.3)	(0.3)	(0.3)	(0.02)	(0.02)	(0.02)
data	89.4	88.3	87.6	3.43	3.08	2.91
	(0.3)	(0.2)	(0.3)	(0.02)	(0.02)	(0.02)
	Non-graduates' IQ, 75^{th} percentile			*Non-graduates' disadvantage, 75^{th} percentile*		
model	108.2	107.7	106.2	4.99	4.70	4.57
	(0.2)	(0.3)	(0.3)	(0.02)	(0.02)	(0.03)
data	107.9	107.6	106.2	4.99	4.69	4.55
	(0.2)	(0.2)	(0.3)	(0.02)	(0.03)	(0.03)

Notes: The table reports the mean and standard deviation over 10,000 bootstrap samples (at the respective minimum-distance estimates obtained setting $\rho = 0.4$) of model-predicted vs empirical values of eight untargeted moments targets. A college cohort is defined by the period of actual of potential college attendance, which is an individual's age plus 20. Cross-sectional response weights are applied. Sample: USoc, 22,175 white respondents born in the UK in 1940-1984 with non-missing education and intelligence information (see Table 1).

Table A-8: Minimum-distance estimates of model parameters for $\rho = 0.3$

[A] Parameter estimates

	College cohort 1960-1974	1975-1989	1990-2004
γ	6.183	5.437	3.832
	(0.022)	(0.020)	(0.017)
τ	−3.440	−3.070	−1.981
	(0.028)	(0.025)	(0.022)
δ	0.055	0.051	0.009
	(0.002)	(0.002)	(0.002)
β	0.015	0.012	0.027
	(0.001)	(0.001)	(0.002)
α	0.609	0.741	0.928
	(0.013)	(0.013)	(0.016)
N	7,103	8,329	6,743

[B] Labor market targets

	College cohort 1960-1974	1975-1989	1990-2004
1. College-to-school workforce ratio, ξ			
model	0.224	0.328	0.483
	(0.007)	(0.009)	(0.013)
data	0.224	0.328	0.483
	(0.007)	(0.009)	(0.014)
2. College-to-school earnings ratio, r			
model	1.737	1.617	1.546
	(0.008)	(0.006)	(0.007)
data	1.736	1.617	1.546
	(n/a)	(n/a)	(n/a)

[C] Intelligence targets

	College cohort 1960-1974	1975-1989	1990-2004
3. Graduates' IQ, $\mathbb{E}(\Theta \vert K=1)$			
model	110.2	109.2	108.2
	(0.4)	(0.4)	(0.4)
data	110.3	109.0	108.2
	(0.4)	(0.3)	(0.3)
4. Non-graduates' IQ, $\mathbb{E}(\Theta \vert K=0)$			
model	97.8	97.0	96.0
	(0.2)	(0.2)	(0.3)
data	97.7	97.0	96.0
	(0.2)	(0.2)	(0.2)

[D] Disadvantage targets

	College cohort 1960-1974	1975-1989	1990-2004
5. Graduates' disadvantage, $\mathbb{E}(H \vert K=1)$			
model	3.87	3.58	3.24
	(0.03)	(0.03)	(0.03)
data	3.86	3.58	3.23
	(0.03)	(0.03)	(0.03)
6. Non-graduates' disadvantage, $\mathbb{E}(H \vert K=0)$			
model	4.32	4.02	3.89
	(0.02)	(0.02)	(0.02)
data	4.32	4.02	3.90
	(0.02)	(0.02)	(0.02)

Notes: The table reports the mean and standard deviation of minimum-distance (MD) estimates of model parameters over 10,000 bootstrap samples, setting $\rho = 0.3$, and of model-predicted vs empirical values of the six targets. The MD criterion function is given by equation (32), and the weighting matrix is the identity matrix. The Online Appendix to Section 5.1 provides more computational details. The intelligence score is expressed in IQ units in the table but in hundreds IQ units in the estimation, so as to reduce the order of magnitude of the estimated γ and τ. A college cohort is defined by the period of actual of potential college attendance, which is an individual's age plus 20. Cross-sectional response weights are applied. Sample: USoc, 22,175 white respondents born in the UK in 1940-1984 with non-missing education and intelligence information (see Table 1).

