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Political Participation and Party Preferences

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Abstract. Political behavior of citizens includes political participation and preferences. We show with UK data that political behavior is affected by individual characteristics that are also determining educational attainment, including cognitive abilities and intelligence.

Our analysis reconciles the rational choice assumption with the acquisition of costly political information, which would otherwise give only negligible benefits. We disentangle the causal pathways by identifying effects operating directly and those operating indirectly, in particular through education and income. We address the issue of endogeneity of cognitive skills using polygenic scores, and show that an important component of the causal factors is genetic.

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1. Introduction

1.1. **Overview of Main Hypotheses.** Political behavior, which is the immediate object of our study, has two dimensions. One dimensions is the participation in the political process. We understand participation here in a wide sense, spanning activities that include voting, membership in a political organization, as well as the activity of acquiring information on current events. Being informed about political events, or any facts that are relevant for a sound evaluation of politics, is a prerequisite for effective participation in the political process. The second dimension is that of political preference over parties or policies. For example political preferences are expressed in voting. Our interest is determining which characteristics of the population of citizens affect political behavior.

The first hypothesis we consider is that individual characteristics affecting educational attainment also affect political participation in a significant and sizable way. The effect on participation is stronger and more persistent than on political affiliation. If this hypothesis is true, then the distribution of these characteristics in the population may shape in the long run the political process and ultimately the institutions of a nation.

There are various paths through which this effect operates; one is education, which operates directly and indirectly through the second, income. Higher intelligence implies higher income and so different incentives in participation. But there is no clear evidence or way in which income should affect participation. Education affects income, but can also directly affect political participation. So we have to separate the effects going through income, through education, and separately. To guide this analysis, we formulate our second hypothesis: higher income induces higher participation, and thus, as higher education induces higher income, the same holds for education. We leave the door open to the existence of a direct, additional effect. We find that even after we condition on income the additional effect is clear. This suggests an additional possible path: cognitive skills and education make information acquisition not just more useful, but less costly. We thus turn to the link between intelligence and voting channeled by information acquisition, considering the theory first.

The second hypothesis is that higher intelligence and cognitive skills may induce higher participation through lower cost of information acquisition. We set our analysis within the tradition of rational choice. There is no model in rational choice that links explicitly intelligence to participation. A first simple approach considers that the dilemma posed by the voter's paradox becomes more severe with higher intelligence. If this is the case, then higher intelligence should reduce participation. But there is another way in which intelligence may operate: higher intelligence implies lower cost of information acquisition implies higher quality of information. And within rational choice models higher quality of information may imply higher participation (through the swing voter's curse).

The rational choice model linking information to participation faces a serious problem: the information acquisition paradox. If information is only useful for political choice, why should voters acquire costly information if the benefit is small? The cost of acquiring information is higher than the cost of voting, so the information acquisition paradox is even more severe than the voter's paradox, and is in fact at the heart of the theories claiming that voters' behavior is ultimately irrational, or dictated by preferences that have nothing to do with the choices object of the vote. The natural solution we propose is that the assumption that the information necessary for political choices is only useful for political choices is perhaps analytically convenient but false. Thus our third hypothesis is that information has a joint output: it is useful for the citizen's economic activity and for voting.

We finally address an important and subtle endogeneity problem. Intelligence is measured at older age, and is potentially affected by education. So a causal conclusion derived from the results mentioned so far might appear unwarranted. Our fourth and final hypothesis is that genetic factors affecting educational attainment also positively affect political participation, even after we control for them in their role on education and income. We consider the Polygenic Score for education years, a measure of the genetic attitude of an individual to acquire education, and find that this is the case.

We conclude that individual characteristics affect the two dimensions of political behavior in very different ways. Political participation is a long run characteristic of individual behavior. Becoming informed about political events cannot be achieved in a few days of reading specialized press. A good knowledge of the prerequisites is essential, and acquiring this knowledge is a process that takes time. Political preferences are a consequence of the understanding of the political process, but dictated by the contingencies of the present political situation, the specific historical events of the moment, party platforms and political leaders.

In the rest of the introduction we develop this overview and provide links to existing literature.

1.2. **Education and Political Participation.** Considerable evidence on education as strong predictor of voter turnout has been accumulating in the past (see Milbrath and Goel (1977); Wolfinger and Rosenstone (1980); Kam and Palmer (2008); Campbell (2010); Mayer (2011); Willeck and Mendelberg (2022)). Broadly, three explanations are offered for the favorable effect of education on political participation (see Willeck and Mendelberg (2022) for a recent survey). In the first, standard, model, education is a *direct cause* of political participation because it provides the basic knowledge, the conceptual tools and the skills necessary for a meaningful participation. A second explanation, known as *pre-adult socialization*, traces the roots of education back to earlier stages of development of personal virtues like empathy, honesty, benevolence, and critical thinking skills. In the third theory, education is mostly a *proxy* for a latent variable that affects both education and political participation. The precise nature of this variable is not determined: social status is a favorite candidate (Willeck and Mendelberg (2022), pages 92-95.)

Some of these explanations implicitly accept the possibility that cognitive skills, such as the ability to think critically, may be crucial in explaining differences in political behavior, irrespective of whether these differences are produced by education or a natural ability of the individual. But no such link is explicitly provided.

1.3. **Participation and Rational Choice.** The concept of participation given here is narrower than the one used in the political science literature, where political participation is broadly defined as "behavior designed to affect outcomes, such as the choice of government personnel and policies (Seligson and Booth (1976)), distribution of public goods (Barnes et al. (1984)), or even more broadly (Conge (1988) as "any action or inaction .. which intentionally or unintentionally opposes or supports some feature of a government or community."). The narrower definition has the merit of making measurement and test of hypotheses possible.

Citizens may decide whether and how much they participate in political life for many reasons. For example, voters may vote, or acquire information for ethical reasons, such as civic duty (Feddersen and Sandroni, 2006), of for altruism (because they consider the well-being of others: Fowler (2006); Edlin et al. (2007); Ali and Lin (2013)). If this is the case, then there is little to explain, or perhaps differences in individual behavior are reduced to ethical or pro-social attitudes. Although these considerations may be important to some, they are unlikely to explain a substantial fraction of the phenomena in which we are interested.

We assume, following a standard approach in economics, and partly in political science, (Myerson and Weber (1993); Myerson (2000, 2002)), that the decisions concerning the acquisition of information, and participation in political life, are modeled based on a rational choice weighing costs and benefits.

A first simple approach might lead us to think that more intelligent citizens have lower participation. Higher cognitive skills appear to make the incentives to become informed on matters relevant to political life even weaker. A relatively more sophisticated decision maker should be, if anything, less prone to illusions that his choice may be relevant. The awareness of the irrelevance of the choices based on this information should induce more intelligent people not only to participate less, for example by not voting, but also by not acquiring the information that might be useful in ranking alternative policies according to their consequences.

This simple prediction may change if one considers more precisely the rational motivation for voting, as for example indicated by the swing voter's curse. This idea (as presented in (Feddersen and Pesendorfer, 1997, 1999; Feddersen, 2004; McMurray, 2013; Jackson and Tan, 2013)) and its corollary on the choice of abstention, is that a citizen who holds inferior information may find that the best action is to abstain from voting, even when voting has zero cost. The reason is that, if the voter conditions his vote on the event in which he is pivotal, then he realizes that his vote in that event is more likely than not to resolve the tie in favor of the worst option. These models provide an easy and natural link between individual characteristics such as cognitive skills, and the political behavior which is the object of our study. If intelligence lowers the cost of information, then these models naturally predict that citizens with lower cognitive skills should be more likely to abstain. As an example of work spelling out this link, Martinelli (2006, 2007) examines conditions under which a rational voter would acquire information. [1]

Limiting the range of rationality to strict political choice is a conceptual limit of a tradition which is at the opposite side of the spectrum, which claims to debunk the "myth of the rational voter" (an expression that returns frequently: Moreno (1975); Gelman (2010); Caplan (2011)) and emphasizes instead the irrationality of voting. The analysis in this tradition proceeds in two main steps: first, it establishes that acquiring information to decide voting is irrational from the point of view of individual utility maximization, because the effect of the vote is in any case negligible; and thus, if information is only useful for political choice, the benefits it provides are negligible. Second,

[1]The aim of these studies is to find conditions under which this limited acquisition may still lead to good choices.

there are systematic errors in information driven by preferences directly on beliefs. Assuming that the strength of this preference over beliefs is inversely proportional to intelligence produces a theory that predicts larger participation of the comparatively less intelligent.

1.4. **Political Human Capital.** This literature is elegant but highly abstract, and typically considers political behavior as separate and isolated from the rest of the social and economic activity of the citizen. In particular, it ignores the joint benefits derived from acquisition of information which is relevant for political evaluations. For example, being informed on the future prospects of inflation, employment, real estate or stock market performance provides elements useful to decide among alternative political programs and the parties; but obviously it also has the direct benefit, for the individual, of making good choices in the day to day management of his assets. According to this more comprehensive view, political participation is best conceived as a manifestation of a special form of human capital, that of political understanding; we call this *political human capital*.

This specialized form of human capital shares the important characteristics of the general human capital. First, as any other form of capital, physical or human, this knowledge requires slow accumulation, facing constant depreciation, or innovations that make previous knowledge obsolete. Second, just as is the case for physical capital, human capital exhibits joint production, yielding two or more outputs simultaneously. Some of the output is directly useful to the private life of a citizen, and some is useful for political and collective decision making. Third, the relationship between political participation and political or party preferences is not straightforward. For example, an individual who expresses no preference for any party in all elections is probably simply just not interested in politics. An individual who expresses constant preferences for the same party, in all elections, might choose out of habit or family tradition rather than informed deliberation. An individual in some intermediate position, who expresses preference for one party in an election and for a different party or no party at all in another election might very likely be the most informed of the three.

1.5. **Individual Characteristics and Political Affiliation.** Intelligence has two ways to affect political preferences and voting behavior. One is through its effect on the income and wealth of the citizen. Different levels of income and wealth induce different incentives when alternative policies are evaluated, and thus different levels of participation as well as different political preferences. For example, it is natural to expect that lower income may induce a citizen to favor redistributive policies that, at least in the immediate term, may favor him. The other way in which intelligence and general cognitive abilities affect political behavior is through its effects on the processing of political information. We need to disentangle the two pathways, and this is one of the main purposes of the analysis that follows.

1.6. **Outline of the Paper.** The analysis proceeds as follows. In section 2 we describe the datasets and the main variables we use. In section 3 we disentangle the two main pathways (operating through education and income) from intelligence to political participation and to political preferences. To this end, we estimate a SEM which includes earnings, education and political behavior. The analysis in this section is an important step beyond establishing a simple correlation between intelligence and political behavior. But it ignores two important potential sources of endogeneity of variables that are instead taken as independent. First, intelligence as measured in the dataset may be influenced by education. We address this by introducing in the analysis (section 4) the information on the genotype of individuals, which is available for a subset of participants to the survey. We summarize this information with the Polygenic Score for education years. Second, education, earnings and voting choices are part of a system of variables that interact at equilibrium. In sections 5 we formulate a testable equilibrium model of education choice, income earning, and voting behavior. We estimate the parameters in section 6 and find support for the conclusions reached in the regression analysis. Section 7 concludes.

2. Data

We use the UK Household Longitudinal Study (UKHLS), commonly known as Understanding Society. This is the largest household panel study in the UK, covering about 40,000 individuals in each wave since 2009. The participants were sampled from the UK population in 2009, and are followed every year. Starting from wave 2, the follow-up sample also includes the former British Household Panel Survey (BHPS)[2] respondents. The survey encompasses a wide range of topics, including education, earnings, cognitive abilities and political preferences. We review here those that are directly relevant for our investigation.

2.1. **Full Survey.**

[2]The BHPS is a predecessor of the UKHLS. The BHPS ran from 1991 to 2008 covering about 10,000 individuals. In the final wave of the BHPS the respondents were asked if they wished to continue as part of the UKHLS; about 80% did.

Political preferences. In each wave, the respondents are asked about their political preferences, both on the extensive and intensive margins. In particular, they are asked whether they support or are close to some party and if so, which party they are aligned with. Questions concerning support or closeness to a given party are mutually exclusive, i.e., each respondent was asked only one of those questions. We construct the alignment variable, called *party align*, as the maximum of the variable support or feeling close to. We then use this information in our analysis, constructing two indicator variables. The first is *Political Participation*, which is equal to *party align* if *party align* is strictly larger zero. The second is *Preference for Conservative*, which is equal to 1 if *party align* is equal to 1 (indicating a preference for the Conservative party), conditional on *party align* being different from zero. For a more detailed description of variables and comparison to aggregate voter turnout and vote shares, see section A.1 in the Appendix.

Political beliefs. In addition to alignment and voting behaviour, the survey collected opinions of respondents on various aspects of their participation to the political process. We focus attention on the variables describing the subjective estimates each respondent gave of the quality of one's qualification (*Qualified*), one's political information (*Informed*), the cost of acquiring information (*Too costly*), and the belief on the effectiveness of the vote (*Decisive*). The *Qualified*, *Informed* and *Too costly* variables are categorical on a scale from 0 (strongly disagree) to 4 (strongly agree). The variable *Decisive* is categorical on a scale from 0 (very unlikely) to 10 (very likely). For a more detailed description of these variables, see section B.1 in the appendix.

Education. The survey contains a variable describing the highest qualification reached by the individual. The variable has six categories: degree, other higher degree, A-level or equivalent, GCSE [3] or equivalent, other and no qualification. This variable is updated in every wave, taking into account newly acquired qualifications, if applicable. Using this categorical variable we define a binary degree indicator D_i that takes value of 1 whenever individual i reports having a degree as highest qualification in any wave.

Earnings. In each wave the respondents are asked about their employment status, jobs and earnings. We use monthly labour earnings, deflated using the CPI excluding rent, maintenance repairs

[3]GCSE is the General Certificate of Secondary Education. There is no clear equivalent of GCSE in the United States. The closest category is a high school diploma or a General Educational Development (GED) credential.

and water charges. Using the panel dimension, we estimate earnings-age profiles, construct predicted lifetime earnings and compute their discounted present values for each individual. For more details, see A.2.

Intelligence score. In wave 3, participants were administered a set of five cognitive tests: word recall (immediate and delayed), serial 7 subtraction, number series, verbal fluency and numeric ability. The UKHLS dataset summarizes the results into counts of correct answers in each test. We apply principal component analysis to these variables, and use the first principal component as the intelligence score.

Our working sample consists of the respondents in wave 3 who were born between 1945 and 1990, and with non-missing intelligence score and college degree indicator.

2.2. **METADAC subsample.** The survey also provides genetic information for a subset of nearly 10,000 individuals. We refer to this dataset as METADAC subsample. [4] Our working sample contains more than 5,500 individuals with genetic information.

The scope of variables available in the METADAC is similar to that in the full survey with few caveats. First, due to data privacy concerns, the earnings information is grouped in 50-quantiles. We observe in which quantile individual earnings are as well as the quantile bounds in each wave. See Section C.3 for further details on how we use this information to construct discounted predicted lifetime earnings for genotyped individuals. Second, we do not have access to the response weights or sampling variables in the METADAC subsample. This may affect inference properties of the estimators in the polygenic analysis. As a robustness check, we repeat the baseline analysis with observed IQ score in the METADAC subsample and compare them with those in the full sample. As will be seen later, the results are similar both quantitatively and qualitatively. This is encouraging and boosts our confidence in the polygenic analysis conducted on the subsample.

For further details about the dataset, see section C in the Appendix. We describe the computation of polygenic scores in Section 4.

3. Regression analysis

In this section we analyze statistical models of political participation (section 3.1) and affiliation (section 3.2).

[4] Before 2020, the genotype data access was managed by the METADAC.

Our analysis here relies on a Structural Equations Model (SEM). Figure 1 presents the general form of the SEM we use for variables describing Political Behavior; the behavior may be either Participation or Affiliation. The key individual characteristic of interest is the intelligence score. However, the regression equations include other covariates omitted from the figure such as gender, race, birth cohort, age polynomial, parental background, and time trends. There are three equations corresponding to three outcomes: college indicator, earnings (current or lifetime), and political behaviour. Each outcome is allowed to affect the subsequent outcomes as well. The college indicator is included in the earnings and political behaviour equations, and the earnings variable is added to the political behaviour equation.

The aim of this analysis is to separate the effect of political behavior of intelligence that operates through acquisition of education and income from the direct effect.

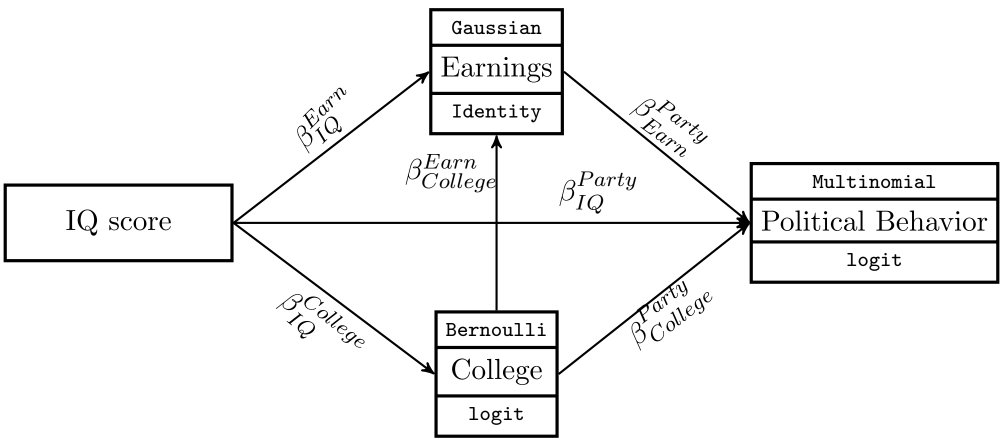

FIGURE 1. SEM diagram

Notes: the figure plots the schematic representation of theSEMmodel we estimate. Earnings variable may stand for current real monthly earnings (as of wave 3) and/or the discounted presented value of predicted lifetime earnings. Thus, it can actually expand to mean two equations of similar type. The regressions additionally control for gender, race, birth cohort, parental background and survey wave indicators as well as second-order polynomial in age interacted with college and/or intelligence score. These are not drawn in the diagram for simpler exposition.

