Supplementary Material

Predicting political beliefs with polygenic scores for cognitive performance and educational attainment

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Abstract

Intelligence is correlated with a range of left-wing and liberal political beliefs. This may suggest intelligence directly alters our political views. Alternatively, the association may be confounded or mediated by socioeconomic and environmental factors. We studied the effect of intelligence within a sample of over 300 biological and adoptive families, using both measured IQ and polygenic scores for cognitive performance and educational attainment. We found both IQ and polygenic scores significantly predicted all six of our political scales. Polygenic scores predicted social liberalism and lower authoritarianism, within-families. Intelligence was able to significantly predict social liberalism and lower authoritarianism, within families, even after controlling for socioeconomic variables. Our findings may provide the strongest causal inference to date of intelligence directly affecting political beliefs.

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1. Additional summary statistics

Table S1: Additional summary statistics

Variable	N	Mean	SD	Min	Pctl. 25	Pctl. 75	Max
Age at intake	619	15	2	11	14	16	21
Age at follow-up 3	619	32	2.7	25	30	34	41
Years of education	611	16	1.9	12	14	16	20
Income	605	60	41	0	35	75	340
Log income	605	3.8	1.1	0	3.6	4.3	5.8

Note: Income is before taxes and in the unit of thousands of US dollars.

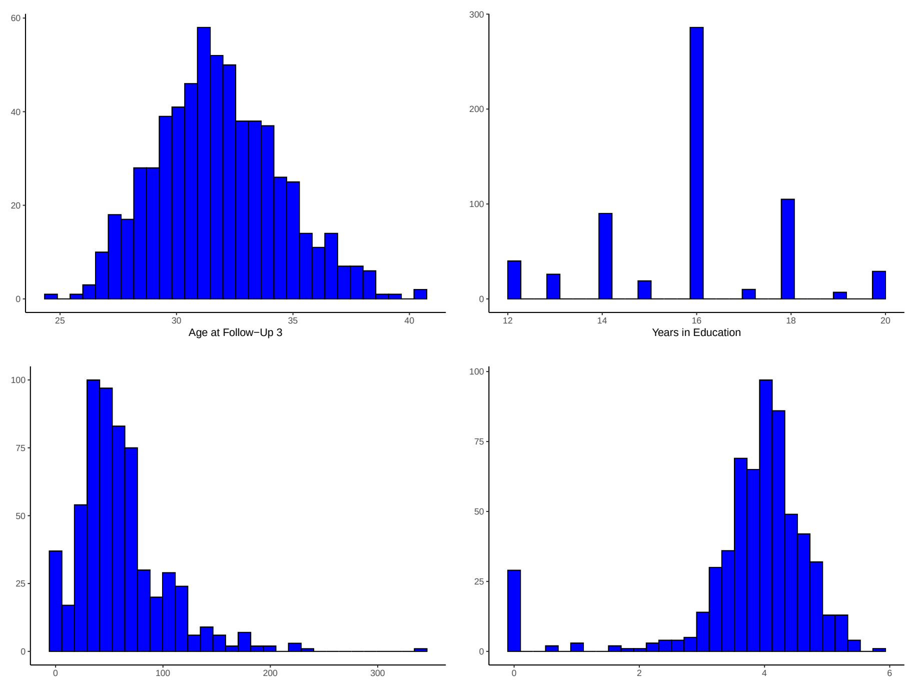

Figure S1: Histograms of control variables. Y axes represent counts.

2. Genotyping and polygenic scores

The Sibling Interaction and Behavior Study (SIBS) has been genotyped along with other cohorts from the Minnesota Center for Twin and Family Research (MCTFR; Miller et al., 2012). Participants were genotyped for 527,829 single nucleotide polymorphism (SNP) markers using Illumina's Human660W-Quad array. After initial quality control and imputation described in Miller et al. (2012), we removed SNPs with call rate < 0.01, MAF < 0.01 and HWE $p < 10^{-7}$. This was done separately for individuals of East Asian versus those of European ancestry.

For the European ancestry sample, polygenic scores were taken from the polygenic index repository (Becker et al., 2021). Our polygenic scores in the Asians were derived from GWAS summary statistics for a two phenotypes; cognitive performance (CP; Lee et al., 2018) and educational attainment (EA; Lee et al., 2018). Cognitive performance refers to a score on an IQ test and is a euphemism for intelligence. Educational attainment refers to the number of years an individual has spent in education. The EA polygenic score is employed because it is trained on a large sample ($N \approx 770,000$) compared to the CP polygenic score ($N \approx 250,000$), potentially allowing for greater power. It also will proxy mental abilities and traits relevant to educational success in addition to the g factor of intelligence.

For the Asiansm Polygenic scores (PGSs) were created using PRS-CS (Ge et al., 2019). The tool uses a Bayesian approach to infer posterior SNP effect sizes using a shrinkage factor specific to each SNP. All optional parameters were left at their default values. LD reference panels for East Asians were constructed from the 1000 Genomes Project.

The first five genetic principal components are created with PLINK 1.9 and created separately for the European and East Asian genotyped samples within the MCTFR cohorts. Following standard practice, to create the principal components, SNPs were pruned for low linkage disequilibrium. We removed SNPs from windows of 1000 kilobases with a pairwise r^2 greater than 0.1 with any other variant. Upon pruning a window, the next window was 5 kilobases further along the genome.