Table A-9: Quality of match for eight untargeted moments at minimum-distance estimates of model parameters for $\rho = 0.3$

	Intelligence distribution			**Disadvantage distribution**		
	College cohort			College cohort		
	1960-1974	1975-1989	1990-2004	1960-1974	1975-1989	1990-2004
	Graduates' IQ, 25^{th} percentile			*Graduates' disadvantage, 25^{th} percentile*		
model	102.1	101.3	99.8	3.14	2.80	2.54
	(0.5)	(0.4)	(0.4)	(0.04)	(0.03)	(0.03)
data	103.0	101.6	100.3	3.12	2.79	2.51
	(0.5)	(0.3)	(0.4)	(0.04)	(0.03)	(0.03)
	Graduates' IQ, 75^{th} percentile			*Graduates' disadvantage, 75^{th} percentile*		
model	118.1	118.0	117.3	4.52	4.21	3.86
	(0.5)	(0.3)	(0.3)	(0.04)	(0.04)	(0.03)
data	117.7	117.6	117.0	4.53	4.23	3.85
	(0.4)	(0.3)	(0.3)	(0.05)	(0.04)	(0.04)
	Non-graduates' IQ, 25^{th} percentile			*Non-graduates' disadvantage, 25^{th} percentile*		
model	89.2	88.2	87.5	3.42	3.08	2.92
	(0.3)	(0.3)	(0.3)	(0.02)	(0.02)	(0.02)
data	89.4	88.3	87.6	3.43	3.08	2.91
	(0.3)	(0.2)	(0.3)	(0.02)	(0.02)	(0.02)
	Non-graduates' IQ, 75^{th} percentile			*Non-graduates' disadvantage, 75^{th} percentile*		
model	108.1	107.7	106.2	4.99	4.70	4.57
	(0.2)	(0.3)	(0.3)	(0.02)	(0.02)	(0.03)
data	107.9	107.6	106.2	4.99	4.69	4.55
	(0.2)	(0.2)	(0.3)	(0.02)	(0.03)	(0.03)

Notes: The table reports the mean and standard deviation over 10,000 bootstrap samples (at the respective minimum-distance estimates obtained setting $\rho = 0.3$) of model-predicted vs empirical values of eight untargeted moments targets. A college cohort is defined by the period of actual of potential college attendance, which is an individual's age plus 20. Cross-sectional response weights are applied. Sample: USoc, 22,175 white respondents born in the UK in 1940-1984 with non-missing education and intelligence information (see Table 1).

Table A-10: Minimum-distance estimates of model parameters for $\rho = 0.5$

[A] Parameter estimates

	College cohort 1960-1974	1975-1989	1990-2004
γ	6.175	5.430	3.830
	(0.022)	(0.022)	(0.021)
τ	-3.438	-3.046	-1.984
	(0.028)	(0.025)	(0.026)
δ	0.055	0.046	0.008
	(0.002)	(0.002)	(0.002)
β	0.015	0.013	0.028
	(0.001)	(0.001)	(0.002)
α	0.821	0.927	1.083
	(0.012)	(0.012)	(0.014)
N	7,103	8,329	6,743

[B] Labor market targets

	College cohort 1960-1974	1975-1989	1990-2004
1. College-to-school workforce ratio, ξ			
model	0.224	0.328	0.484
	(0.007)	(0.009)	(0.013)
data	0.224	0.328	0.483
	(0.007)	(0.009)	(0.014)
2. College-to-school earnings ratio, r			
model	1.736	1.617	1.557
1	(0.007)	(0.006)	(0.022)
data	1.736	1.617	1.545
	(n/a)	(n/a)	(n/a)