3.1. **Political Participation.** We begin with the analysis of factors affecting political participation. The hypothesis we test is that political participation is determined by a general information acquisition behaviour. An agent can seek information about political parties as well as the general state of the economy, perhaps for the purpose of political choice, economic choice or for personal interest. We present the logistic regression analysis of this hypothesis using the variables *Qualified*, *Informed*, *Too costly* and *Decisive* in Table B.6. The table describes how these variables are related to political participation. To set a benchmark, the marginal effect of college is 6.0 percentage points (pp), and that of male 1.9 pp. The marginal effects of information-related variables are comparable in size to college or larger: 5.1 pp for Qualified, 7.1 pp for Informed, −2.2 pp for Too Costly, and 9.4 pp for Decisive.

In columns 3 and 6 of Table B.6 we introduce the variable *investment income* (that is, the income in pounds from interest and dividends) [5] for a test of our hypothesis that information on economic facts may be collected in part for better management of the individual's specific conditions. The result supports the stated hypothesis: the marginal effect of a 1 standard deviation higher investment income is associated with 2.5 pp higher probability of political participation. Although the inclusion of the investment income variable does not affect other coefficients Table B.6, the last column in Table B.7 shows that being informed about political process is positively associated with higher investment income.

These variables have a significant and sometimes surprising correlation with the intelligence score (see Table B.7). Again considering standardized variables, we see that both college (0.45 sd) and IQ score (0.11 sd) positively affect *Informed*; similar result for the variable *Qualified* (0.54 and 0.13 sd, respectively). The estimate of cost is reduced by college (0.22 sd) and IQ score (0.06 sd). It is surprising that the standardized estimate of whether vote is decisive is *positively* related to both college (0.10 sd) and IQ score (0.02 sd). This result is the opposite one might expect following the logic of rational choice and the assumption that higher cognitive abilities takes an individual closer to a behavior consistent with that theory.

We now turn to the estimation of the SEM. The table 1 presents the results of the model of political participation presented in Figure 1. The signs of estimated coefficients of commonly used variables are consistent with existing results in the literature; the size effect can be used as a benchmark for the other variables. Being male is associated with 6.7 to 7 pp higher participation probability. A college degree increases the probability by about 12 pp.

Estimates relating to variables that are more directly interesting for our hypothesis confirm our predictions. The discounted present value of earnings exhibit a positive value (about 5 pp per 1 sd higher lifetime earnings). The standardized measure of intelligence (IQ score) has a significant effect (5.4 pp), similar in size to male, and approximately half of the variable college. Thus, the

[5] The variable used in the analysis is obtained by taking the variable the $fimninvnet\_dv$ (see https://www.understandingsociety.ac.uk/documentation/mainstage/variables/fimninvnet_dv/) and deflating it. We then take the inverse hyperbolic sine (IHS) transformation of the resulting variable. For an in depth analysis of the income variable, see https://www.understandingsociety.ac.uk/wp-content/uploads/working-papers/2019-08.pdf

results suggest that indeed some relationship between cognitive skills and political participation can be explained by higher earnings. We also note that current monthly earnings appear irrelevant once lifetime earnings are controlled for. This is consistent with political participation being a long-run decision.

	Dependent variable: political participation		
	1	2	3
Male	0.067***	0.068***	0.069***
	(0.002)	(0.003)	(0.003)
Age	0.008***	0.009***	0.009***
	(0.001)	(0.001)	(0.001)
IQ score	0.055***	0.054***	0.054***
	(0.002)	(0.002)	(0.002)
College	0.128***	0.109***	0.110***
	(0.003)	(0.003)	(0.003)
Real monthly earnings (std)	0.024***		-0.005***
	(0.001)		(0.002)
DPV of real monthly earnings (std)		0.050***	0.054***
		(0.002)	(0.002)
Obs.	194,441	139,707	139,707

Table 1. Political participation and individual characteristics

Notes: The table reports marginal effects computed after SEM estimation. Each SEM estimation included three equations: college equation, earnings equation and political participation equation. The table reports marginal effects from the political participation equation only. Standard errors (reported in parentheses) are computed using Delta method. The political participation indicator variable is estimated using logit regression. The earnings equation is estimated using simple OLS regression and college equation - using logit regression. Real Monthly Earnings (RME) and DPV of RME are standardized (mean=0 and SD=1). All regressions control for gender, race, birth cohort, parental background and survey wave indicators as well as interactions between college, intelligence scores and age. The regressions are unweighted.

3.2. **Political Affiliation.** In this section, we present the regression estimates of the relationship between intelligence and individual party choices. As for political participation we fit a structural equation model, as presented in Figure 1 to the data. In Table 2 we present the marginal effects of selected variables on probabilities of alignment with Conservative, Labour or Liberal Democratic parties. The coefficient estimates derived from the SEM are reported in Tables B.1 and B.2. The baseline (that is, excluded) outcome in the multi-nomial logit is the Labour Party.

The table shows that higher intelligence is strongly associated with a higher probability of Conservative and Liberal Democratic party choices, even after controlling for college education and earnings. We remark that this result is based on choices made in the decade between 2010 and 2020 (see Section A.1 and in particular Figure A.1). Our general hypothesis is that intelligence enables a more sophisticated behaviour in response to the current situation, not a particular ideological perspective.

We now explore the channels through which intelligence influences political choices in that decade. The results in Table 2 show negative association between college degree and the probability of Conservative Party choice. Having a college degree is associated with 7-9 pp lower probability of Conservative party choice. On the other hand, having higher intelligence (1 std above mean) is associated with 1.1-2.7 pp higher probability of alignment with Conservative party.

This could be interpreted as suggesting that college education swings the students towards more liberal preferences holding the earnings trajectory constant. [6] Alternatively, it might also be a result of selection bias if students with initially high liberal preferences are more likely to go to a university.[7]

Considering the earnings channel, the results in table 2 show that higher earnings are associated with a higher probability of Conservative Party choice. The estimation results across columns (1) - (3) correspond to estimations where either current earnings, or discounted present value (DPV) of lifetime earnings, or both, were included in the estimation. Thus, we consider the possibility that the probability of Conservative Party choice responds to both earning potential and evolution of earnings over the life-cycle. For example, a one sd higher value of DPV of earnings increases the probability of Conservative party choice by about 4.6 pp. Holding the earnings potential constant, a value of current earnings which is one sd higher further increases the probability by 2.4 pp. Since

[6]Apfeld et al. (2023) find that attending a university induces liberal views among students that marginally get admitted into a university. Klein (2005) documents "one-party campus" among faculty members at UC Berkeley and Stanford in favour of Democratic Party supporters. Thus, education may have a causal effect on political views via campus environment. Cantoni et al. (2017) find that the school curriculum can have a direct effect on the political attitudes of the students.

[7]Using within-sibling analysis in the BHPS and the UKHLS, Simon (2022) shows that direct causal effect of education on political views is small and may actually go in the opposite direction (increasing support for Conservative Party). Similarly, Marshall (2016) shows that an extra year at high school induced by the ROSLA reform of 1947 increases support for the Conservative Party. Souto-Otero (2011) argues that higher education has been a more central topic for the Labour party than Conservative Party. Thus, it could also be that Labour Party supporters placed greater importance on obtaining higher education. More recently, Acemoglu et al. (forthcoming) show that Norwegian education reform increased support for the Labour Party mainly due to a sense of gratitude for the reform.

	Dependent variable: party alignment		
	1	2	3
Panel A: Conservative party			
Male	0.002	0.005**	-0.001
	(0.003)	(0.003)	(0.003)
Age	0.006***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)
IQ score	0.027***	0.013***	0.011***
	(0.002)	(0.002)	(0.002)
College	-0.065***	-0.084***	-0.086***
	(0.003)	(0.003)	(0.003)
Real monthly earnings (std)	0.047***		0.024***
	(0.001)		(0.002)
DPV of real monthly earnings (std)		0.064***	0.046***
		(0.002)	(0.002)
Panel B: Labour party (base outcome)			
Male	-0.014***	-0.019***	-0.015***
	(0.003)	(0.003)	(0.003)
Age	0.004***	0.004***	0.005***
	(0.001)	(0.001)	(0.001)
IQ score	-0.056***	-0.043***	-0.042***
	(0.002)	(0.003)	(0.003)
College	0.062***	0.067***	0.068***
	(0.003)	(0.004)	(0.004)
Real monthly earnings (std)	-0.021***		-0.017***
	(0.001)		(0.002)
DPV of real monthly earnings (std)		-0.024***	-0.011***
		(0.002)	(0.003)
Panel C: Liberal Democrats			
Male	-0.014***	-0.016***	-0.016***
	(0.002)	(0.002)	(0.002)
Age	-0.001**	-0.001*	-0.001*
	(0.000)	(0.001)	(0.001)
IQ score	0.020***	0.020***	0.020***
	(0.001)	(0.002)	(0.002)
College	0.036***	0.031***	0.031***
	(0.002)	(0.002)	(0.002)
Real monthly earnings (std)	0.002***		0.000
	(0.001)		(0.001)
DPV of real monthly earnings (std)		0.003***	0.003***
		(0.001)	(0.001)
Obs.	144,385	105,207	105,207

Table 2. Party affiliation and individual characteristics

Notes: The table reports marginal effects computed after SEM estimation. Each SEM estimation included three equations: college equation, earnings equation and party affiliation equation. The table reports marginal effects from the party affiliation equation only. Standard errors (reported in parentheses) are computed using Delta method. The party affiliation equation is estimated using multinomial logit regression with possible choices being Conservative, Liberal Democrats and other parties, all relative to Labour party choice. The earnings equation is estimated using simple OLS regression and college equation - using logit regression. Real Monthly Earnings (RME) and DPV of RME are standardized (mean=0 and SD=1). All regressions control for gender, race, birth cohort, parental background and survey wave indicators as well as interactions between college, intelligence scores and age. The regressions are unweighted.

the earnings-age profile typically has an increasing and concave shape, the association between party choice and income also becomes stronger over the life-cycle.

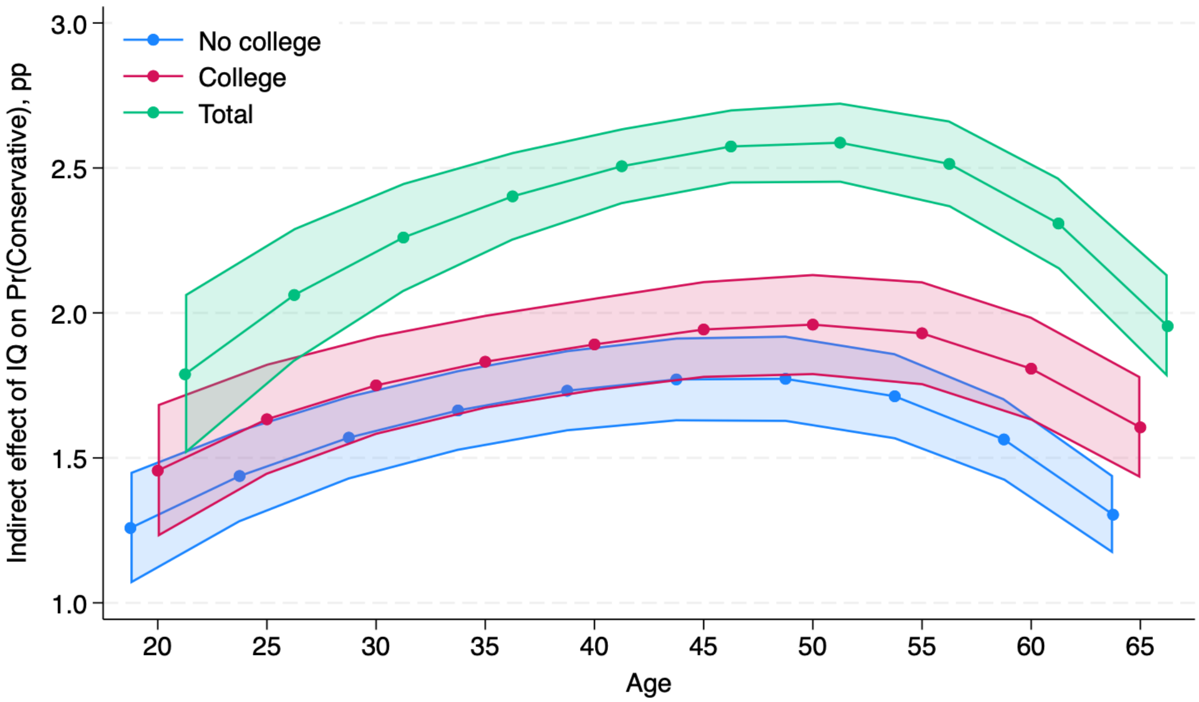

FIGURE 2. Marginal effect of IQ on Conservative Party choice via income

Notes: the figure plots the marginal effects of a standard deviation increase in intelligence score on the probability of alignment with Conservative Party. The marginal effects were computed given theSEMestimates reported in B.2. The shaded areas correspond to 95% confidence interval.

Figure 2 provides a graphical illustration of the marginal effect of intelligence on the choice of the Conservative Party through the income channel over the life cycle.[8] Using the notation in Figure 1, the marginal effects are computed as follows. The marginal effect of intelligence on Conservative Party choice via income channel given college is given by the variable ME_e, defined as:

$$\text{ME}_e = \beta_{IQ}^{Earn} \beta_{Earn}^{Party} \qquad | \qquad e \in \{NC, C\} \tag{1}$$

The blue line in 2 corresponds to marginal effect given no college; the orange line, the marginal effect given college degree. Higher intelligence gives a slightly larger boost to the earnings of college-educated workers. Therefore, we also see that the point estimates of marginal effects on the Conservative Party choice are higher for college-educated workers.

[8]We note that symmetric and concave shape of the curves is because the regressions control for second-order polynomial in age.

The green line corresponds to a total marginal effect taking into account higher probability of obtaining a college degree and is computed as follows:

$$\mathrm{ME}_{\mathrm{total}} = \mathrm{ME}_{NC}(1-\pi) + \mathrm{ME}_{C}\pi + \beta_{IQ}^{College}\beta_{College}^{Earn}\beta_{Earn}^{Party} \tag{2}$$

Since getting a college-degree increases the lifetime earnings of individuals, the total marginal effect is higher at all ages. In addition to that, getting a college degree puts the worker on a steeper career path. Hence, we see a strong life-cycle pattern in marginal effects across ages.

4. Genetic Information: Polygenic Scores

The results we have seen are produced by the estimation of SEM, as presented in figure 1. This analysis ignores the fact that some variables in the statistical model are endogenous. First, the intelligence variable, based on the five cognitive tests administered during the survey, ignores the fact that intelligence may be affected by education and family background. Second, college decisions, earnings, and party choices are the outcome of choices made by agents in the economy, and thus also endogenous.

To address the first problem, we use information on the Polygenic Score for Education Years (PGS EY). A PGS is an individual-specific score that measures the risk or predisposition of an individual to exhibit a certain trait. The PGS is computed as a weighted sum of a person's genotype, where the weights are obtained from a Genome-Wide Association study ($GWAS$). A $GWAS$ identifies common genetic variants that contribute to specific traits (see Dudbridge (2013) or Uffelmann et al. (2021) for a primer on the topic). The variants considered in the study are in the form of Single Nucleotide Polymorphisms (SNP)'s, which represent variations at a single position in a DNA sequence among individuals. Such studies span the entire genome (hence the Genome-Wide qualification) and involve a very large number of individuals. [9] The study estimates a coefficient measuring how much any variant is associated with the trait of interest. To deal with the second issue, we develop and estimate a dynamic model in which individuals make education and political choices given their individual characteristics and labour market returns. The results of this analysis will be presented in the next section.

4.1. **Computation of the PGS's.** The PGS is computed as a sum of individual's genotype, weighted by GWAS coefficients. Since genotypes are inherited in blocks rather than independently

[9] The latest GWAS of educational attainment includes data from 3 million individuals (Okbay, 2022).

at each position, variants located nearby are correlated with each other. Existence of this non-zero correlation is known as linkage disequilibrium (LD). This correlation must be taken into account to avoid biases in the computation of the polygenic score.

We use two different ways to correct for LD. A simple way is to narrow the full set of variants to the most significant mutually independent set. This solution is referred to as the *clumping* algorithm. To identify the set of mutually independent SNPs we need a so-called LD matrix that gives correlation structure of SNPs. We compute the LD matrix in a METADAC subset passing typical quality control (QC) filters. For details, see section C.2 in the Appendix.

We also compute PGS using the LDpred2 algorithm (Privé et al., 2020). Unlike the clumping algorithm, LDpred2 uses all variants from the GWAS table, but scales them down taking into account the LD patterns. This solves the overfitting problem of the naive polygenic score and uses all available information. As a result, LDpred2 PGS generally outperforms alternative scoring methods in terms of predictive power (Ni et al., 2021). For a short overview of the algorithm and details of implementation, see section C.2 in the Appendix. Figure C.3 in the Appendix shows that LDpred2 PGS has higher correlation with observed variables in the METADAC. The correlation between LDpred2 PGS EY (polygenic score for years of education calculated using the LDpred2 algorithm) and the observed educational attainment is 21.7%, and the correlation with observed intelligence score is 22.8%. For comparison, the clumped PGS EY correlation is 13.3% and 13.6%, respectively. Therefore, we use LDpred2 PGS in our baseline specifications.