3. Modelling approach

Let us assume a simplified model of political beliefs as represented in the graph in Figure S2. The graph depicts a series of continuous variables in bold, known as nodes, that have linear causal effects represented by arrows, with the standardized effect sizes written next to them. Omitted from the graph is error variance for each variable.

We assume that **IQ** has effect β on political belief (**POL**). Identifying β from a univariate regression is not possible in the presence of confounding variables. Variables that affect both **IQ** and **POL** will induce covariation between **IQ** and **POL** that will bias an estimate derived from a univariate linear regression.

We assume three sources of confounding. $\mathbf{PGS_{CP}}$ is the polygenic score for cognitive performance which is assumed to have effect γ on **IQ** and direct pleiotropic effect α on **POL**. It is through the path with effect α that $\mathbf{PGS_{CP}}$ acts as a genetic confounder. **F** represents the shared environmental component of intelligence, the effect of being brought up in the same family. It affects

IQ and also incidentally affects **POL**. The polygenic score $\mathbf{PGS_{CP}}$ and shared environment **F** may have the average parental polygenic score **Parental PGS** as a common cause, if heritable traits of the parents affect the offspring trait through "genetic nurture." The third source of confounding is **E**, which represents factors idiosyncratic to the individual that cause both **IQ** and **POL**. We should note that the letter **E** is typically used to refer to the nonshared environment in behavioural genetics. Here, **E** may have a slightly broader interpretation capturing both the nonshared environment and genetic variation in **IQ** not captured by the polygenic score $\mathbf{PGS_{CP}}$. This is because the polygenic score is an imperfect index of the genotype and is only composed of common genetic variants.

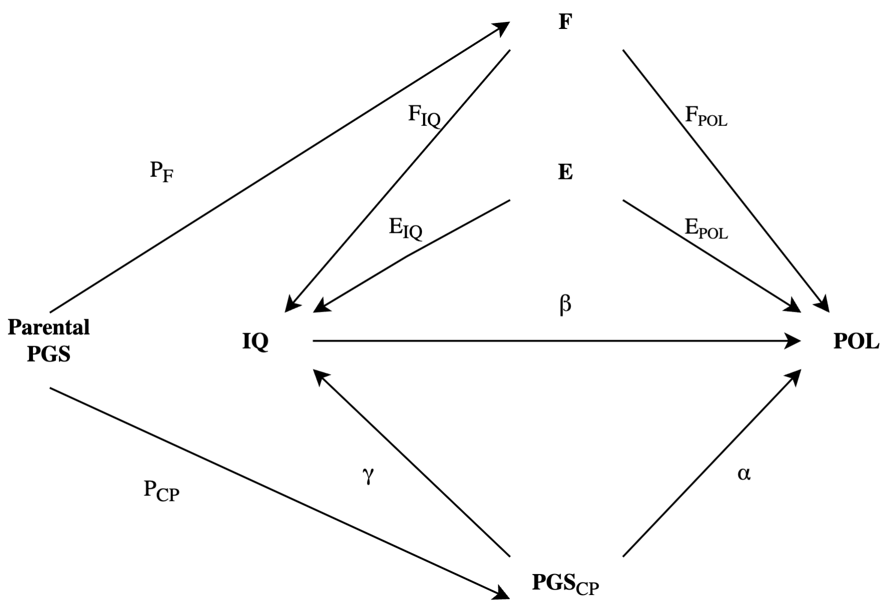

Figure S2: Model of political beliefs. Bold text is used to denote the nodes of the model, which constitute continuous variables. Arrows represents linear causal effects from one variable to another. Text, not in bold, represent effect sizes. Residual variances are not shown in the diagram.

To calculate the estimands of different models, we first calculate the covariances between the different variables using Wright's (1934) path-tracing rules. Then we put these covariances into the formulas for the regression betas for each model. When using fixed effects, we calculate the estimands after first taking differences. Differences between siblings in **IQ**, $\mathbf{PGS_{CP}}$, **E** and **POL** have no covariance with **F** or **Parental PGS**.

A naive estimate of β is biased by genetic confounding ($\gamma\alpha$), confounding from the nonshared environment ($E_{IQ}E_{POL}$) and confounding from the shared environment ($F_{IQ}F_{POL}$). The formula and estimand is shown in Table S2.

Ideally we would statistically control for the relevant confounds of **F**, **E** and $\mathbf{PGS_{CP}}$. By partialing out the effects of confounds we may identify the effect β of **IQ** on **POL**. Unfortunately, this approach is impossible because we have no measurement of **E**. We can, however, control for **F** using family fixed effects. This estimate of $\beta_{OLS\text{-}FE}$ at least removes omitted-variable bias arising from the shared environment.