[C] Intelligence targets

	College cohort 1960-1974	1975-1989	1990-2004
3. Graduates' IQ, $\mathbb{E}(\Theta \mid K = 1)$			
model	110.2	109.1	108.2
	(0.4)	(0.4)	(0.5)
data	110.3	109.0	108.2
	(0.4)	(0.3)	(0.3)
4. Non-graduates' IQ, $\mathbb{E}(\Theta \mid K = 0)$			
model	97.7	97.0	96.0
	(0.2)	(0.2)	(0.3)
data	97.7	97.0	96.0
	(0.2)	(0.2)	(0.2)

[D] Disadvantage targets

	College cohort 1960-1974	1975-1989	1990-2004
5. Graduates' disadvantage, $\mathbb{E}(H \mid K = 1)$			
model	3.87	3.58	3.24
	(0.03)	(0.03)	(0.03)
data	3.86	3.58	3.23
	(0.03)	(0.03)	(0.03)
6. Non-graduates' disadvantage, $\mathbb{E}(H \mid K = 0)$			
model	4.32	4.03	3.89
	(0.02)	(0.02)	(0.02)
data	4.32	4.03	3.90
	(0.02)	(0.02)	(0.02)

Notes: The table reports the mean and standard deviation of minimum-distance (MD) estimates of model parameters over 10,000 bootstrap samples, setting $\rho = 0.5$, and of model-predicted vs empirical values of the six targets. The MD criterion function is given by equation (32), and the weighting matrix is the identity matrix. The Online Appendix to Section 5.1 provides more computational details. The intelligence score is expressed in IQ units in the table but in hundreds IQ units in the estimation, so as to reduce the order of magnitude of the estimated γ and τ. A college cohort is defined by the period of actual of potential college attendance, which is an individual's age plus 20. Cross-sectional response weights are applied. Sample: USoc, 22,175 white respondents born in the UK in 1940-1984 with non-missing education and intelligence information (see Table 1).

Table A-11: Quality of match for eight untargeted moments at minimum-distance estimates of model parameters for $\rho = 0.5$

	Intelligence distribution			**Disadvantage distribution**		
	College cohort			College cohort		
	1960-1974	1975-1989	1990-2004	1960-1974	1975-1989	1990-2004
	Graduates' IQ, 25th percentile			*Graduates' disadvantage, 25th percentile*		
model	102.1	101.2	99.8	3.14	2.80	2.54
	(0.5)	(0.4)	(0.4)	(0.04)	(0.03)	(0.03)
data	103.0	101.6	100.3	3.12	2.79	2.51
	(0.5)	(0.3)	(0.4)	(0.04)	(0.03)	(0.03)
	Graduates' IQ, 75th percentile			*Graduates' disadvantage, 75th percentile*		
model	118.1	117.9	117.3	4.52	4.20	3.86
	(0.5)	(0.3)	(0.3)	(0.04)	(0.04)	(0.03)
data	117.7	117.6	117.0	4.53	4.23	3.85
	(0.4)	(0.3)	(0.3)	(0.05)	(0.04)	(0.04)
	Non-graduates' IQ, 25th percentile			*Non-graduates' disadvantage, 25th percentile*		
model	89.2	88.2	87.4	3.42	3.08	2.92
	(0.3)	(0.3)	(0.3)	(0.02)	(0.02)	(0.02)
data	89.4	88.3	87.6	3.43	3.08	2.91
	(0.3)	(0.2)	(0.3)	(0.02)	(0.02)	(0.02)
	Non-graduates' IQ, 75th percentile			*Non-graduates' disadvantage, 75th percentile*		
model	108.1	107.7	106.1	4.99	4.70	4.57
	(0.2)	(0.2)	(0.3)	(0.02)	(0.02)	(0.03)
data	107.9	107.6	106.2	4.99	4.69	4.55
	(0.2)	(0.2)	(0.3)	(0.02)	(0.03)	(0.03)

Notes: The table reports the mean and standard deviation over 10,000 bootstrap samples (at the respective minimum-distance estimates obtained setting $\rho = 0.5$) of model-predicted vs empirical values of eight untargeted moments targets. A college cohort is defined by the period of actual of potential college attendance, which is an individual's age plus 20. Cross-sectional response weights are applied. Sample: USoc, 22,175 white respondents born in the UK in 1940-1984 with non-missing education and intelligence information (see Table 1).