4.2. **PGS and Political Behaviour.** We perform the SEM estimation given in figure 1 in the METADAC dataset using both polygenic scores, PGS EY (LDpred2) and PGS EY (Clumped). In this case too the SEM contains three equations: one for college decision, one for lifetime earnings, and one for political behaviour. Political behaviour is measured by either the political participation indicator or the party affiliation choices. The estimation results are presented in tables B.3 (for political participation) and B.4 (for party affiliation). In both tables, the signs of the estimated coefficients in the equations for *College* and *DPV earnings* are as expected. In the *College* equation, IQ score has a large coefficient on college (marginal effect around around $18 - 19$ pp). The PGS EY has a slightly lower, but still statistically significant coefficient (marginal effect around 7.0-9.8 pp depending on the specification with LDpred2 PGS EY and 5.2pp with Clumped PGS EY). For the *DPV earnings* equation, college has a large and significant coefficient, comparable in magnitude across different specifications (marginal effect between 0.4 sd and 0.6 sd across Panels A-C). Even after controlling for college indicator, measures of intelligence also have large positive effect on lifetime earnings: 1 sd higher observed IQ score has a marginal effect of 0.24 sd and 1 sd higher LDpred2 PGS EY has a marginal effect of 0.04-0.07 sd.

	Dependent variable: political participation			
	1	2	3	4
Male	0.061***	0.061***	0.065***	0.058***
	(0.006)	(0.006)	(0.006)	(0.006)
Age	0.010***	0.010***	0.010***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)
IQ score	0.064***		0.057***	
	(0.005)		(0.005)	
PGS EY (LDpred2)		0.046***	0.040***	
		(0.004)	(0.004)	
PGS EY (Clumped)				0.033***
				(0.004)
College	0.115***	0.130***	0.110***	0.135***
	(0.007)	(0.007)	(0.007)	(0.007)
DPV of real monthly earnings (std)	0.054***	0.064***	0.052***	0.066***
	(0.004)	(0.004)	(0.004)	(0.004)
Obs.	31,843	31,843	31,843	31,843

Table 3. Political participation, individual characteristics and polygenic scores

Note: The table reports marginal effects computed after SEM estimation. Each SEM estimation included three equations: college equation, earnings equation and political participation equation. The table reports marginal effects from the political participation equation only. Standard errors (reported in parentheses) are computed using Delta method. The political participation indicator variable is estimated using logit regression. The earnings equation is estimated using simple OLS regression and college equation - using logit regression. Real Monthly Earnings (RME) and DPV of RME are standardized (mean=0 and SD=1). All regressions control for gender, race, birth cohort, parental background and survey wave indicators as well as interactions between college, intelligence scores and age. The regressions are unweighted.

Our focus here is on the estimates for the political behaviour variables. We present the marginal effects computed from the SEM estimates in tables 3 and 4 for political participation and party affiliation, respectively. A value of the PGS for EY (computed with LDpred2) 1 sd higher is associated with 4.0-4.6 pp higher probability of political participation. The marginal effect of the PGS EY (LDpred2) is slightly lower than that of observed IQ score or lifetime earnings. We also note that (see model 3 and 4) when PGS EY (LDpred2 of CLUMP) is included together with the observed IQ score, marginal effect estimates of both slightly decrease, but remain comparable to the estimates in models reported in columns 1 and 2. We conclude that the genetic component and observed intelligence/education capture different and relatively independent channels. This result is consistent with the fact that the PGS EY reports effects on educational attainment different from the simple intelligence of even cognitive skills, such as conscientiousness and motivation.

The picture is different when political behaviour is measured by party affiliation (see table 2). Observed IQ score appears is important for affiliation decisions compared to PGS EY. A one sd higher observed IQ score is associated with 3.1-3.2 pp higher probability of Conservative party choice. A one sd higher PGS EY, however, appears insignificant for the probability of Conservative party choice. The effect of College is negative on Conservative party choice.

5. Equilibrium Model of Education, Earnings and Voting

In this section we go beyond the descriptive and regression analysis. Instead, we formulate a model of voting where citizens take into account the incentives given by their skills, their investment in education, and future income.

Time is discrete; the time unit is one year. There is a set of efforts S, with $s \in S$. The set of individual characteristics is Θ, including intelligence values. The set of education levels is $E \equiv \{NC, C\}$, with $e \in E$. Given a pair (s, θ) there is a probability $\pi(s, \theta)$ of getting $e = C$. The probability is increasing in both variables, with positive complementary.

Each individual lives for T periods; the set of ages is $A \equiv \{1 \leq a \leq T\}$. In the initial period there is a given distribution over $E \times \Theta \times A$. At the end of the T periods the individual is replaced by one with same θ; thus we are assuming that the distribution over Θ constant in time. The wage function we assume later is time invariant.

There are two parties, for simplicity, $d \in \{C, L\}$. In every period one of the two parties is in power. With some probability it stays in power uncontested, or elections take place. If elections take place then the number of people who are actually able to vote is determined as outcome of a Poisson distribution. Then they vote. There a value $x \in X$, a set of aggregate states. This is the state of the economy that changes randomly and (for the moment) exogenously: that is we do not try to make it the outcome of the individual choices of agents in the economy. The value x describes the inequality on the distribution of income. This value can change with different economic conditions, and thus x describes how favorable the economic situation is for each of the

	Dependent variable: party alignment			
	1	2	3	4
Panel A: Conservative party				
Male	0.007*	0.006*	0.008*	0.006*
	(0.007)	(0.006)	(0.007)	(0.006)
Age	-0.002*	-0.001	-0.002*	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
IQ score	0.032***		0.031***	
	(0.005)		(0.005)	
PGS EY (LDpred2)		0.002	-0.001	
		(0.004)	(0.004)	
PGS EY (Clumped)				0.007**
				(0.004)
College	-0.098***	-0.106***	-0.094***	-0.110***
	(0.007)	(0.007)	(0.007)	(0.007)
DPV of real monthly earnings (std)	0.059***	0.063***	0.059***	0.063***
	(0.004)	(0.004)	(0.004)	(0.004)
Panel B: Labour party (base outcome)				
Male	-0.029***	-0.026***	-0.030***	-0.025***
	(0.007)	(0.007)	(0.007)	(0.007)
Age	0.016***	0.015***	0.016***	0.015***
	(0.002)	(0.002)	(0.002)	(0.002)
IQ score	-0.046***		-0.045***	
	(0.005)		(0.005)	
PGS EY (LDpred2)		-0.010***	-0.006**	
		(0.004)	(0.004)	
PGS EY (Clumped)				-0.016***
				(0.004)
College	0.075***	0.062***	0.072***	0.066***
	(0.008)	(0.008)	(0.008)	(0.007)
DPV of real monthly earnings (std)	-0.011***	-0.019***	-0.011***	-0.019***
	(0.004)	(0.004)	(0.004)	(0.004)
Panel C: Liberal Democrats				
Male	-0.022***	-0.025***	-0.022***	-0.025***
	(0.004)	(0.004)	(0.004)	(0.004)
Age	-0.008***	-0.008***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
IQ score	0.027***		0.027***	
	(0.003)		(0.003)	
PGS EY (LDpred2)		0.011***	0.008***	
		(0.003)	(0.003)	
PGS EY (Clumped)				0.014***
				(0.003)
College	0.038***	0.060***	0.036***	0.060***
	(0.005)	(0.005)	(0.005)	(0.005)
DPV of real monthly earnings (std)	-0.003*	0.003**	-0.003**	0.003**
	(0.002)	(0.002)	(0.002)	(0.002)
Obs.	24,625	24,625	24,625	24,625

TABLE 4. Political affiliation, individual characteristics and polygenic scores

Note: The table reports marginal effects,from the political participation equation only, computed after SEM estimation. Each SEM estimation included three equations: college equation, earnings equation and political participation equation. Standard errors (in parentheses) are computed using Delta method. The political participation indicator variable is estimated using logit regression. The earnings equation is estimated using simple OLS regression and college equation - using logit regression. Real Monthly Earnings (RME) and DPV of RME are standardized (mean=0 and SD=1). All regressions control for gender, race, birth cohort, parental background and survey wave indicators as well as interactions between college, intelligence scores and age. The regressions are unweighted.

two parties. For example x may describe the difference between median and mean income. When the median income is below the mean then re-distributive policies are likely to win.

In the first period each individual of type θ decides a costly effort level s (with some cost $c(s)$, where c is increasing in s). The function π then decides the probability of college. This section of the model is equivalent to the assumption that there is a probability on college achievement that is increasing in θ. In all periods the individual decides the vote for one of the parties if an election occurs, by choosing the one that maximizes his expected future utility. If no election occurs he expresses a preference for one of the two parties, by stating what the person would vote if an election did take place, which is the one we observe in the data.

The vector (e, θ, a) describes individual characteristics, the vector (x, d) economy wide characteristics. We call $V(e, \theta, a; x, d)$ the value for the individual. In every period his utility is given by the wage function w with value $w(e, \theta, a, x)$; the individual gets an income equal to wages net of taxes; that is he has utility

$$U(\theta, e, a; x, d) = w(e, \theta, a, x)(1 - \tau(d)) + T(d),$$

where $T(d)$ is a transfer policy of party in power d.

Since there is no maximization problem agents solves in periods $a \geq 1$, her value function can be written as follows. At terminal age $a = L$, the value function is equal simply to the period utility.

$$V(\theta, e, L; x, d) = U(\theta, e, L; x, d) \tag{3}$$

At every other period $a < L$, her value function is computed as

$$\begin{aligned} V(\theta, e, a; x, d) = {} & U(\theta, e, a; x, d) + \\ & + \mathbb{E}_{X'|X}\left[\delta V(\theta, e, a+1; x', d') + (1-\delta) V(\theta, e, a+1; x', d)\right] \end{aligned} \tag{4}$$

where the continuation values of next period $(a + 1)$ are averaged over possible realizations of aggregate economy state $X'|X$ and party in power d' in the next period. He takes the transition function T on the aggregate state as given and the transition on the party in power given by the probability of an election taking place and the voting of others as given, for x and distribution on education and θ. Given the value functions, the party preferences of each agent is:

$$d^{\star}(\theta, e, a, x) = C \tag{5}$$

if and only if

$$V(\theta, e, a, x, C) > V(\theta, e, a, x, L).$$

Therefore, if election is called, which happens with probability δ in each period, then all agents cast votes and a new party in power is determined by the majority rule $\tilde{d}(x) = C$ if and only if:

$$\int_{\Theta\times E\times A} \left[\mathbb{1}\left\{d^\star(\theta, e, a, x) = C\right\} - \mathbb{1}\left\{d^\star(\theta, e, a, x) = L\right\}\right] dF(\theta, e, a) > 0. \tag{6}$$

Substituting 6 into 4:

$$\begin{aligned} V(\theta, e, a; x, d) &= U(\theta, e, a; x, d)+ \\ &+ \mathbb{E}_{X'|X}\left[\delta V(\theta, e, a+1; x', \tilde{d}(x)) + (1-\delta)V(\theta, e, a+1; x', d)\right] \end{aligned}$$

5.1. **Education choice.** In the first period, each individual has to decide how much effort to put in to get college education. Thus, she solves

$$\max_s \pi(\theta, s)\mathbb{E}_X V(\theta, C, 1; x, \tilde{d}(x)) + (1-\pi(\theta, s))\mathbb{E}_X V(\theta, NC, 1; x, \tilde{d}(x)) - \psi\frac{s^2}{2} \tag{7}$$

where $-\psi\frac{s^2}{2}$ is the utility cost of exerting effort s.

If the probability of getting a college degree has the functional form

$$\pi(\theta, s) = \min\left\{\max\left\{s\theta, 0\right\}, 1\right\},$$

then, the optimal effort function is given by

$$s^\star(\theta) = \min\left\{\max\left\{\frac{\theta\mathbb{E}_X\Delta V(\theta)}{\psi}, 0\right\}, \frac{1}{\theta}\right\} \tag{8}$$

where $\mathbb{E}_X\Delta V(\theta) = \mathbb{E}_X V(\theta, C, 1; x, \tilde{d}(x)) - \mathbb{E}_X V(\theta, NC, 1; x, \tilde{d}(x))$ is the expected lifetime benefit the agent enjoys from getting a college degree before she can observe any information about aggregate state. Since effort is costly, the optimal effort is capped from above by $\frac{1}{\theta}$, which delivers a college degree with certainty.

Hence, the probability of getting a college degree at equilibrium is

$$\pi^\star(\theta) = \min\left\{\max\left\{\frac{\theta^2\mathbb{E}_X\Delta V(\theta)}{\psi}, 0\right\}, 1\right\} \tag{9}$$

5.2. **Government.** The government is constrained by a budget constraint, requiring that the total of the tax revenues is equal to the total of the transfers. We assume that the tax revenues are equally split between agents:

$$T(x,d) = \tau(d) \int_{\Theta \times E \times A} w(\theta,e,a,x) dF(\theta,e,a) \tag{10}$$

5.3. **Population distribution.** Given the above decisions, population distribution can be represented with the following joint density function

$$f(\theta,e,a) = \begin{cases} \frac{\pi^\star(\theta) f(\theta)}{A} & \text{if } e = C \\ \frac{(1-\pi^\star(\theta)) f(\theta)}{A} & \text{if } e = NC \end{cases} \tag{11}$$

5.4. **Voting Choice Probability.** We operate in our estimation of choice probabilities using the random utility model, where agents choose between parties based on the value functions as well as choice-specific error term. That is, the rule for preferring Conservative party is now

$$V(\theta,e,a,x,C) + \xi(C) > V(\theta,e,a,x,L) + \xi(L)$$

Thus, the choice probabilities can be written as

$$\Pr(d^\star = C|\theta,e,a,x) = \Pr\left(\xi(L) - \xi(C) < \Delta V(\theta,e,a,x)|\theta,e,a,x\right)$$

where $\Delta V(\theta,e,a,x) \equiv V(\theta,e,a,x,C) - V(\theta,e,a,x,L)$.

We follow a standard approach and assume that $\xi(i) \in \Xi$ is distributed *i.i.d.* extreme value, which implies that $\xi(L) - \xi(C)$ is distributed logistically. Therefore, the choice probability becomes

$$\Pr(d^\star = C|\theta,e,a,x) = \frac{\exp\left(\kappa \Delta V(\theta,e,a,x)\right)}{1 + \exp\left(\kappa \Delta V(\theta,e,a,x)\right)} \tag{12}$$

where κ is equivalent to inverse standard deviation of $\xi(L) - \xi(C)$.

We further modify the choice probability by including a constant term γ:

$$\Pr(d^\star = C|\theta,e,a,x) = \frac{\exp\left(\kappa \Delta V(\theta,e,a,x) + \gamma\right)}{1 + \exp\left(\kappa \Delta V(\theta,e,a,x) + \gamma\right)} \tag{13}$$

This term will capture common shift in political preferences in the data that is not accounted for by the model. This can arise, for example, if parties change their positions to some issue that the public care about while keeping the tax rates unchanged. In the data, we would see it as a shift in preferences from one year to the next. Therefore, by including year-specific γ terms we can remove such common trends.

6. Estimation

The model defined in the previous section characterizes choice of political party $d^\star$ as a function of individual characteristics (θ, e, a) and aggregate state x. The parameters of interest in this model is a vector $\Omega = \left(\kappa, \{\gamma_t\}_{t=1}^T, \psi\right)$ where κ captures the importance of value function differential in explaining the observed choices, $\{\gamma_t\}_{t=1}^T$ captures aggregate trends in party choices over time and ψ is a scale parameter. In this section, we describe our estimation strategy of this model.

6.1. **Likelihood function.** Given the choice probability in equation (13) and college probability in equation (9), the contribution of observation at time t of individual i to the sample likelihood is

$$\begin{aligned} L_{it}(\Omega; Y_{it}) = &\Pr(d^\star = C|\theta_i, a_{it}, e_i, x_t)^{\mathbb{1}\{d_{it}=C\}} \left(1 - \Pr(d^\star = C|\theta_i, a_{it}, e_i, x_t)\right)^{1-\mathbb{1}\{d_{it}=C\}} \times \\ &\times \pi^\star(\theta_i)^{\mathbb{1}\{e_i=C\}} \left(1 - \pi^\star(\theta_i)\right)^{1-\mathbb{1}\{e_i=C\}} \end{aligned}$$

where θ_i is IQ score of individual i, e_i is the indicator whether she has college degree, a_{it} is her age at time t, d_{it} is her observed party choice in the data, x_t is the aggregate state and $Y_{it} = (\theta_i, e_i, a_{it}, d_{it}, x_t)$ denotes a vector of observed variables. We then write the sample log-likelihood as

$$\mathcal{L}(\Omega; Y) = \sum_{i=1}^{N} \sum_{t=1}^{T} \ln L_{it}(\Omega; Y_{it}) \tag{14}$$

The definition of individual party choice probability further depends on the wage function, tax and transfer functions.

First, we map the individual characteristics into state vectors used in the model. We assume that the intelligence variable is distributed normally: $\Theta \sim \mathcal{N}\left(\mu_\theta, \sigma_\theta^2\right)$ where $\mu_\theta = 100$ and $\sigma_\theta = 15$. In our estimation we limit the support of the variable to ± 4 sd. We also make sure that our grid for Θ includes all the observed values of IQ score variable, which enables us to compute the log-likelihood value for each specific observation in the data. We then compute the marginal density $f(\theta)$ at each value in the grid, and rescale them to sum up to one. We map the observed college indicator to the grid of education levels E. We also assume that age grid $A \sim \mathcal{U}\{0, 45\}$ is shifted down from the observed ages by 20. That is, $a = 0$ corresponds to age 20 and $a = 45$ corresponds to age 65.