Where our research goes beyond prior work in estimating β is through the use of polygenic scores. The advantage of using a genetic estimate of cognitive performance, instead of the phenotype, is that it has no covariance with the nonshared environment **E**. A naive approach would be to regress **POL** on $\mathbf{PGS_{CP}}$. This estimate of $\beta_{OLS\text{-}PGS}$ captures the direct genetic effect α, the indirect effect $\gamma\beta$ going through **IQ** and confounding $P_{CP}P_F[F_{IQ}\beta+F_{POL}]$ arising from a gene-environment correlation $P_{CP}P_F$ with the shared environment. The confounding from the shared environment can be removed via controlling for family fixed effects to yield $\beta_{OLS\text{-}PGS_{CP}\text{-}FE}$. It should be noted that under our assumed model, using family fixed effects or controlling for the **Parental PGS** produces the same estimand for models using the polygenic score as an explanatory variable. As such, we refer to these two methods interchangeably in this subsection.

If α is small and γ is positive, the sign of $\beta_{OLS\text{-}PGS_{CP}\text{-}FE}$ shows whether the effect β is positive or negative, but interpretation of the size of the effect is impossible without knowing how large γ is. Thus the regression of **POL** on $\mathbf{PGS_{CP}}$ provides us with very little information regarding the importance of intelligence for political beliefs. Instead, we opt to use $\mathbf{PGS_{CP}}$ as an instrument for **IQ** in a two-stage least-squares (2SLS) model. The estimands for this approach, with ($\beta_{2SLS\text{-}FE}$) and without controlling for the shared environment (β_{2SLS}), are presented in Table S2.

Notice that $\beta_{2SLS\text{-}FE}$ estimates the effect of intelligence β plus the direct pleiotropic effect α divided by γ. If there is no pleiotropic effect of the polygenic score on political belief, the "exclusion restriction" holds and this approach identifies the effect of **IQ** on **POL**.

Table S2: Model Estimands

Estimate	Formula	Estimand
$\beta_{OLS\text{-}IQ}$	$\frac{COV(IQ,POL)}{VAR(IQ)}$	$\beta+\gamma\alpha+E_{IQ}E_{POL}+F_{IQ}F_{POL}$
$\beta_{OLS\text{-}IQ\text{-}FE}$	$\frac{COV(IQ,POL\|Family)}{VAR(IQ\|Family)}$	$\beta+\gamma\alpha+E_{IQ}E_{POL}$
$\beta_{OLS\text{-}PGS_{CP}}$	$\frac{COV(PGS_{CP},POL)}{VAR(PGS_{CP})}$	$\gamma\beta+\alpha+P_{CP}P_F[F_{IQ}\beta+F_{POL}]$
$\beta_{OLS\text{-}PGS_{CP}\text{-}FE}$	$\frac{COV(PGS_{CP},POL\|Family)}{VAR(PGS_{CP}\|Family)}$	$\gamma\beta+\alpha$
β_{2SLS}	$\frac{COV(PGS_{CP},POL)}{COV(PGS_{CP},IQ)}$	$\beta+\frac{\alpha+P_{CP}P_F F_{POL}}{\gamma+P_{CP}P_F F_{IQ}}$
$\beta_{2SLS\text{-}FE}$	$\frac{COV(PGS_{CP},POL\|ParentalPGS)}{COV(PGS_{CP},IQ\|ParentalPGS)}$	$\beta+\frac{\alpha}{\gamma}$

Unfortunately our best approach $\beta_{2SLS\text{-}FE}$ is still biased if there is direct pleiotropy. We should note that every other approach also includes α in its estimand and is thus also biased by direct pleiotropy. This is a problem common to all previously performed approaches rather than being a problem unique to the approach performed in this paper. The difference between $\beta_{2SLS\text{-}FE}$ and $\beta_{OLS\text{-}IQ\text{-}FE}$ is that the latter phenotypic approach is biased by the nonshared environment and direct pleiotropy. However, the $\beta_{2SLS\text{-}FE}$ puts a greater weight on the direct pleiotropy α from the polygenic score since it is divided by γ instead of being multiplied by it. On the other hand, $\mathbf{E}$ also captures some genetic variation from rare variants, not used in the polygenic score. This means it is not certain whether using the polygenic score as an instrument involves more confounding from direct pleiotropy than the phenotypic approach. In other words, using the polygenic score as instrument removes environmental confounding but it is unclear if it increases the bias from genetic confounding.

There are a few assumptions we have made implicitly in the theoretical model above, which may not apply to the data we analyse. Firstly, we assume no carryover effects whereby one sibling's polygenic score or intelligence influences the other's political beliefs. This would cause the fixed effect models to differ in their estimands to models controlling for parental polygenic scores. Given that carryover effects are likely to be small, we refrain from trying to test for them with the sample in this paper. In the true model, genetic nurture effects from the mother and father may differ. Our primary concern is to control for the parental polygenic scores to exclude confounds, meaning controlling for the average polygenic score is sufficient. Although controlling for maternal and paternal polygenic scores separately would allow us to test for differing genetic nurture effects, we would not have the statistical power to identify such differences.

There are some further possible causal pathways we ignore for simplicity. We suppose that the parental genotype only alters political beliefs through the shared environment for intelligence. It may be that parental cognitive ability does not just create a more intellectual environment, which happens to support certain political beliefs, but also directly changes other aspects of the shared environment relevant to political beliefs. Including this pathway would increase the algebraic complexity of the environmental confounding in our estimands, but would not alter the estimands when fixed effects are employed.

Another simplification is to ignore potential differences between certain estimands introduced by cross-assortative mating. This type of mating may cause, for example, genetic variants for intelligence on one chromosome to be in linkage disequilibrium with variants for liberal politics on other chromosomes. Controlling for the parental polygenic score or using family fixed effects removes this form of confounding (Young, 2023), because Mendelian independent assortment means that there will be no tendency for an offspring inheriting the allele increasing trait 1 at a site heterozygous in the parent to also inherit the allele increasing trait 2 at an unlinked site.

Our sample includes some siblings who are adoptees rather than biological siblings. This reduces the covariance between child and parent's polygenic scores, and thus may reduce the environmental confounding in our models which do not use fixed effects or parental polygenic scores. Theoretically if our sample was only made of randomly assigned adoptees, we would not need to control for family effects to have no confounding from the shared environment.

Many of our adoptees were Asian. As discussed in the Methods section, in this group the polygenic scores have a weaker predictive power. We deal with this using the method of fully-interacted 2SLS, which we call multi-ancestry interacted Mendelian randomization. Since the method calculates a weighted average across the European and Asian groups, our estimand for $\beta_{2SLS\text{-}FE}$ may differ if either β or $\frac{\alpha}{\gamma}$ differ between the groups. We perform additional analyses only using Europeans or only Asians in Supplementary Section 4. Since these siblings are not biologically related to the parents, controlling for parental polygenic scores will not reduce the bias from cross-trait assortative mating.

Another assumption we have made is that our variables are measured without error. The reliabilities of our measures of IQ and political beliefs are good, as discussed in the main paper. As such, we do not consider attenuation arising from measurement error to be of particular importance in our analyses.

In the theoretical model in Figure S2, for the sake of simplicity, we ignore some variables that we do control for in regression models. These include age, sex and the first five genetic principal components.

4. Supplementary Results

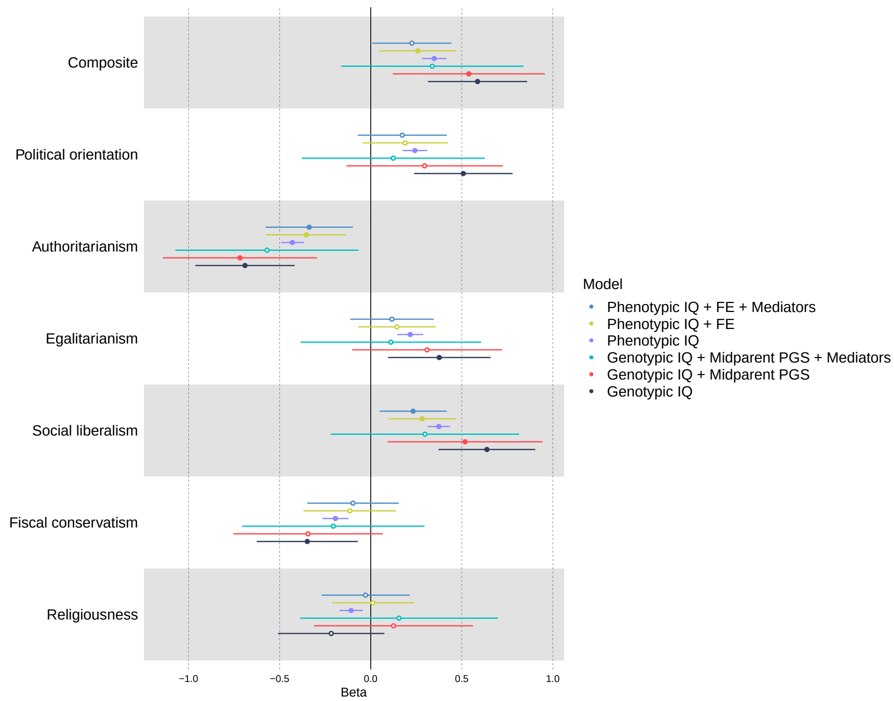

Figure S3: Intelligence and political belief, removing white adoptees from models controlling for the midparent polygenic score. The data points represent the regression betas of IQ. The 95% confidence intervals are clustered at the family level. Estimates are colored in if they are significant after a Benjamini-Hochberg correction for multiple testing at $p < 0.05$. Models are labeled by their most important right-hand-side variables. In the phenotypic models the estimates are obtained from ordinary least squares; in the genotypic models, two-stage least squares (2SLS) with the CP polygenic score as the instrument. FE stands for family fixed effects. Models using midparent PGS control for the mean polygenic score of the parents. Putative mediators include years of education and the logarithm of income. All models include controls for sex, age, an East Asian dummy variable and the first five genetic principal components, interacted with the East Asian variable.