Second, we define the aggregate state variable x_t as a weighted sum of three aggregate variables: annual GDP growth, unemployment rate and CPI inflation. We use estimated coefficients from the wage equation as weights. We then discretize the aggregate score using Tauchen algorithm

(Tauchen (1986)) which returns a grid of five states and respective transition matrix. For further details on income equation see Section A.3 and for discretisation - Section A.4 in the Appendix.

We separately estimate wage equation as a function of (θ_i, e_i, a_{it}) and aggregate state x_t. We do so in two steps. In the first step we estimate the wage equation with a vector of aggregate variables. We then use the estimated coefficients of aggregate variables as weights to combine them into single aggregate score. In the second step we estimate the wage equation replacing the vector of aggregate variables with the aggregate score. Given the estimated coefficients, we generate a wage matrix at each value of individual and aggregate states $w(\theta, e, a, x)$. For further details see Section A.2 in the Appendix.

Next, we define a flat tax schedule as a function of party in power. Figures A.7 and A.8 in the Appendix show that tax burden is usually lower when a Conservative government is in power. [10] We assume that $\tau(d) = 0.2$ when Conservative Party is in power and $\tau(d) = 0.3$ when Labour Party is in power. Given the tax function $\tau(d)$, the transfers are easily computed from equation (10).

The stationary population distribution can be calculated from equation (11). We already defined the marginal density of intelligence $f(\theta)$ and marginal probability of age $f(a)$ when creating the respective state grids. We assume these distributions remain unchanged over time. The marginal probability of education state e depends on the model solution in equation (9).

6.2. **Parameter Estimation.** We estimate the model by maximizing the log-likelihood in equation (14). The vector of estimated parameters Ω includes (ψ, κ, γ). The γ parameter consists of both a constant term as well as linear combination of additional covariates such as gender, birth cohort indicators and survey year indicators. These parameters help capture common shift in choice probabilities that are not explained by the model.

Table 5 reports the estimation results for the parameters of interest (ψ, κ). Since the party choice probability is defined by a logistic function, the estimated parameter $\hat{\kappa}$ (introduced in equation (12)) can be interpreted as log odds ratio of choosing Conservative Party. When converted to the odds ratio, the estimate indicates that a unit increase in ΔV increases the odds of Conservative Party choice by almost 50%.

[10] The level of tax burden computed in the UKHLS/BHPS and the ONS table differ due to different variable definitions. In the UKHLS/BHPS we compute the tax burden as the difference between gross and net income. Therefore, it includes income tax burden as well as other income witholdings. In the ONS table the tax burden only uses payments marked as income tax. However, in some instances income tax payments exceed earned income or can even be negative, which suggests that taxable income may include other types of income as well. Nevertheless, both figures show similar dynamics over the years.

	Log OR
$\ln(\psi)$	12.967
	(0.005)
κ	0.403
	(0.026)
Obs.	86,286

TABLE 5. Model parameter estimates

Notes: the table reports ML estimates of model parameters. The estimation additionally controlled for common shifts in party choice probabilities attributed to gender, birth cohorts and survey year. The conventional standard errors are reported in parentheses.

Figure 3 plots the marginal effect of intelligence on party choice probabilities. The total marginal effect is computed according to equation (16) and takes into account the marginal effect of intelligence on college probability.

$$\frac{\partial \Pr(d^\star = C|\theta, e, a, x)}{\partial \theta} = \Pr(d^\star = C|\theta, e, a, x)\,(1 - \Pr(d^\star = C|\theta, e, a, x))\,\kappa \frac{\partial \Delta V}{\partial \theta} \tag{15}$$

$$\begin{aligned} \frac{\partial \Pr(d^\star = C|\theta, a, x)}{\partial \theta} &= \frac{\partial \Pr(d^\star = C|\theta, NC, a, x)}{\partial \theta}(1 - \pi^\star(\theta)) + \\ &+ \frac{\partial \Pr(d^\star = C|\theta, C, a, x)}{\partial \theta}\pi^\star(\theta) + \\ &+ \left[\Pr(d^\star = C|\theta, C, a, x) - \Pr(d^\star = C|\theta, NC, a, x)\right] \frac{d\pi^\star(\theta)}{d\theta} \end{aligned} \tag{16}$$

The marginal effects conditional on degree status (blue and orange curves) are computed according to the equation (15). The sign of the marginal effect is determined by $\frac{\partial \Delta V}{\partial \theta}$. The value function of the worker depends on consumption, which in turn depends on net income. Both gross and net income are increasing in intelligence. But more importantly, higher intelligence has larger effect on net income under lower taxes, which is more likely with a Conservative Party. Therefore, it is of no surprise that ΔV is also increasing in θ. The shape of the marginal effects over the life cycle is driven by both the shape of income profile and aging.

7. CONCLUSIONS

The paradox of voting (going back to Condorcet et al. (1793) and Downs (1957)) notes that in a large election the expected benefits from casting a vote is substantially lower than the expected benefits, and thus a rational voter should simply not vote. But the cost of casting a vote is usually limited to few minutes of activity. In contrast, the cost of acquiring information relevant for casting

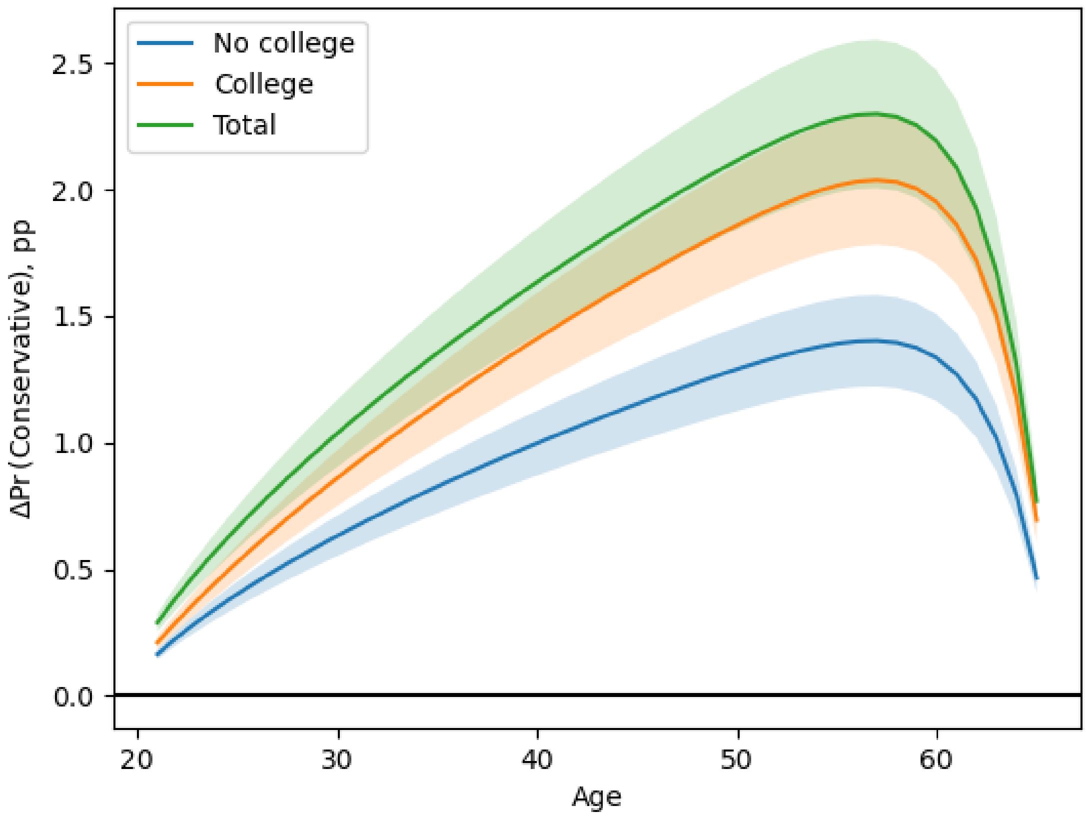

FIGURE 3. Marginal effect of IQ on Conservative Party choice

Notes: the figure plots the marginal effect of a standard deviation increase in intelligence score on probability of choosing the Conservative Party. The marginal effects were computed at mean intelligence score and base categories of covariates (males born in 1945-50 observed in 2009). The shaded areas correspond to 95% confidence interval.

an informed vote is considerably larger than casting a vote in itself. A rational agent (as modeled in Feddersen and Pesendorfer (1996); Feddersen (2004); McMurray (2013)) may decide the degree of participation depending on the quality of information, and thus, proceeding backward, decide how much political information should be acquired. This reasoning implies the paradox of political information acquisition, and a conclusion that most people should be totally ignorant of political facts.

We claimed here that the supposed paradox may be just a faulty conclusion derived from a narrow setting of the problem as that of a trade-off between costs of acquiring political information and the benefits derived strictly and exclusively from political participation and voting. In this paper we have cast the problem of acquisition of political information in a more appropriate sense of acquiring information that is eventually also relevant in political choices, but is also essential in running one's economic activity.

We adopted the assumption that the cost of any politically relevant information is eventually produced by a cost-benefit comparison, and thus the cost of information processing is crucial. Since intelligence, and more generally cognitive abilities, influence substantially this cost, we predicted that they should also affect political participation. Intelligence and cognitive abilities may also have an indirect effect through education and income, and these distinct pathways have been analyzed.

We do in fact find that intelligence affects political participation, even more decidedly than the political preferences, that is the parties and programs supported in the elections. But intelligence and cognitive abilities are not the only factor influencing political participation. We may take as an illustration a different behavior, educational attainment. Many traits affect educational attainment of an individual. Intelligence is one of them, but others, such as conscientiousness, play an important role in success in education. Thus, we should expect that the activity of information processing that underlies political participation, which has a similar nature, should be influenced by such constellation of traits. For example the role of academic intrinsic motivation (Gottfried et al. (2001)) in acquisition of education, or that of curiosity (Deci and Ryan (1981); Markey and Loewenstein (2014)) as the individual trait inducing acquisition of information for its own sake.

We find support for this hypothesis when we consider a measure of individual ability and inclination for information processing that cannot be considered endogenous, namely the one provided by the polygenic score for educational attainment. As expected, the role of the PGS is strong, and it is so particularly in the case of political participation.

An important implication of these findings is that the institutional arrangements of a nation are ultimately influenced by the distribution of characteristics in a population. In turn, this distribution ultimately and in substantial part determined by the distribution of the genotype in that population.

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A. Data processing details

A.1. **Political preferences.** In each wave, the respondents are asked whether they support or are close to some party and if so, which party they are aligned with. The variables are categorical: value 0 means supporting/feeling close to no party, 1 means supporting/feeling close to Conservative party, 2 - Labour party, 3 - Liberal Democrats and 4 - supporting or feeling close to all other parties.

In addition, in waves 2 and 7-12 some respondents were instead asked whether they voted in last general elections (GE) and if so, for which party they voted. This variable has similar categories as the alignment variables, with values ranging from 0 to 4. A.1 plots the sample shares of people aligned to some party or those who voted in last general elections over time. For comparison, we also plot the overall voter turnout in the UK (see Watson et al. (2020)). The figure shows that the reported vote shares in the sample are considerably higher than the overall turnout in the UK. This can be explained by "consistent over-reporting of voter turnout" in surveys (Ansolabehere and Hersh, 2017). Therefore, we prefer using the political alignment variables in the analysis.

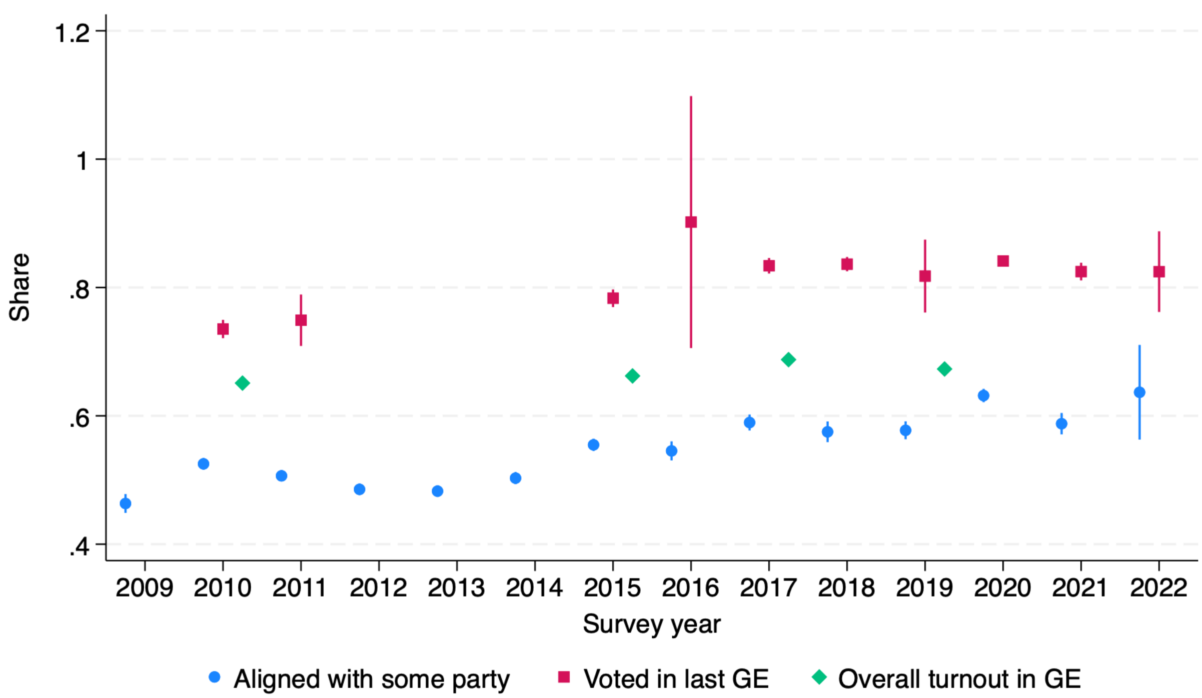


Figure A.1. Political preferences across waves

Notes: the alignment indicator consists of individuals who either report supporting or feeling close to some political party. The overall turnout in GE is computed from the data released by the House of Commons Library (Watson et al., 2020). The averages are weighted with cross-sectional response weights from wave 3. The whiskers correspond to 95% confidence interval around sample averages.

Figure A.2 plots the proportions of the working sample who report being aligned with a given party. For comparison, the markers correspond to overall vote share received by the corresponding parties in general elections, computed from the House of Commons Library data (Watson et al., 2020). Overall, party choices in the sample match closely party votes shares in GE. Using the party

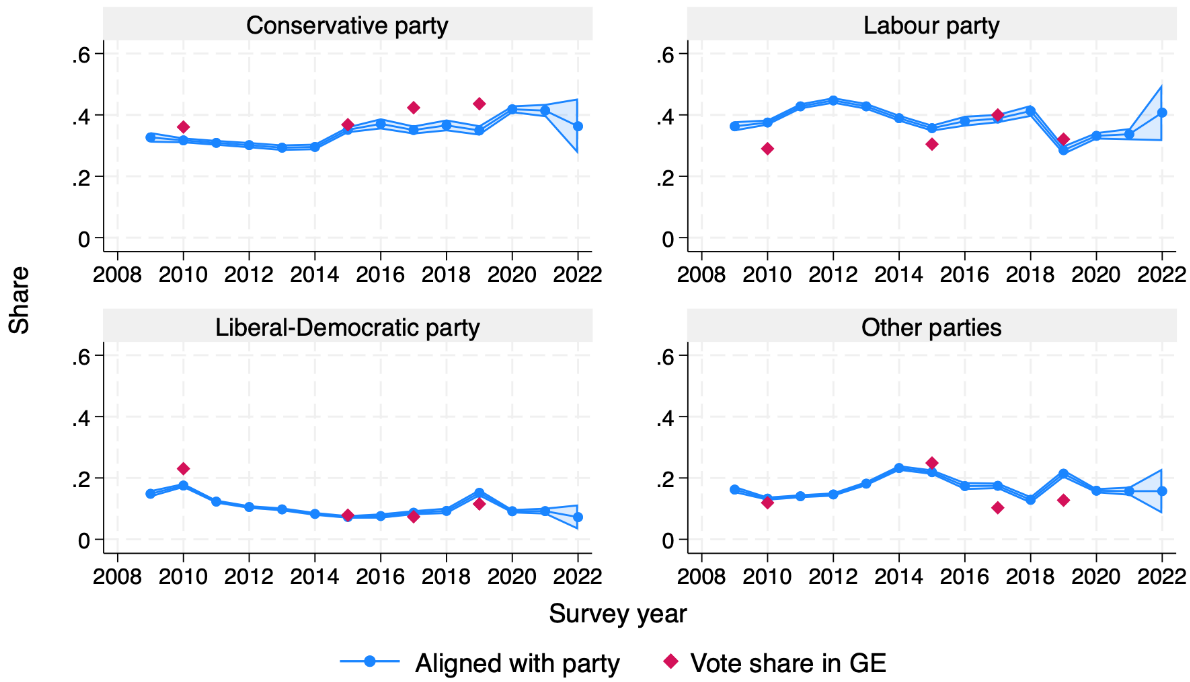


FIGURE A.2. Party choices across waves

Notes: the figure plots the proportion of working sample reporting being aligned with a given party. The overall vote share in GE is computed from the data released by the House of Commons Library (Watson et al., 2020). The sample averages are weighted with cross-sectional response weights from wave 3. The shaded areas correspond to 95% confidence interval around sample averages.

alignment variable we construct two indicator variables. The first is *Political Participation*, which is equal to *party align* if *party align* is strictly larger zero. The second is *Preference for Conservatuve*, which is equal to 1 if *party align* is equal to 1 (indicating a prefernce for the Conservative party), conditional on *party align* being different from zero.