Table S3: First-stage regressions

	Dependent variable: IQ		
	(1)	(2)	(3)
CP PGS	0.241***	0.304***	0.227***
	(0.042)	(0.066)	(0.062)
Midparent PGS		−0.024	−0.012
		(0.049)	(0.049)
CP PGS×EAS	0.024	−0.043	−0.017
	(0.066)	(0.083)	(0.079)
EAS	0.001	0.166	0.193
	(0.188)	(0.323)	(0.292)
Age	0.253***	−0.092	−0.123*
	(0.039)	(0.051)	(0.048)
Sex (Female = 1)	−0.431***	−0.403***	−0.503***
	(0.086)	(0.097)	(0.098)
Years of education			0.277***
			(0.041)
Log Income			0.051
			(0.043)
F-statistic of instruments	28.5	18.3	11.6
Observations	767	438	426
R^2	0.158	0.168	0.263

Note: $^{*}p$ <0.05; $^{**}p$ <0.01; $^{***}p$ <0.001. Cluster robust standard errors are shown in parentheses. Continuous variables are standardized, whilst dummy variables are not. EAS is a dummy variable for being an Asian adoptee. The first five genetic principal components and their interactions with EAS are omitted. First-stage regressions are reported for when the political composite is the dependent variable.

Table S4: Reduced Models

	Dependent variable: Political Composite		
	(1)	(2)	(3)
CP PGS	0.151^{**}	0.180^{*}	0.106
	(0.048)	(0.092)	(0.089)
Midparent PGS		−0.008	−0.005
		(0.069)	(0.069)
CP PGS×EAS	−0.022	−0.052	−0.042
	(0.076)	(0.111)	(0.107)
EAS	−0.050	0.143	0.258
	(0.212)	(0.313)	(0.304)
Age	-0.077^{*}	−0.091	−0.102
	(0.038)	(0.051)	(0.052)
Sex (Female = 1)	0.072	0.078	−0.116
	(0.089)	(0.103)	(0.102)
Years of education			0.331^{***}
			(0.047)
Log Income			−0.063
			(0.044)
Observations	767	438	426
R^2	0.052	0.062	0.150

Note: $^{*}p$ <0.05; $^{**}p$ <0.01; $^{***}p$ <0.001. Cluster robust standard errors are shown in parentheses. Continuous variables are standardized, whilst dummy variables are not. EAS is a dummy variable for being an Asian adoptee. The first five genetic principal components and their interactions with EAS are omitted.

Table S5: Effect of IQ within biological and adoptive families

	Dependent variable:						
	Composite (1)	Political orientation (2)	Authoritarianism (3)	Egalitarianism (4)	Social liberalism (5)	Economic Conservatism (6)	Religiousness (7)
IQ	0.267^{*}	0.150	-0.329^{*}	0.152	0.291^{**}	−0.151	0.003
	(0.128)	(0.149)	(0.128)	(0.129)	(0.103)	(0.156)	(0.136)
IQ * Bio	−0.058	0.013	−0.080	−0.064	−0.049	0.168	0.054
	(0.235)	(0.218)	(0.230)	(0.254)	(0.203)	(0.289)	(0.232)
Age	0.004	−0.006	−0.003	−0.002	0.029	0.013	0.005
	(0.053)	(0.055)	(0.058)	(0.053)	(0.050)	(0.057)	(0.047)
Sex (Female = 1)	0.261	0.524^{*}	−0.200	0.239	0.258	−0.203	0.221
	(0.219)	(0.218)	(0.222)	(0.226)	(0.198)	(0.243)	(0.184)
Family fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	670	679	670	670	670	671	670
R^2	0.809	0.776	0.783	0.794	0.834	0.764	0.817

Note: $^{*}p$ <0.05; $^{**}p$ <0.01; $^{***}p$ <0.001. Cluster robust standard errors are shown in parentheses. Continuous variables are standardized, whilst dummy variables are not. Bio is a dummy variable, taking the value of 1 when the sibling has a biological sibling and 0 when not the case.

Table S6: Effect of IQ in parents versus offspring

	Dependent variable:						
	Composite (1)	Political orientation (2)	Authoritarianism (3)	Egalitarianism (4)	Social liberalism (5)	Fiscal Conservatism (6)	Religiousness (7)
IQ	0.220**	0.100	−0.331***	0.096	0.225***	−0.114	−0.010
	(0.071)	(0.081)	(0.074)	(0.081)	(0.057)	(0.084)	(0.069)
IQ×Parent	−0.031	−0.002	0.092	0.053	0.049	0.116	0.013
	(0.096)	(0.142)	(0.114)	(0.113)	(0.092)	(0.126)	(0.112)
Parent	−0.711	−1.275	0.710	−0.252	−1.048	0.470	0.821
	(0.587)	(0.717)	(0.712)	(0.691)	(0.598)	(0.683)	(0.625)
Age	0.010	0.029	−0.010	0.001	0.013	−0.010	−0.002
	(0.018)	(0.022)	(0.022)	(0.021)	(0.019)	(0.021)	(0.020)
Sex (Female = 1)	0.166	0.382**	−0.098	0.181	0.162	−0.134	0.222
	(0.128)	(0.129)	(0.142)	(0.146)	(0.113)	(0.138)	(0.113)
Observations	930	938	930	930	930	931	929
R^2	0.773	0.720	0.713	0.722	0.793	0.707	0.772

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$. Cluster robust standard errors are shown in parentheses. Continuous variables are standardized, whilst dummy variables are not. Parent is a dummy variable, taking the value of 1 when the individual is a parent and 0 when the individual is one of the offspring.