A.2. **Earnings process in regression analysis.** In each wave, the respondents are asked about their employment status, hours worked and earnings. We use these variables to construct hourly wages and deflate them with the CPI excluding rent, maintenance repairs and water charges. Thus, for each individual in the sample we have up to twelve real hourly wage observations in the data.

Using this data, we predict the discounted present value of lifetime earnings (DPV earnings) following the methodology in Ichino et al. (2024). We use the sample corresponding to full-time work (at least 25 hours a week) between ages 20 and 65 where earnings information does not exceed the top-coded limit of £100,000 a year. Equation 17 describes the regression equation we use to estimate earnings age profile. We regress log real hourly wages on indicators for time trend, indicators for ages between 20-50 and 61-65 years and allowing the age effects to vary with gender and college, fully interacted. It is well known that flexible estimation of time, age and cohort effects requires additional constraint since these variables are perfectly collinear. The regression we fit imposes the restriction that wage profile is flat between ages 50 and 60, which can be justified by common theories of lifecyle earnings.

$$\ln w_{it} = \beta_0 + \sum_{a \in \mathcal{A}} (\phi_a + \psi_a X_i) + \xi_t + u_i + v_{it} \tag{17}$$

where $\mathcal{A} = \{20, \ldots, 50, 61, \ldots, 65\}$ and X_i includes gender indicator F_i, college indicator C_i and their interaction $F_i \times C_i$.

Given the estimation results we obtain predicted wages at each age, including the estimated individual fixed effects $\hat{u}_i$ and disregarding time effects $\hat{\xi}_t$.

$$\hat{w}_{ia} = \hat{\beta}_0 + \sum_{a \in \mathcal{A}} \left(\hat{\phi}_a + \hat{\psi}_a X_i \right) + \hat{u}_i \tag{18}$$

Even though the earnings age profile is restricted to only vary with college degree, the level of wages retains correlation with other variables such as intelligence via the inclusion of $\hat{u}_i$.

Finally, we calculate the DPV of earnings as follows

$$\hat{w}_i = \sum_{a=20}^{65} \left(\frac{\hat{w}_{ia}}{1 + 0.03} \right)^{a-19} \tag{19}$$

A.3. **Earnings process in the model.** We process income data for the model slightly differently. First, the income variable includes other sources besides labour earnings. The UKHLS data set includes data on personal incomes, collected for all waves and from all individuals of age larger than 16. Data consist of (1) Earnings from main and second jobs; (2) Social security benefits; (3) State and private benefits; (4) Private transfers and investment income. [11] In particular, the variable investment income reports income from interest and dividends in the last 12 months. [12] Second, we substitute flexible time and age fixed effects with other functional forms to simplify the modelling of income process. Instead of age fixed effects we assume that log income profile has logarithmic relationship with age. The time fixed effects are in turn substituted by aggregate variables (CPI inflation, unemployment rate and GDP growth rate) and linear time trend. Below we describe how we obtain the income function $w(\theta, e, a, x)$ step by step.

Since we do not model firm side of the economy, we could estimate the income process $w(\theta, e, a, x)$ in the data and take it as given. We observe gross income y, intelligence θ, degree status e and age a of each individual i over time t. In addition, we merge the data with three aggregate variables: annual GDP growth[13], unemployment rate[14] and annual CPI inflation[15].

[11] https://www.understandingsociety.ac.uk/wp-content/uploads/working-papers/2019-08.pdf

[12] See https://www.understandingsociety.ac.uk/wp-content/uploads/working-papers/2019-08.pdf, page 19:

> **Investment income** All respondents receive the household finances module which asks for income from interest and dividends in the last 12 months (to the nearest pound). To reduce missing data, where respondents cannot give an exact amount they are presented with a series of unfolding brackets where they can bound their annual investment income."

[13] https://www.ons.gov.uk/economy/grossdomesticproductgdp/timeseries/ihyp/pgdp

[14] https://www.ons.gov.uk/employmentandlabourmarket/peoplenotinwork/unemployment/timeseries/lf2q/lms

[15] https://www.ons.gov.uk/economy/inflationandpriceindices/timeseries/l55o/mm23

Table A.1. Income profile estimations

	(1) log(real income)	(2) log(real income)
log(age)	0.406***	0.405***
	(0.019)	(0.019)
Degree=1 × log(age)	0.048**	0.076***
	(0.016)	(0.014)
log(age) × Std IQ	0.029*	0.031*
	(0.013)	(0.013)
Degree=1 × log(age) × Std IQ	0.001	0.001
	(0.013)	(0.013)
Aggregate score		0.921***
		(0.118)
GDP growth	-0.001	
	(0.001)	
Unemployment rate	-0.037***	
	(0.005)	
CPI inflation	0.012**	
	(0.004)	
Degree=1 × Aggregate score		-0.417**
		(0.134)
Degree=1 × GDP growth	0.010***	
	(0.003)	
Degree=1 × Unemployment rate	0.027***	
	(0.007)	
Degree=1 × CPI inflation	-0.020*	
	(0.008)	
Year	-0.030***	-0.028***
	(0.002)	(0.002)
Constant	66.206***	62.352***
	(4.570)	(4.258)
Obs.	168,908	168,908

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Then, we fit the following fixed effects regression to the log of gross income:

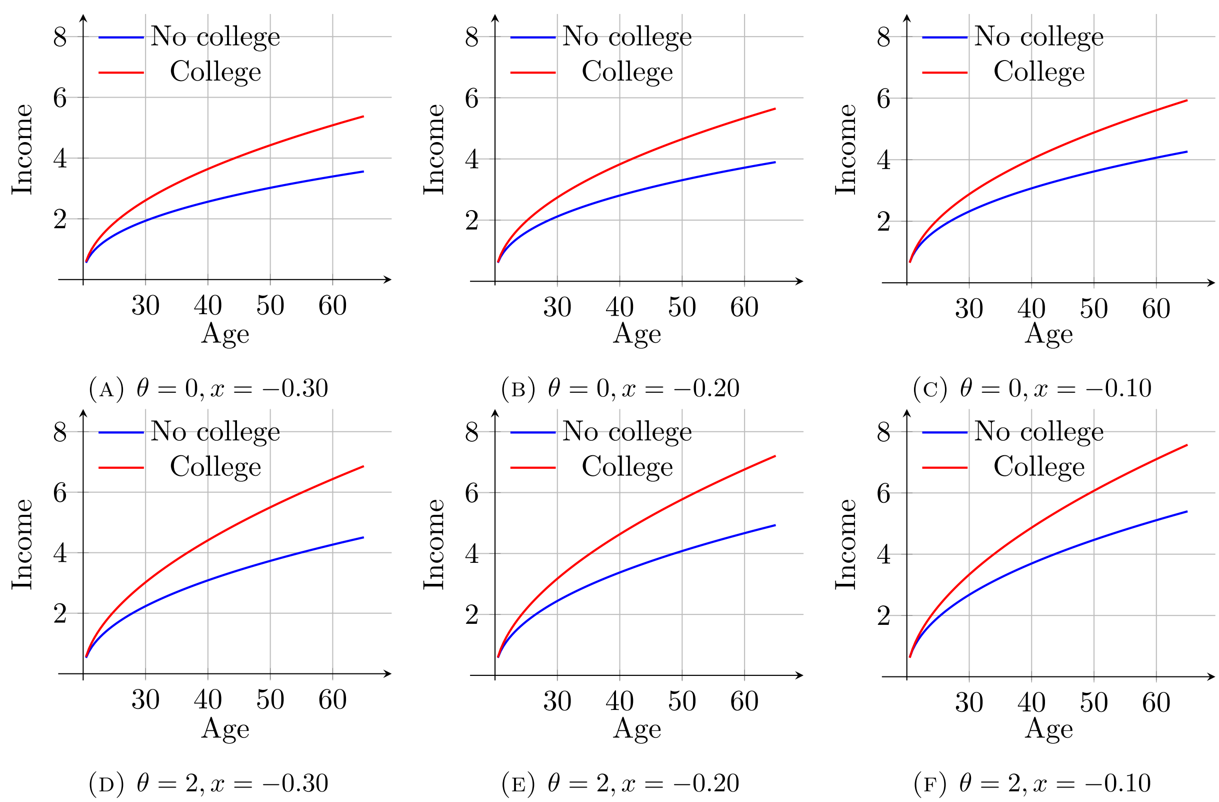
$$\ln y_{it} = \alpha_0 + (\alpha_{1,e} + \alpha_{2,e}\theta_{it}) \ln a_{it} + \tilde{\delta}_e \tilde{x}_t + \gamma t + u_i + \varepsilon_{i,t} \tag{20}$$

where $\tilde{x}_t$ is the vector of GDP growth, unemployment rate and CPI inflation at time t. Thus, we assume that age profile has logarithmic functional form. The coefficients $\alpha_{1,e}$ describe education-specific slopes of age profiles, and similarly $\alpha_{2,e}$ describe how education-specific age profile slopes change with every standard deviation change in intelligence θ. Furthermore,we assume that aggregate states may also influence income of individuals differently depending on their degree status; hence, $\tilde{\delta}_e$ is education-specific. We also replace time fixed effects with linear time trend to be able to estimate the coefficients $\tilde{\delta}_e$. Table A.1 reports the estimation results of 20 in column (1).

Using the estimated coefficients we combine the three aggregate indicators into single aggregate score: $x_t = \hat{\hat{\delta}}_{\text{no degree}}\tilde{x}_t$. Then, we repeat the estimation of 20 but using the aggregate score x_t in place of the three aggregate indicators. Column (2) in A.1 reports the corresponding results. We use these estimates to define the income function in the model:

$$w(\theta, e, a, x) = \exp\Big((\hat{\alpha}_{1,e} + \hat{\alpha}_{2,e}\theta)\ln a + \hat{\delta}_e x\Big) \tag{21}$$

Figure A.3 provides graphical illustration of $w(\theta, e, a, x)$ at selected values of θ and x.



(A) $\theta = 0, x = -0.30$ (B) $\theta = 0, x = -0.20$ (C) $\theta = 0, x = -0.10$

(D) $\theta = 2, x = -0.30$ (E) $\theta = 2, x = -0.20$ (F) $\theta = 2, x = -0.10$

FIGURE A.3. Income profiles for the model

A.4. **Aggregate score.** The original aggregate series in $\tilde{x}_t$ as well as aggregate score x_t are continuous variables. To use it as a state variable, we discretise the score using Tauchen algorithm.

We fit an AR(1) regression to the aggregate score

$$x_t = \mu + \rho x_{t-1} + \zeta_t, \qquad \zeta_t \sim \mathcal{N}(0, \sigma_\zeta^2)$$

The estimation results are reported in A.2.

Table A.2. Aggregate score AR(1) estimation

	(1) Aggregate score
ρ	0.885
	(0.103)
μ	-0.023
	(0.023)
Obs.	30
σ_ζ	.0326272

Standard errors in parentheses

This process implies the following grid of aggregate states and corresponding transition matrix

$$X = \begin{pmatrix} -0.2951 & -0.2462 & -0.1973 & -0.1483 & -0.0994 \end{pmatrix}$$

$$T = \begin{pmatrix} 0.6573 & 0.3143 & 0.0280 & 0.0003 & 0.0000 \\ 0.1782 & 0.5401 & 0.2629 & 0.0187 & 0.0002 \\ 0.0122 & 0.2144 & 0.5467 & 0.2144 & 0.0122 \\ 0.0002 & 0.0187 & 0.2629 & 0.5401 & 0.1782 \\ 0.0000 & 0.0003 & 0.0280 & 0.3143 & 0.6573 \end{pmatrix}$$

A.4 plots the continuous and discretised versions of the aggregate score.

A.5. **Elections.** In the model, elections occur randomly in each period with probability δ. This is equivalent to assuming that elections are governed by a random variable following an exponential distribution with rate δ.

We use the list of general elections in the UK between 1918 and 2019[16] and fit the exponential distribution to the length of time between elections. The estimated parameter $\hat{\delta}^{ML} = 0.2574 (SE = 0.0505)$.

The aggregate information about election results also provides us with the opportunity of comparing the political preferences in the UKHLS to the population. A.6 plots the average party support in the UKHLS against the aggregate vote shares at most recent general election over time[17].

A.6. **Tax rates.** Figure A.7 plots two measures of tax burden. The left panel plots the difference between net and gross income in the UKHLS/BHPS as a share of gross income. The right panel plots average ratio of income tax paid and earned income published by the ONS.

We also use the tax schedules published by the HM Revenue & Customs office for years 1948-2022. Given data on median annual earnings published by the ONS, we calculate income taxes due implied by the tax schedule in the corresponding year. Figure A.8 plots the calculated income taxes due on median income. The level of tax burden is higher than in Figure A.7, but qualitatively it offers similar conclusion. Periods with Conservative party in power are associated with lower tax burden on individuals.

[16] https://commonslibrary.parliament.uk/research-briefings/cbp-8647/

[17] For example, we assign vote shares from 2010 election to all observations in 2011 - 2014.

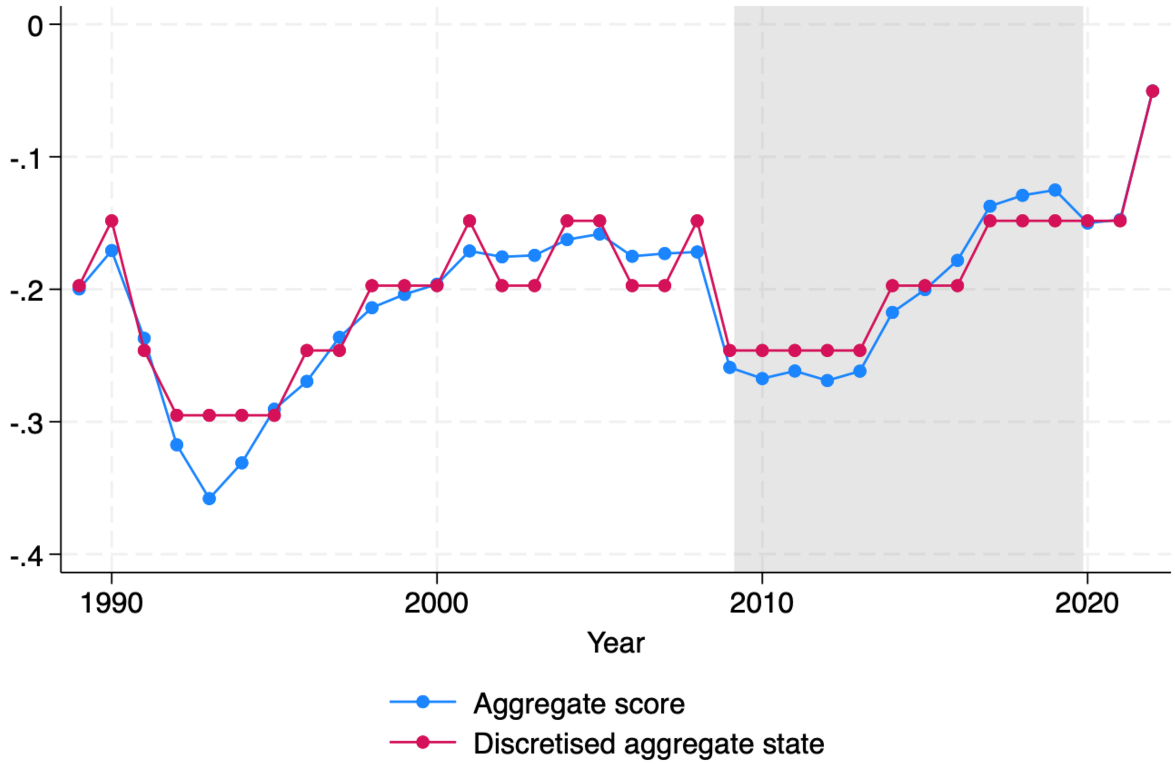


FIGURE A.4. Aggregate score

Note: The figure plots the continuous and discretised versions of the aggregate score. The score is constructed as a weighted sum of annual GDP growth, unemployment rate and CPI inflation with weights given by the $\delta_{\text{no degree}}$ coefficients estimated from 20. The three input series are published by the Office for National Statistics. The shaded area corresponds to the timeline of the UKHLS waves.