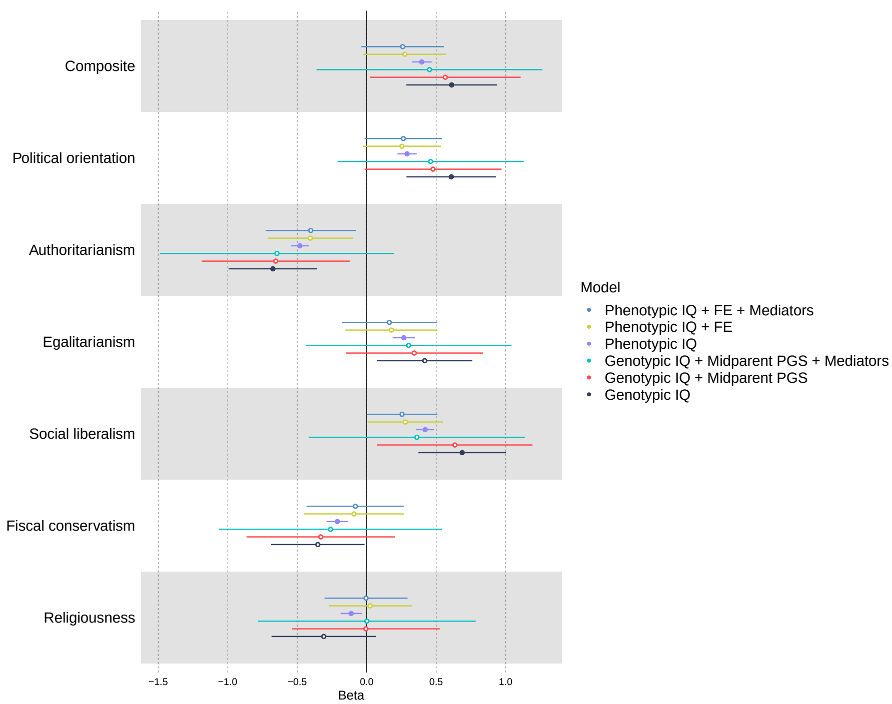

Figure S4: Intelligence and socio-political belief using Europeans only. The data points represent the regression betas of IQ. In the phenotypic model these are OLS estimates; in the genotypic model, 2SLS estimates with the CP polygenic score as the instrument. Confidence intervals are set at the 95% level and standard errors are clustered at the family level. Estimates are colored in if they are significant after a Benjamini-Hochberg correction for multiple testing at $p < 0.05$. FE stands for use of Family Fixed Effects. Models using midparent PGS control for the mean CP polygenic score of the parents. Mediators include years of education and the logarithm of income. All models include controls for sex and age. The genotypic IQ models additionally control for the first five genetic principal components.

Table S7: First-stage regressions using Europeans only

	Dependent variable: IQ		
	(1)	(2)	(3)
CP PGS	0.238^{***}	0.292^{***}	0.205^{***}
	(0.041)	(0.064)	(0.061)
Midparent PGS		-0.027	-0.003
		(0.072)	(0.071)
Age	0.260^{***}	-0.045	-0.060
	(0.040)	(0.072)	(0.068)
Sex (Female = 1)	-0.391^{***}	-0.344^{*}	-0.484^{***}
	(0.105)	(0.133)	(0.130)
Years in Education			0.300^{***}
			(0.049)
Log Income			0.043
			(0.063)
F-statistic of instruments	37.5	16.8	8.7
Observations	556	227	222
R^2	0.158	0.163	0.277

Note: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. Cluster robust standard errors are shown in parent. Continuous variables are standardized, whilst dummy variables are not. First stage regressions are reported for when the political composite is the dependent variable.