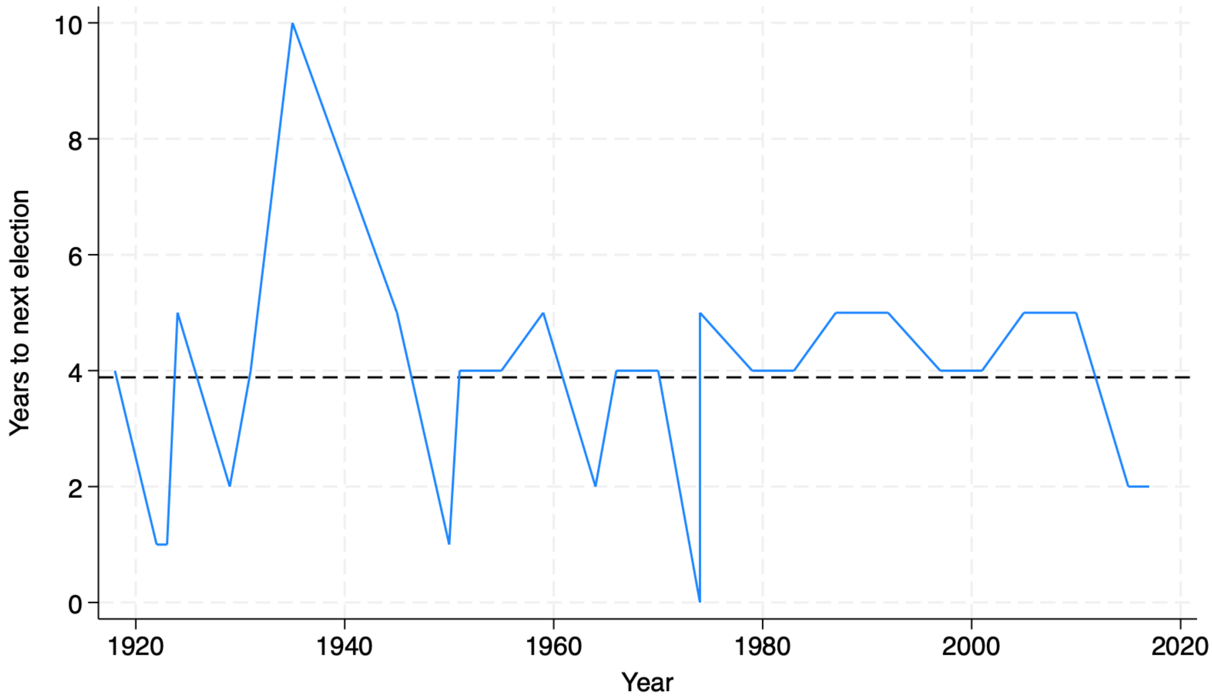


Figure A.5. Election arrival rate

Note: The figure plots the time interval between general elections in the UK since 1918 (blue solid line) against the average interval using estimated arrival rate $\hat{\delta}^{ML}$ (black dashed line). The data on general election results between 1918 and 2019 is published by the Commons Library.

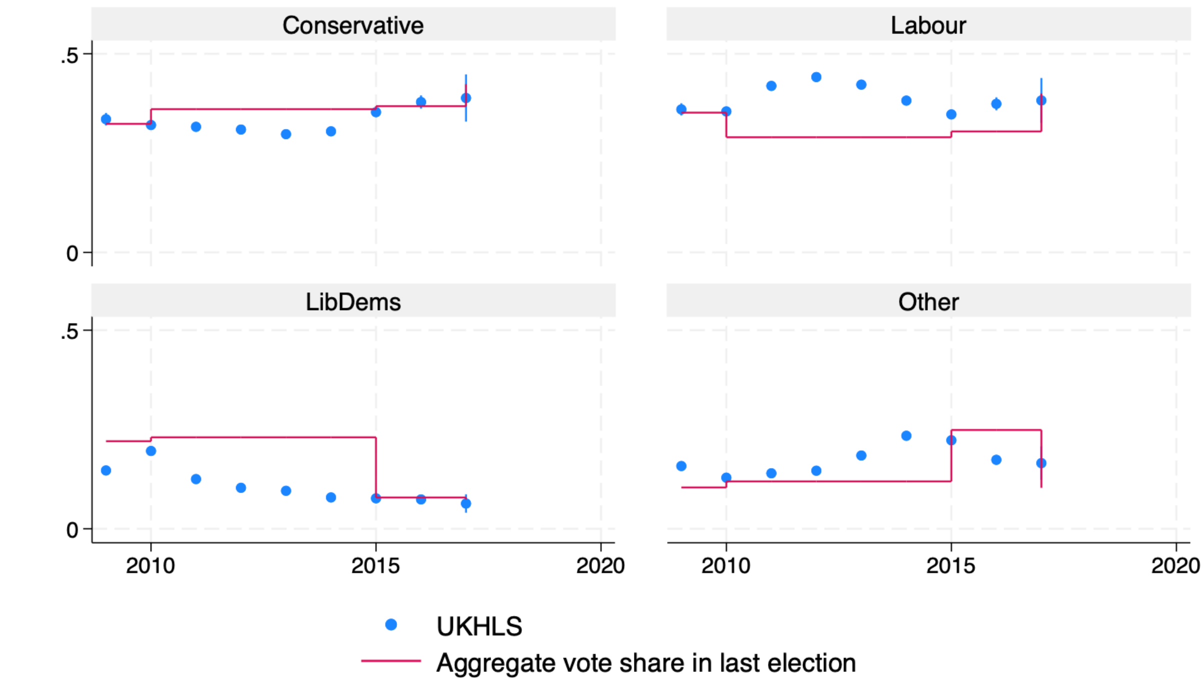
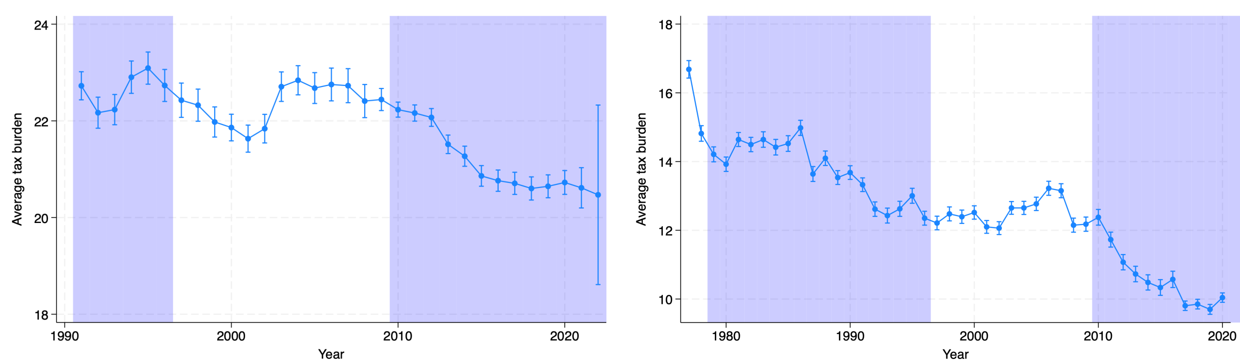


FIGURE A.6. Political preferences in the UKHLS and aggregate vote shares

Note: The figure plots sample proportions supporting a given party over time in the UKHLS (blue dots) against the aggregate vote shares at most recent general election (red line). The data on general election results between 1918 and 2019 is published by the Commons Library.



(A) UKHLS and BHPS

(B) ONS

FIGURE A.7. Income tax and party in power

Notes: the figure plots the average income tax payments as a share of gross income. The left panel computes the tax burden given gross and net incomes in the UKHLS (2009-) and the BHPS (1991-2008). Therefore, the tax burden estimates includes income taxes as well as other direct taxes withheld from gross income. The right panel uses the income tax and gross income data published by the ONS in the "Effects of taxes and benefits on UK household income, 1977-2021" table. The shaded areas correspond to years when the Conservative party was in power.

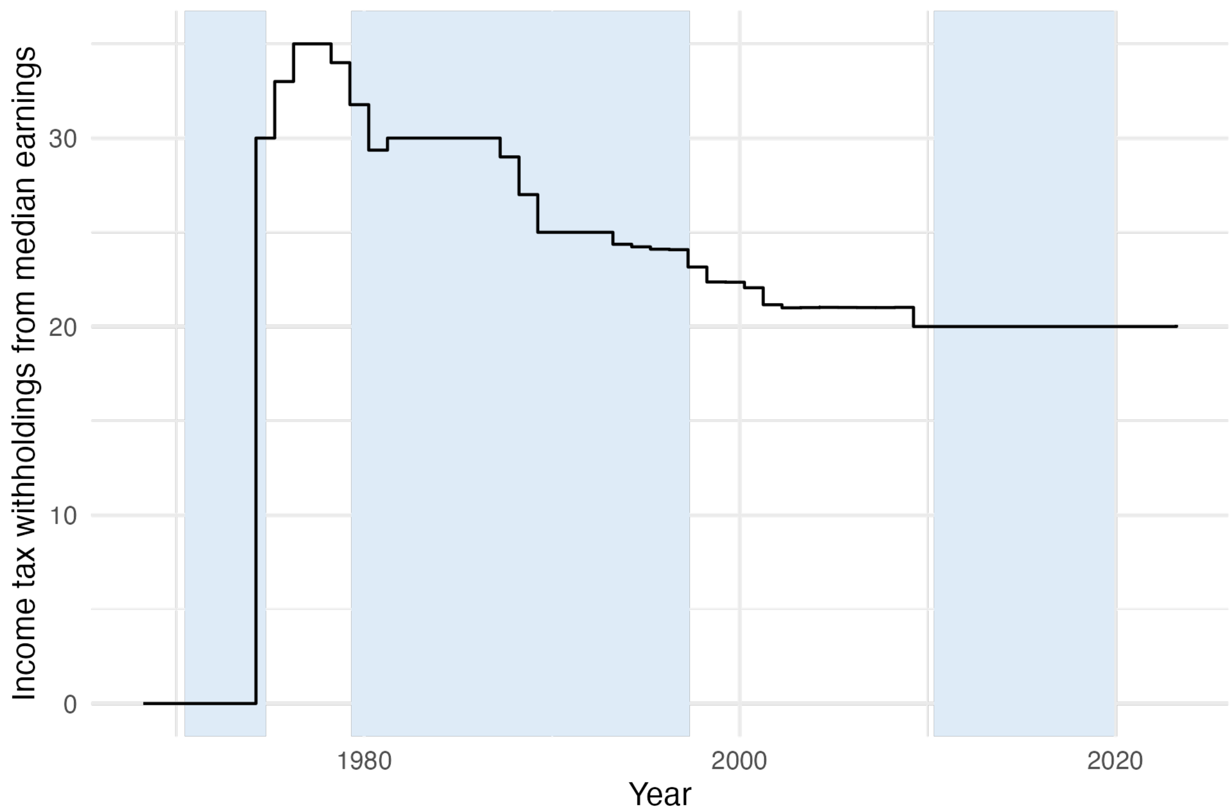


Figure A.8. Taxes due on median earnings

Notes: the figure plots income taxes due given median annual earnings. Median annual earnings data published by the ONS and available for years 1968-2023. The tax schedules are published by the HM Reveue & Customs office and available for years 1948-2022. The shaded areas correspond to periods when the Conservative party was in power.

B. Additional Data Analysis

In the next two tables (B.1 and B.2) we report the results of the SEM estimation for political participation and political preferences; the marginal effects are presented in the main text.

	Dependent variables:			
	College	DPV RME	RME	Participation
Panel A: current real monthly earnings only				
Male	0.011		0.562***	0.271***
	(0.010)		(0.004)	(0.010)
Age			-0.009***	0.034***
			(0.001)	(0.003)
IQ score	0.880***		0.249***	0.231***
	(0.006)		(0.003)	(0.008)
College			0.665***	0.526***
			(0.006)	(0.012)
Degree x IQ score			0.034***	-0.021*
			(0.005)	(0.011)
RME (std)				0.096***
				(0.005)
Panel B: discounted lifetime earnings only				
Male	0.011	0.389***		0.274***
	(0.010)	(0.004)		(0.012)
Age				0.038***
				(0.004)
IQ score	0.880***	0.233***		0.223***
	(0.006)	(0.003)		(0.010)
College		0.547***		0.447***
		(0.005)		(0.014)
Degree x IQ score		0.068***		-0.013
		(0.005)		(0.013)
DPV RME (std)				0.201***
				(0.007)
Panel C: current and discounted lifetime earnings				
Male	0.011	0.389***	0.562***	0.279***
	(0.010)	(0.004)	(0.004)	(0.012)
Age			-0.009***	0.038***
			(0.001)	(0.004)
IQ score	0.880***	0.233***	0.249***	0.225***
	(0.006)	(0.003)	(0.003)	(0.010)
College		0.547***	0.665***	0.449***
		(0.005)	(0.006)	(0.014)
Degree x IQ score		0.068***	0.034***	-0.013
		(0.005)	(0.005)	(0.013)
RME (std)				-0.022**
				(0.009)
DPV RME (std)				0.216***
				(0.009)

Table B.1. Political participation, intelligence and earning potential

Notes: Estimation results from SEM, equation of political behavior only. The political participation indicator variable: logit regression. The standardized earnings equations: OLS regression. The college degree equation: logit regression. Real Monthly Earnings (RME) and DPV of RME are standardized (mean=0 and SD=1). All regressions control for gender, race, birth cohort, parental background and survey wave indicators. The regressors are also interacted with a second-order polynomial in age to capture possible life-cycle effects (omitted from the table). Conventional standard errors reported in parentheses.

	Dependent variables:			Party affiliation		
	College	RME	DPV RME	Dependent variables:		
				Conservative	LibDem	Other
Panel A: current real monthly earnings only						
Male	-0.005	0.576***		0.040***	-0.114***	0.167***
	(0.011)	(0.004)		(0.014)	(0.020)	(0.015)
Age		-0.009***		0.011***	-0.017***	-0.060***
		(0.001)		(0.004)	(0.006)	(0.005)
IQ score	0.869***	0.252***		0.339***	0.351***	0.193***
	(0.006)	(0.004)		(0.012)	(0.018)	(0.012)
College		0.654***		-0.336***	0.213***	-0.315***
		(0.007)		(0.016)	(0.024)	(0.019)
Degree x IQ score		0.032***		-0.309***	-0.016	-0.048***
		(0.005)		(0.016)	(0.023)	(0.018)
RME (std)				0.212***	0.074***	-0.095***
				(0.007)	(0.010)	(0.008)
Panel B: discounted lifetime earnings only						
Male	-0.005		0.397***	0.063***	-0.115***	0.199***
	(0.011)		(0.005)	(0.016)	(0.023)	(0.018)
Age				0.007	-0.018**	-0.059***
				(0.005)	(0.007)	(0.006)
IQ score	0.869***		0.239***	0.231***	0.304***	0.156***
	(0.006)		(0.003)	(0.014)	(0.022)	(0.015)
College			0.537***	-0.417***	0.151***	-0.231***
			(0.005)	(0.019)	(0.028)	(0.021)
Degree x IQ score			0.062***	-0.236***	0.017	-0.003
			(0.005)	(0.019)	(0.027)	(0.021)
DPV RME (std)				0.272***	0.087***	-0.176***
				(0.009)	(0.012)	(0.011)
Panel C: current and discounted lifetime earnings						
Male	-0.005	0.576***	0.397***	0.032**	-0.125***	0.200***
	(0.011)	(0.004)	(0.005)	(0.016)	(0.023)	(0.018)
Age		-0.009***		0.007	-0.018**	-0.059***
		(0.001)		(0.005)	(0.007)	(0.006)
IQ score	0.869***	0.252***	0.239***	0.222***	0.301***	0.156***
	(0.006)	(0.004)	(0.003)	(0.014)	(0.022)	(0.015)
College		0.654***	0.537***	-0.432***	0.147***	-0.230***
		(0.007)	(0.005)	(0.019)	(0.028)	(0.021)
Degree x IQ score		0.032***	0.062***	-0.236***	0.017	-0.004
		(0.005)	(0.005)	(0.019)	(0.027)	(0.021)
RME (std)				0.124***	0.042***	-0.003
				(0.011)	(0.015)	(0.013)
DPV RME (std)				0.185***	0.057***	-0.175***
				(0.012)	(0.016)	(0.015)

Table B.2. Party choice, intelligence and earning potential

Notes: Estimation results from SEM. The party choice categorical variable: multinomial logit regression. The standardized earnings equation: OLS regression. The college degree equation: logit regression. Real Monthly Earnings (RME) and DPV of RME are stadardized (mean=0 and SD=1). The regressions control for gender, race, birth cohort, parental background and survey wave indicators. The regressors are also interacted with a second-order polynomial in age to capture possible life-cycle effects, but these are omitted from the table. The results across columns differ only in the set of variables used for capturing the earnings channel. Conventional standard errors reported in parentheses.

	Dependent variables:		
	College	DPV RME	Participation
Panel A: observed IQ score only			
Male	0.039**	0.457***	0.251***
	(0.019)	(0.008)	(0.025)
Age			0.040***
			(0.008)
IQ score	0.993***	0.232***	0.267***
	(0.012)	(0.005)	(0.022)
College		0.459***	0.484***
		(0.010)	(0.032)
Degree x IQ score		0.041***	-0.025
		(0.010)	(0.032)
DPV RME (std)			0.221***
			(0.016)
Panel B: LDPred2 PGS EY only			
Male	0.091***	0.463***	0.249***
	(0.018)	(0.008)	(0.025)
Age			0.040***
			(0.008)
LDpred2 PGS EY	0.490***	0.072***	0.258***
	(0.010)	(0.005)	(0.018)
College		0.610***	0.547***
		(0.009)	(0.029)
Degree x LDpred2 PGS EY		-0.001	-0.168***
		(0.009)	(0.027)
DPV RME (std)			0.261***
			(0.016)
Panel C: observed IQ score and LDpred2 PGS EY			
Male	0.055***	0.457***	0.266***
	(0.019)	(0.008)	(0.025)
Age			0.040***
			(0.008)
IQ score	0.927***	0.225***	0.225***
	(0.012)	(0.005)	(0.022)
LDpred2 PGS EY	0.371***	0.042***	0.238***
	(0.010)	(0.005)	(0.019)
College		0.445***	0.461***
		(0.010)	(0.033)
Degree x IQ score		0.040***	0.005
		(0.010)	(0.033)
Degree x LDpred2 PGS EY		-0.004	-0.173***
		(0.008)	(0.028)
DPV RME (std)			0.211***
			(0.016)
Panel D: clumped PGS EY only			
Male	0.079***	0.460***	0.236***
	(0.018)	(0.008)	(0.025)
Age			0.040***
			(0.008)
Clumped PGS EY	0.257***	0.051***	0.195***
	(0.009)	(0.005)	(0.018)
College		0.625***	0.569***
		(0.008)	(0.028)
Degree x Clumped PGS EY		0.029***	-0.162***
		(0.008)	(0.027)
DPV RME (std)			0.270***
			(0.015)

Table B.3. Political Participation *SEM*

Note: Logit model for College and Political Participation. Age in years. College, Male are 0-1 variable. IQscore, PGSEY are standardized to mean 0 and SD = 1. See main text for the computation of the PGSEY score.