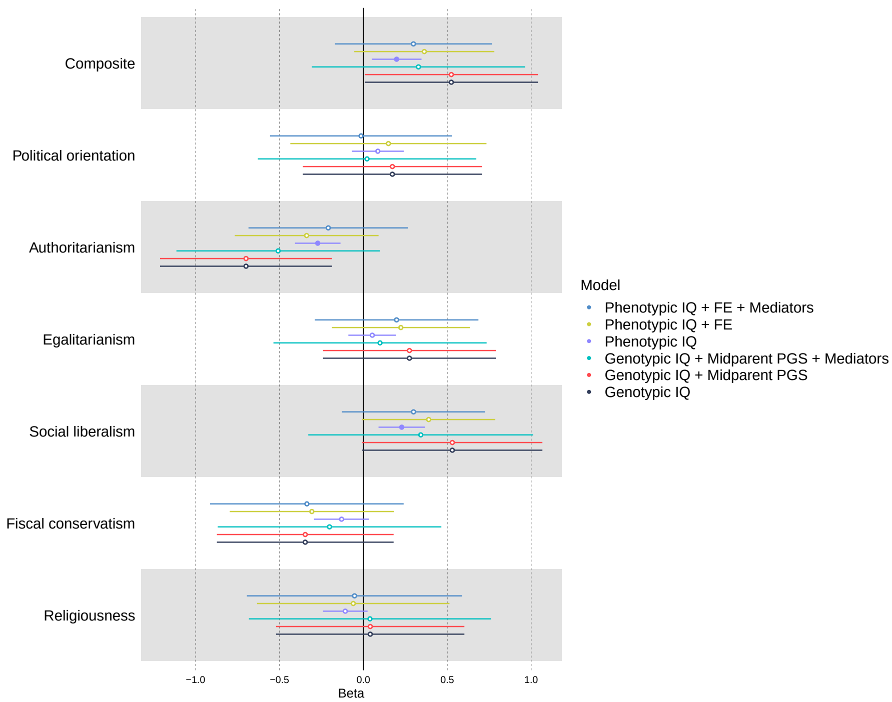

Figure S5: Intelligence and socio-political belief using Asians only. The plotted betas represent the regression betas of IQ. In the phenotypic model these are OLS estimates and 2SLS estimates in the genotypic IQ models. Confidence intervals are set at the 95% level and standard errors are clustered at the family level. Estimates are colored in if they are significant after a Benjamini-Hochberg correction for multiple testing at $p < 0.05$. FE stands for use of Family Fixed Effects. Models using midparent PGS control for the mean polygenic score of the parents. Mediators include years of education and the logarithm of income. All models include controls for sex and age. The genotypic IQ models additionally control for the first five genetic principal components.

Table S8: First stage regressions using Asians only

	Dependent variable: IQ		
	(1)	(2)	(3)
CP PGS	0.274^{***}	0.274^{***}	0.224^{***}
	(0.053)	(0.053)	(0.051)
Age	-0.138	-0.138	-0.181^{**}
	(0.071)	(0.071)	(0.066)
Sex (Female = 1)	-0.472^{***}	-0.472^{***}	-0.532^{***}
	(0.141)	(0.141)	(0.144)
Years in Education			0.269^{***}
			(0.067)
Log Income			0.067
			(0.061)
F-statistic of Instruments	18.6	18.6	12.6
Observations	211	211	204
R^2	0.178	0.178	0.259

Note: $^{*}p$ <0.05; $^{**}p$ <0.01; $^{***}p$ <0.001. Cluster robust standard errors are shown in brackets. Continuous variables are standardized, whilst dummy variables are not. First stage regressions are reported for when the Political composite is the dependent variable.

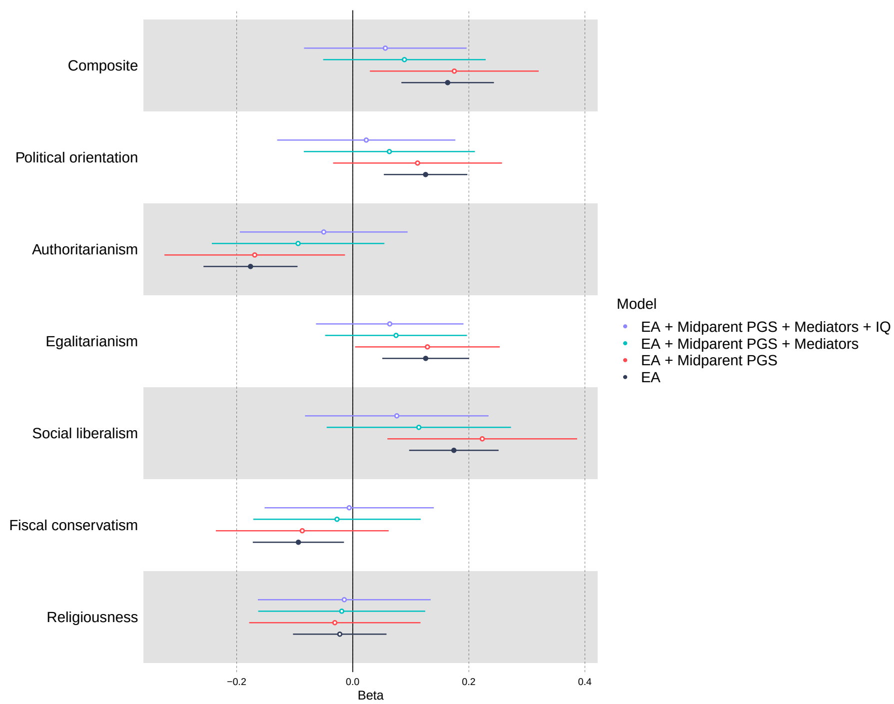

Figure S6: EA PGS and socio-political belief using Europeans only. The plotted betas represent the regression betas of the EA polygenic score. Confidence intervals are set at the 95% level and standard errors are clustered at the family level. Estimates are colored in if they are significant after a Benjamini-Hochberg correction for multiple testing at $p < 0.05$. Midparent PGS is mean EA PGS of the parents. Mediators include years of education and income. All models include controls for sex, age and the first five genetic principal components.