	Dependent variables:		Party affiliation		
	College	DPV RME	Dependent variables:		
			Conservative	LibDem	Other
Panel A: observed IQ score only					
Male	0.005	0.467***	0.097***	-0.128***	0.361***
	(0.020)	(0.008)	(0.032)	(0.045)	(0.041)
Age			-0.046***	-0.116***	-0.079***
			(0.010)	(0.014)	(0.013)
IQ score	0.981***	0.238***	0.347***	0.395***	0.048
	(0.013)	(0.006)	(0.029)	(0.045)	(0.037)
College		0.455***	-0.397***	0.153***	-0.274***
		(0.011)	(0.041)	(0.058)	(0.054)
Degree x IQ score		0.033***	-0.393***	-0.033	-0.062
		(0.011)	(0.041)	(0.056)	(0.053)
DPV RME (std)			0.194***	0.003	-0.269***
			(0.018)	(0.026)	(0.028)
Panel B: LDPred2 PGS EY only					
Male	0.056***	0.472***	0.085***	-0.153***	0.360***
	(0.019)	(0.008)	(0.032)	(0.044)	(0.041)
Age			-0.044***	-0.114***	-0.079***
			(0.010)	(0.014)	(0.013)
LDpred2 PGS EY	0.469***	0.069***	0.103***	0.158***	0.055*
	(0.010)	(0.005)	(0.024)	(0.037)	(0.031)
College		0.604***	-0.475***	0.339***	-0.262***
		(0.009)	(0.036)	(0.048)	(0.047)
Degree x LDpred2 PGS EY		0.002	-0.181***	-0.136***	-0.127***
		(0.009)	(0.033)	(0.044)	(0.044)
DPV RME (std)			0.229***	0.078***	-0.261***
			(0.018)	(0.025)	(0.028)
Panel C: observed IQ score and LDpred2 PGS EY					
Male	0.022	0.468***	0.100***	-0.124***	0.367***
	(0.020)	(0.008)	(0.032)	(0.045)	(0.041)
Age			-0.046***	-0.115***	-0.079***
			(0.010)	(0.014)	(0.013)
IQ score	0.919***	0.231***	0.331***	0.380***	0.039
	(0.013)	(0.006)	(0.030)	(0.045)	(0.037)
LDpred2 PGS EY	0.353***	0.038***	0.064***	0.122***	0.055*
	(0.010)	(0.005)	(0.025)	(0.037)	(0.032)
College		0.443***	-0.380***	0.145**	-0.269***
		(0.011)	(0.041)	(0.059)	(0.054)
Degree x IQ score		0.032***	-0.368***	-0.013	-0.041
		(0.011)	(0.041)	(0.057)	(0.054)
Degree x LDpred2 PGS EY		0.001	-0.134***	-0.124***	-0.124***
		(0.009)	(0.034)	(0.045)	(0.045)
DPV RME (std)			0.194***	0.000	-0.272***
			(0.018)	(0.026)	(0.028)
Panel D: clumped PGS EY only					
Male	0.041**	0.469***	0.082***	-0.158***	0.353***
	(0.019)	(0.008)	(0.032)	(0.044)	(0.041)
Age			-0.043***	-0.115***	-0.078***
			(0.010)	(0.014)	(0.013)
Clumped PGS EY	0.241***	0.046***	0.105***	0.182***	0.016
	(0.009)	(0.005)	(0.024)	(0.036)	(0.031)
College		0.618***	-0.504***	0.333***	-0.269***
		(0.009)	(0.035)	(0.047)	(0.046)
Degree x Clumped PGS EY		0.039***	-0.098***	-0.049	-0.037
		(0.009)	(0.032)	(0.044)	(0.043)
DPV RME (std)			0.229***	0.075***	-0.257***
			(0.018)	(0.025)	(0.028)

TABLE B.4. Political Preferences SEM. Vote for the Conservative Party.

Note: Logit model for College and Political Affiliation. Age in years. College, Male are 0-1 variable. IQscore, PGSEY are standardized to mean 0 and SD = 1. See main text for the computation of the PGSEY score.

B.1. **Motivation for Political Participation.** The variables considered as potential measures of motivation for political participation are listed below. For the first three, respondents were asked to state whether they agreed or disagreed with the statements in quotes, on a five items scale from "Strongly Agree (=1)" to "Strongly Disagree (=5)". We recode these values on a scale from 0 (strongly disagree) to 4 (strongly agree). The answers to these questions give some measure of the subjective evaluation an individual gives of the competence in politics, and of the cost of political activity. The answer to the last question, given on a scale from 0 to 10, give a measure of how likely the person thinks it is that the vote will affect the outcome.

(1) *(Qualified)* "Qualified to participate in politics"
(2) *(Informed)* "Better informed about politics"
(3) *(Too Costly):* "It takes too much time and effort to be active in politics and public affairs."
(4) *(Decisive):* "On a scale from 0 to 10, where 0 means very unlikely and 10 means very likely, how likely is it that your vote will make a difference in terms of which party wins the election in this constituency at the next general election?"

The variable *IHS investment income* used in the table B.6 below is the Inverse hyperbolic sine (IHS) of the variable reporting the investment income, in real terms. The IHS transformation is used to deal with the zero income observations (rather than adding a positive constant before taking the log). Details on data on income are given in section A.2.

We mentioned in section 3.1 that a positive correlation between a belief that one's vote might be decisive and the two variables of education and IQ may be surprising. We can test whether and how the variable Decisive depends positively also on the $PGS\ EY$. Next table B.5 (see the last equation of the SEM) shows that the relation is positive and significance, even when the information on the IQ score is taken into account. In the following table B.5 we report the SEM for the belief that vote makes a difference (variable *decisive*).

	Decisive (1)	Decisive (2)	Decisive (3)
College			
Male	0.009	0.014	0.011
	(0.011)	(0.012)	(0.011)
IQ score	0.176***		0.159***
	(0.006)		(0.006)
PGS EY		0.101***	0.067***
		(0.006)	(0.006)
Constant	0.259***	0.282***	0.261***
	(0.007)	(0.008)	(0.007)
DPV earnings			
College	0.345***	0.435***	0.335***
	(0.025)	(0.025)	(0.026)
Male	0.656***	0.659***	0.657***
	(0.022)	(0.022)	(0.022)
Age (in years)	-0.008***	-0.008***	-0.009***
	(0.001)	(0.001)	(0.001)
IQ score	0.162***		0.157***
	(0.013)		(0.013)
PGS EY		0.048***	0.027*
		(0.011)	(0.011)
Constant	-0.513***	-0.513***	-0.503***
	(0.050)	(0.051)	(0.050)
Decisive			
DPV earnings	0.023	0.027	0.023
	(0.017)	(0.017)	(0.017)
Age (in years)	-0.006	-0.006	-0.007
	(0.012)	(0.012)	(0.012)
Age^2	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
College	0.104**	0.099**	0.109**
	(0.039)	(0.034)	(0.039)
IQ score	0.137		0.105
	(0.071)		(0.072)
PGS EY		0.151*	0.132*
		(0.065)	(0.067)
Constant	0.135	0.150	0.150
	(0.236)	(0.236)	(0.236)
Obs.	5,609	5,609	5,609

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.5. Belief in Influence *SEM*

Note: Age measured in years. College and Male are 0-1 variables. IQscore, PGSEY are standardized to mean 0 and $SD = 1$. *See main text for the computation of the PGS EY score.*

	Logistic regression			Marginal effects		
	1	2	3	1	2	3
Male	0.308***	0.105***	0.092***	0.070***	0.021***	0.019***
	(0.024)	(0.024)	(0.024)	(0.005)	(0.005)	(0.005)
IQ score	0.266***	0.215***	0.195***	0.060***	0.043***	0.039***
	(0.015)	(0.015)	(0.015)	(0.003)	(0.003)	(0.003)
College	0.621***	0.326***	0.297***	0.142***	0.066***	0.060***
	(0.031)	(0.032)	(0.032)	(0.007)	(0.006)	(0.006)
Qualified		0.257***	0.253***		0.052***	0.051***
		(0.015)	(0.015)		(0.003)	(0.003)
Informed		0.359***	0.355***		0.072***	0.071***
		(0.015)	(0.015)		(0.003)	(0.003)
Too costly		-0.107***	-0.108***		-0.021***	-0.022***
		(0.012)	(0.012)		(0.002)	(0.002)
Decisive		0.466***	0.467***		0.094***	0.094***
		(0.012)	(0.012)		(0.002)	(0.002)
IHS investment income			0.132***			0.026***
			(0.013)			(0.003)
Obs.	70,395	70,395	70,395	70,395	70,395	70,395

Table B.6. Political Participation and Characteristics of Information Acquisition

Note: The table reports the coefficients of the logit regression. All variables except college are standardized with mean zero and standard deviation 1. See section B.1 of the Appendix for precise definitions of variables.

	(1) Qualified	(2) Informed	(3) Too costly	(4) Decisive	(5) Inv income	(6) Inv income
IQ score	0.131***	0.113***	-0.058***	0.018**	0.367***	0.152***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.015)	(0.007)
College	0.541***	0.454***	-0.218***	0.099***	0.609***	0.225***
	(0.015)	(0.015)	(0.014)	(0.015)	(0.033)	(0.016)
Qualified						0.034***
						(0.007)
Informed						0.038***
						(0.007)
Too costly						
Decisive						-0.002
						(0.005)
IHS investment income						
Obs.	76,604	76,603	77,265	75,932	233,063	71,866

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.7. Characteristics of information acquisition, college and intelligence

Note: The table reports the coefficients from linear regression of dependent variables in the columns. All variables except college are standardized with mean zero and standard deviation 1. See section B.1 of the Appendix for precise definitions of variables. All regressions are weighted with wave 3 cross-sectional response weights and control for gender, race, birth cohort, parent's education, time trend and age polynomial. Standard errors clustered at the sampling level are reported in parentheses.

C. METADAC and polygenic scores

C.1. **METADAC dataset.** The UKHLS has additional genotyping information on 9,920 individuals that was collected in waves 2 and 3. In our working sample of 26,643 individuals followed over twelve waves, 5,579 of them have genotype information available. Table C.1 reports summary statistics between subsamples by availability of genotyping information and full sample. Thus, genotyped individuals are older, have higher IQ score and more likely to be of White British origin. They are also more likely to have more educated and working parents, but are themselves less likely to have college degree and have slightly lower predicted earnings. They are also more likely to participate in the political process and be aligned with the Conservative party.

Table C.1. Summary statistics in wave 3 by genotyping status

	Non-genotyped			Genotyped			Full sample		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Male	0.487	(0.500)	21,086	0.470	(0.499)	5,584	0.483	(0.500)	26,670
Age	41.356	(10.990)	21,086	44.376	(10.475)	5,584	42.078	(10.945)	26,670
White British	0.820	(0.384)	21,032	0.965	(0.185)	5,582	0.855	(0.353)	26,614
College	0.324	(0.468)	21,086	0.299	(0.458)	5,584	0.318	(0.466)	26,670
Log real monthly earnings	7.410	(0.895)	16,019	7.418	(0.882)	4,493	7.412	(0.892)	20,512
Predicted wage at age 45	18.956	(10.419)	14,654	18.380	(10.026)	4,075	18.816	(10.327)	18,729
Predicted DPV of earnings (£th)	740.458	(381.934)	14,654	721.503	(369.402)	4,075	735.834	(378.992)	18,729
IQ score	-0.041	(1.022)	21,086	0.131	(0.946)	5,584	-0.000	(1.007)	26,670
Father's years of education[a]	11.947	(3.655)	21,086	12.097	(3.480)	5,584	11.983	(3.614)	26,670
Mother's years of education[a]	11.629	(2.852)	21,086	11.803	(2.482)	5,584	11.670	(2.769)	26,670
Father was working	0.849	(0.358)	21,086	0.883	(0.321)	5,584	0.857	(0.350)	26,670
Mother was working	0.640	(0.480)	21,086	0.686	(0.464)	5,584	0.651	(0.477)	26,670
Aligned with some party	0.483	(0.500)	21,049	0.532	(0.499)	5,578	0.495	(0.500)	26,627
Party aligned with									
Conservative	0.226		4,166	0.270		1,578	0.237		5,744
Labour	0.344		6,350	0.331		1,934	0.341		8,284
LibDem	0.083		1,539	0.106		619	0.089		2,158
Other	0.116		2,144	0.096		563	0.111		2,707

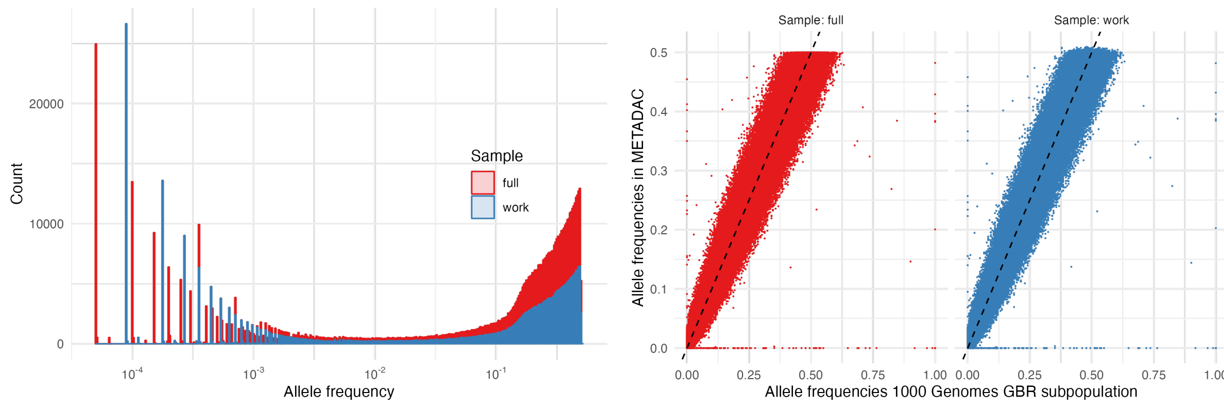
[a] Imputed from average years of education by highest qualification, gender and birth cohort of parent

Note: the table reports summary statistics as of wave 3 in the full working sample (last column) and subsamples defined by the availability of genotype information. The summary statistics are weighted using cross-sectional response weights from wave 3 and adjusted for clustered and stratified sampling of the survey.

The METADAC provides genotyped calls at 518,542 variants[18]. Genotyping rate is quite high: 95% of all variants have fewer than 32 (18) missing observations in the full (working) sample. This corresponds to less than 0.32% of individuals in METADAC. All the variants appear to be bi-allelic SNPs with exactly two alleles and no duplicated variants. However, 130,356 SNPs (or 25% of variants) are fixed in the full METADAC sample, i.e., all individuals in the sample have the same allele at a given locus. The number of fixed SNPs rises in the working METADAC sample to 145,107 SNPs (or 28% of variants)[19]. Nevertheless, the genotype information is consistent with previously published results in 1000 Genomes Project Consortium et al. (2015) (Figure C.1b).

[18]The dataset does not include imputed variants.

[19]This means that genotypic variation came from individuals who are not part of the working sample. The working sample is defined as individuals born in 1950-89 with non-missing college and intelligence information, who were observed at least once between ages 25-65 and who expressed political opinion at least once.



(A) Distribution in the METADAC (B) Comparison to GBR 1000 Genomes

Note: The frequencies in the METADAC calculated in the full sample with 9,920 individuals and working subsample with 5,609 individuals. The working subsample includes individuals born in 1950-89 with non-missing college and intelligence score, observed at least once between ages 25 and 65 and who expressed political opinion at least once. (A) The figure plots the histogram of allele frequencies of genotyped variants in the METADAC dataset. Only interior variants with frequencies strictly in (0, 1) interval are used in the plot. (B) The figure plots allele frequencies of SNPs in the METADAC sample against allele frequencies in GBR subpopulation (91 individuals) in 1000 Genomes Project (1000 Genomes Project Consortium et al., 2015). 403,761 (or 78%) out of 518,542 variants in METADAC were matched to variants in 1000 Genomes. The black dashed line is a 45°line. Only 779 (1,031) of fixed SNPs in the METADAC full (working) sample have non-zero allele frequency in GBR 1000 Genomes. These numbers correspond to 0.6% (0.7%) of all fixed SNPs in the full (working) sample.

Figure C.1. Allele frequencies in the METADAC

C.2. **Details on polygenic scores.** The GWAS coefficients used to generate the polygenic scores were downloaded from Okbay (2022); Savage et al. (2018); Demange et al. (2021). Okbay (2022) estimate GWAS for years of education across multiple biobanks with a total sample of size of more than three million individuals. Savage et al. (2018) estimate GWAS of fluid intelligence score from 269,867 individuals in the UK Biobank. Demange et al. (2021) estimate GWAS of latent cognitive and noncognitive factors using previously published estimates for years of education and cognitive test scores. In particular, they estimate a structural equation model where cognitive latent factor affects both the education and cognitive test score GWAS, while noncognitive factor affects only education GWAS. Table C.2 reports information on number of variants available for each of the phenotype as well as summary statistics of variants matched in the METADAC. It is clear from the table that a large share of non-fixed SNPs in the METADAC are matched to variants from each of the GWAS table.

Given the GWAS estimates and genotype information in the METADAC we compute polygenic scores for each of these phenotypes using a simple linear scoring method.

$$PGS_i = \sum_k \beta_k g_{ik} \tag{22}$$

where β_k is the GWAS coefficient of SNP k and $g_{ik} \in \{0, 1, 2\}$ is the genotype of individual i at locus k. However, naive scoring using full set of matched SNPs produces biased polygenic score due to correlation of genotypes between loci. Such correlation is called linkage disequilibrium (LD) and results from the fact that variants are inherited in blocks.

Table C.2. Overview of GWAS tables

	EY	COBS	CLAT	NCLAT
K total	10,985,947	9,295,118	7,305,956	7,305,956
K in METADAC	278,386	283,886	248,645	248,645
Allele frequencies in full METADAC				
K AF >0	278,053	283,596	248,576	248,576
K AF >0.01	258,097	260,079	246,428	246,428
Mean AF	0.248	0.244	0.266	0.266
SD AF	0.148	0.150	0.138	0.138
Allele frequencies in working METADAC				
K AF >0	278,014	283,533	248,572	248,572
K AF >0.01	258,104	260,081	246,414	246,414
Mean AF	0.248	0.244	0.266	0.266
SD AF	0.148	0.150	0.138	0.138
K in clumped GWAS	1,012	237	235	60
K in LDpred2 GWAS	188,263	189,405	181,089	181,050
Source	Okbay (2022)	Savage et al. (2018)	Demange et al. (2021)	Demange et al. (2021)

Note: The table reports summary statistics for the variants reported in each respective GWAS table. K stands for the variant count; AF stands for allele frequency. Allele frequencies were computed both in the full METADAC sample (9,920 individuals) and working subsample (5,609 individuals). The working subsample includes individuals born in 1950-89 with non-missing college and intelligence score, observed at least once between ages 25 and 65 and who expressed political opinion at least once.

We adjust the GWAS effects for linkage disequilibrium in two different ways. A simple way is to use clumping algorithm. It starts from the most genome-wide significant variant as the first lead SNP and assigns all the SNPs within the radius of 250 kilobases (kb) with the squared correlation coefficient $r^2 > 0.5$ to the first group. Thus, the first lead SNP represents all the SNPs in the first group. The algorithm repeats with the remaining SNPs until all variants with p-values below 5×10^{-8} have been exhausted. The polygenic score is then computed using only the set of lead SNPs. We computed the r^2 coefficients using the METADAC dataset passing the usual quality control (QC) filters.

A second approach uses all variants, but scales them down according to linkage disequilibrium. This method has been first introduced by Vilhjálmsson (2015) as LDpred and later updated by Privé et al. (2021) as LDpred2. In short, the algorithm assumes that true GWAS coefficients are distributed as

$$\beta_k \sim \begin{cases} \mathcal{N}\left(0, \frac{h^2}{Mp}\right) & \text{with probability } p, \\ 0 & \text{otherwise} \end{cases} \tag{23}$$

where h^2 is SNP heritability, M is the number of variants and p is the share of causal variants. Then, given the estimated GWAS effects $\hat{\beta}_k$

$$\beta_k|\hat{\beta}_k \sim \begin{cases} \mathcal{N}\left(\frac{1}{1+\frac{Mp}{nh^2}}\hat{\beta}_k, \frac{1}{1+\frac{Mp}{nh^2}}\frac{1}{n}\right) & \text{with probability } p \\ 0 & \text{otherwise} \end{cases} \tag{24}$$

where n is the number of individuals used in the GWAS estimation. LDpred2 innovates on the estimation of p and h^2 parameters. We follow the methodology described in Privé et al. (2021) whereby we use published LD matrices computed for HapMap3+ variants[20]. Given the LD matrix, the algorithm estimates heritability h^2 and causal share p parameters and scales the estimated GWAS coefficients according to Equation (24).

Figure C.2 plots the GWAS estimates both before (green dots) and after the LD adjustments (clumping - red dots; LDpred2 - blue dots). It provides visual representation of each adjustment algorithm. Clumping selects the most significant uncorrelated SNPs and treats the rest of the variants as if their GWAS contribution is zero. It is also clear from Table C.2 that clumping utilises less than 1% of available variants. LDpred2 maximises the set of variants used to compute the polygnic score, but scales down the GWAS estimates of SNPs in high LD with its neighbours.

In Figure C.3 we show the relationship between the computed polygenic scores and observed phenotypes in the METADAC dataset.

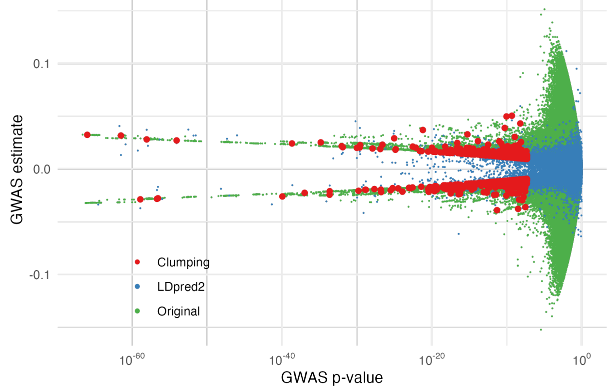
The general consensus in the genomic literature is that LDpred2 produces polygenic scores with the highest predictive power for the respective phenotype compared to alternatives (Ni et al., 2021). It is, therefore, not surprising that PGS computed using LDpred2 GWAS estimates have higher correlation with observed variables compared to PGS computed using clumped GWAS estimates. For example, the correlation between observed years of education and LDpred2 PGS EY is 21.7%, higher than 13.3% correlation with clumped PGS EY. Therefore, we use the polygenic scores computed using LDpred2 adjusted GWAS estimates in our baseline specifications.

C.3. **Predicted earnings profile.** Due to privacy issues, the METADAC subsample only provides 50-quantiles of earnings instead of a continuous variable. Similarly, weekly hours worked are also grouped in 5-hour bins. The unique individual identity variable in the METADAC is different from the one used in the main sample to ensure that the two datasets cannot be matched. This means that we cannot merge predicted lifetime earnings from the full sample and need to generate predicted lifetime earnings directly in the METADAC.

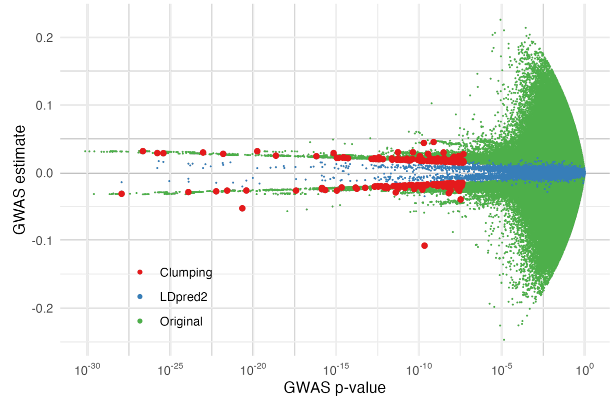
First, we compute lower and upper bounds of hourly wages by dividing the earnings thresholds with a mid-point of hours worked bins. Then, the regression Equation (17) can be adjusted as follows. Denote the lower bound of hourly wages corresponding to earnings quantile q at time t as $w_{qt}^{(1)}$ and the upper bound - as $w_{qt}^{(2)}$.

$$\Pr\left(\ln w_{it} \in \left[w_{qt}^{(1)}, w_{qt}^{(2)}\right]\right) = \Pr\left(v_{it} + u_i \in \left[y_{qt}^{(1)} - \omega(a,i,t), y_{qt}^{(2)} - \omega(a,i,t)\right]\right) \tag{25}$$

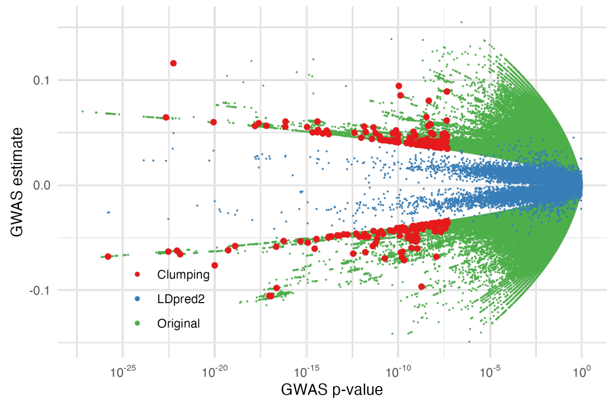
[20]Therefore, SNPs that are used in LDpred2 algorithm have to be present in all three datasets: GWAS table, METADAC genotype table and HapMap3+ table. This is the primary reason why SNP count falls from more than 200K in column 4 to 180-190K in column 14 in Table C.2.



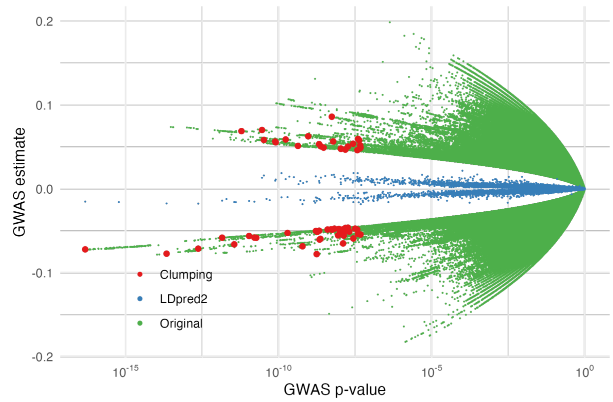
(A) Years of education (EY)



(B) Observed cognitive score (COBS)



(C) Latent cognitive factor (CLAT)



(D) Latent noncognitive factor (NCLAT

Note: The figure plots GWAS estimates before and after LD adjustments by phenotypes. Two LD adjustments are clumping algorithm (as implemented by PLINK2 software) and LDpred2 algorithm (Privé et al., 2021).

FIGURE C.2. GWAS estimates used in polygenic score computation

where $\omega(a,i,t) \equiv \beta_0 + \sum_{a\in\mathcal{A}} (\phi_a + \psi_a X_i) + \xi_t$ is the fitted value of log wages from Equation (17). If we did not have the unobserved individual effect u_i and were interested in estimating the coefficients $(\beta_0, \{\phi_a, \psi_a\}_{a\in\mathcal{A}}, \xi_t)$, we could fit this equation using interval regression. Instead, we use vector of coefficients estimated in the full sample and a random variable specification to recover the term u_i. Thus, we fix $\hat{\omega}(a,i,t) = \hat{\beta}_0 + \sum_{a\in\mathcal{A}} \left(\hat{\phi}_a + \hat{\psi}_a X_i\right) + \hat{\xi}_t$ given the estimated coefficients from Equation (17). We also assume that $u_i \sim \mathcal{N}(m_u, s_u)$ and $v_{it} \sim \mathcal{N}(0, s_v)$, where values m_u and s_u are sample average and variance of $\hat{u}_i$, and s_v - sample variance of $\hat{v}_{it}$ estimated in the full sample among the genotyped individuals[21]. In particular, we estimate $m_u = -0.03$, $s_u = 0.30$ and $s_v = 0.19$.

Therefore, fitting Equation (25) to the METADAC subsample allows us to simulate values of the random effect u_i, which we denote as $\tilde{\mu}_i^{\mathrm{RE}}$ to distinguish from the fixed effects estimator $\hat{u}_i$ from Equation (17). Now, we can proceed with the prediction of lifetime earnings as we did in the full

[21]The full sample of the UKHLS contains an indicator if an individual has been genotyped or not. This allows us to compute sample statistics for the genotyped individuals in the full sample. Observations with genotyped indicator equal to one are the same individuals that make up the METADAC subsample. But we do not have access to a one-to-one mapping between the two subsets.

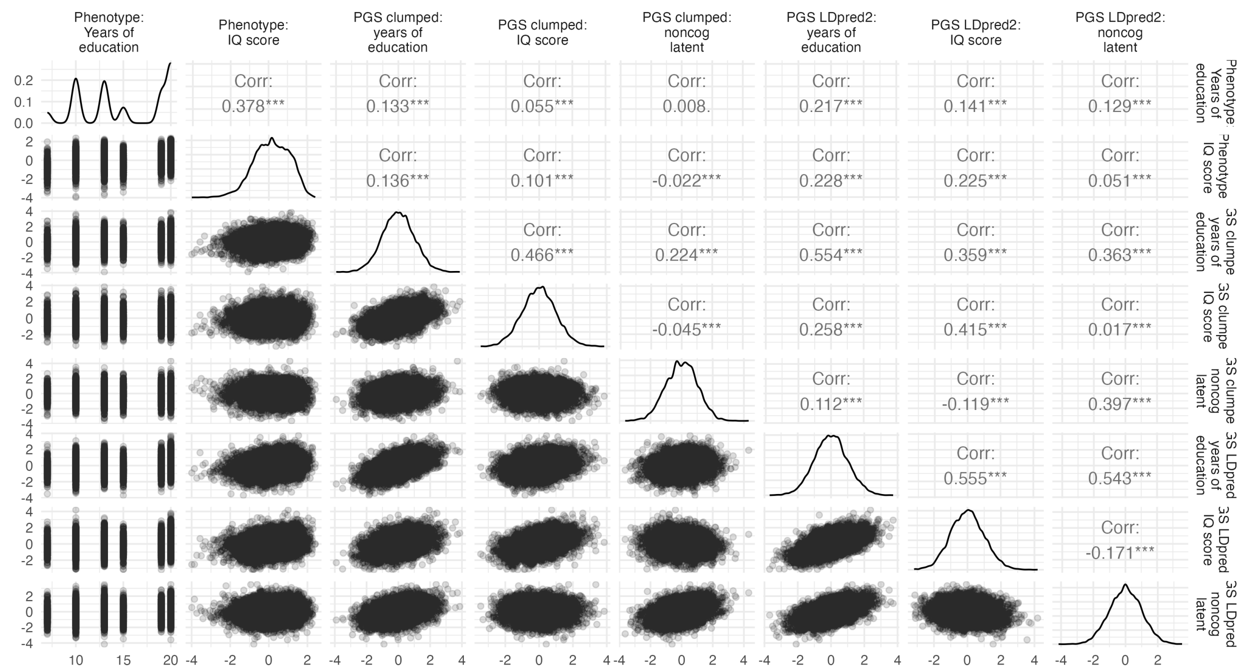


FIGURE C.3. Correlation PGS and Phenotype

Notes: The figure plots the scatterplot matrix (lower triangle), kernel densities (diagonal) and correlation estimates (upper triangle) between variables in the columns and rows. The scatterplots plot variables in columns in y axis against variables in rows in x axis. The stars in correlation estimates correspond to 1% (***), 5% (**) and 10% (*) significance levels. The phenotype variables are observed variables in the METADAC dataset. PGS variables are the polygenic scores computed for METADAC individuals using previously published GWAS estimates. See main text for the discussion of the two methods to compute polygenic scores: clumping and LDpred2.

sample. That is, for every age $a \in \mathcal{A}$ we create variable

$$\tilde{w}_{ia}^{\mathrm{RE}} = \hat{\beta}_0 + \sum_{a \in \mathcal{A}} \left(\hat{\phi}_a + \hat{\psi}_a X_i \right) + \tilde{\mu}_i^{\mathrm{RE}}$$

We then compute the discounted present value of predicted lifetime earnings following Equation (19).

Table C.3 compares the predicted DPV of lifetime earnings between subsamples and prediction algorithms. It reports the results from poisson regressions of DPV earnings on gender, college and IQ score variables. The DPV earnings are computed using FE regression of Equation (17) in the full and genotyped subsamples, and using interval RE regression of Equation (25) in the METADAC subsample. It is clear that despite differences in the prediction method, the predicted earnings have similar correlations with individual characteristics and have similar distributions[22].

[22]The differences in sample sizes between the UKHLS genotyped and METADAC subsamples can be explained by having longer histories in the UKHLS and revisions of underlying data in the UKHLS. At the time of application to the METADAC, the UKHLS had only 8 waves released. Therefore, our METADAC subsample contains up to 8 waves per each individual. In the UKHLS we use up to 12 waves per each individual. Moreover, the UKHLS revises the released data from time to time which can lead to slight discrepancies in retrospective data. METADAC dataset provides variables as of 2020. Hence, any revisions that were applied after are not represented in the METADAC dataset we use.

	(1) UKHLS Full	(2) UKHLS genotyped	(3) METADAC
Male	0.194***	0.247***	0.239***
	(0.001)	(0.001)	(0.001)
College	0.299***	0.286***	0.261***
	(0.001)	(0.001)	(0.002)
IQ score	0.140***	0.149***	0.139***
	(0.000)	(0.001)	(0.001)
College × IQ score	-0.009***	-0.028***	-0.022***
	(0.001)	(0.001)	(0.002)
Constant	6.338***	6.305***	6.321***
	(0.000)	(0.001)	(0.001)
Obs.	18,729	4,075	3,890
Prediction method	FE	FE	Interval RE
Mean DPV earn	717	711	713
SD DPV earn	362	361	351

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE C.3. Comparison of DPV earnings between subsamples and prediction algorithms

Note: the table reports estimation results from poisson regressions of DPV predicted lifetime earnings on gender, college and IQ score of individuals. The UKHLS Full denotes full working sample used in the main analysis; UKHLS genotyped - subset of full working sample for whom genotyping indicator is equal to one. Predicted method FE fits Equation (17) to the full sample panel data; Interval RE fits Equation (25) to the METADAC panel data.