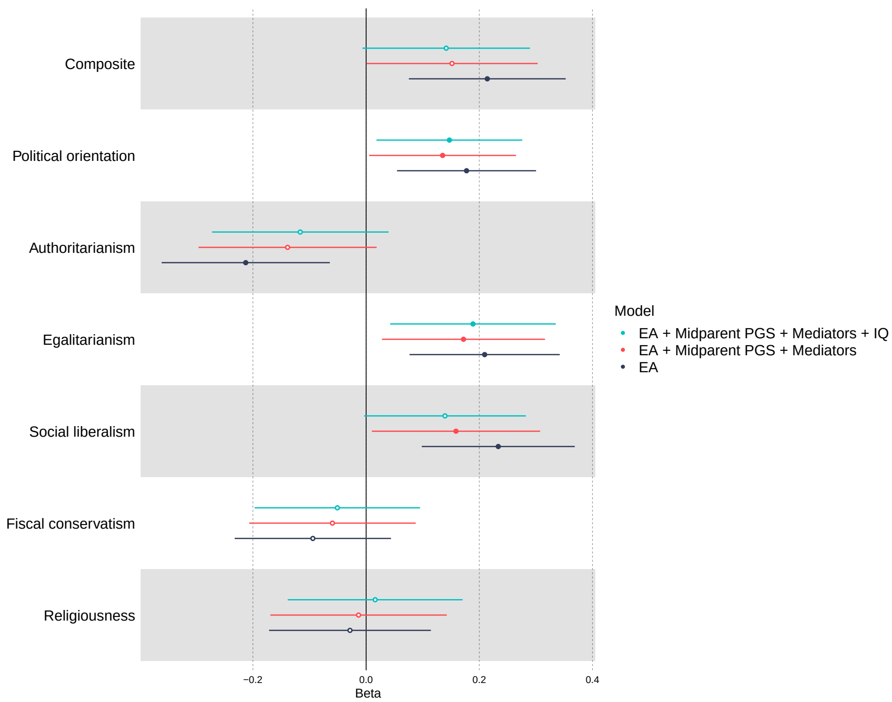

Figure S7: EA PGS and socio-political belief using Asians only. The plotted betas represent the regression betas of the EA polygenic score. Confidence intervals are set at the 95% level and standard errors are clustered at the family level. Midparent PGS is mean EA PGS of the parents. Mediators include years of education and income. All models include controls for sex, age and the first five genetic principal components.

4.1. Testing mediators of cognitive ability

In this paper we have suggested education and income may be important mediators of the effect of cognitive ability on political belief. To test the importance of these socioeconomic variables we regress them on each socio-political belief. Three sets of models are run, the first set has minimal controls. The second set includes family fixed effects and the third set controls for family fixed effects and IQ. The sample includes all biological and adopted siblings, of European and East Asian ancestry. The results are present in Figure S8.

We find education to be associated with left-wing political beliefs, including lower scores on fiscal conservatism. Income is not significant any of the models after corrcting for multiple testing. The effect size of education the political composite is 0.32 ($p < 0.001$). Once family fixed effects are employed, education does not significantly predict any of the variables after adjusting for multiple testing. In no other models, controlling for fixed effects and IQ does income or education significantly predict a political trait. However, the confidence intervals in these models encompass the confidence intervals of income and education when minimal controls are used. As such, we cannot claim that the effect of education or income is entirely explained by confounds with the family environment or cognitive ability.

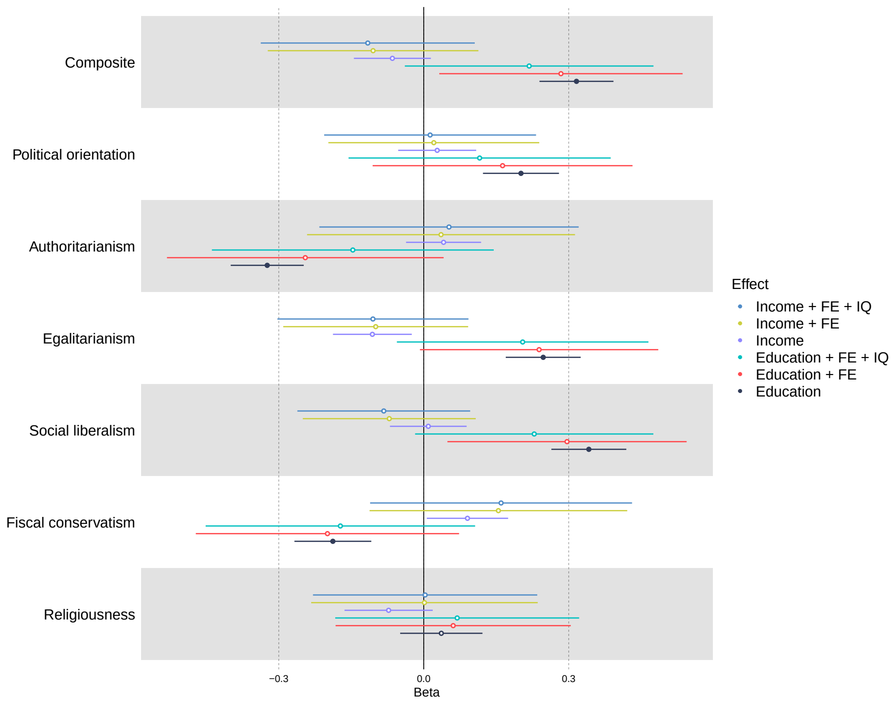

Figure S8: Effect of socioeconomic variables on socio-political belief. The plotted betas represent the regression betas of years of education and income on political beliefs. The model key designates whether the betas are for income or for education. Income and Education are included in each regression. Models with "FE", control for family fixed effects. Models with "IQ" control for intelligence. Confidence intervals are set at the 95% level and standard errors are clustered at the family level. Estimates are colored in if they are significant after a Benjamini-Hochberg correction for multiple testing at $p < 0.05$. All models include controls for sex, age and an East Asian dummy variable.

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