A Polygenic Score for Educational Attainment Partially Predicts Voter Turnout

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Twin and adoption studies have shown that individual differences in political participation can be explained in part by genetic variation. However, these research designs cannot identify which genes are related to voting or the pathways through which they exert influence, and their conclusions rely on possibly restrictive assumptions. In this study, we use three different US samples and a Swedish sample to test whether genes that have been identified as associated with educational attainment, one of the strongest correlates of political participation, predict self-reported and validated voter turnout. We find that a polygenic score capturing individuals' genetic propensity to acquire education is significantly related to turnout. The strongest associations we observe are in second-order midterm elections in the US and EU Parliament elections in Sweden, which tend to be viewed as less important by voters, parties, and the media and thus present a more information-poor electoral environment for citizens to navigate. A within-family analysis suggests that individuals' education-linked genes directly affect their voting behavior but for second-order elections, it also reveals evidence of genetic nurture. Finally, a mediation analysis suggests that educational attainment and cognitive ability combine to account for between 41% and 63% of the relationship between the genetic propensity to acquire education and voter turnout depending on the type of election.

education | voting | polygenic score

Why do some people vote in elections whereas others abstain? This question has profound implications for democratic accountability and representation (1) and has, accordingly, generated a vast empirical literature (2). A consistent finding in this literature is that educational attainment is among the strongest correlates of voter turnout (2). The conventional explanation is that education causally influences political engagement, the logic being that education provides citizens skills (3) and cognitive resources (4) that lower the cost of participating in politics as well as foster a sense of civic duty and political efficacy (3, 5). The implication of this explanation is that exogenously increasing an individual's education attainment will increase their likelihood of voting. However, other scholars have argued that the correlation between education and turnout may be spurious: pre-adult characteristics such as cognitive ability, personality traits, and genetic factors as well as parental socialization cause both the acquisition of education and adult political participation (6, 7). Thus, more education may not necessarily translate into a higher likelihood of voting.

To better understand the relationship between education and voter turnout, we focus on the role of genes related to education and cognitive ability. A genetic basis of voter turnout has been established by studies of twins (8–10) and adoptees (11, 12) and a recent study has reported an association between education-linked genes and voter turnout in a Danish sample of unrelated individuals (13). Since estimated genetic effects based on unrelated individuals may be confounded by assortative mating, population stratification and environmentally mediated parental genetic effects (14), we conduct a within-family analysis based on more than 10,000 sibling pairs in order to evaluate the direct effects of an individual's education-linked genes on their voting behavior. In addition, comparing estimates from between- and within-family models allows us to evaluate the degree to which parents' education-linked genes influence their offspring's political participation via the family environment they create for them (14), a possibility hinted at by past research showing parental education is strongly correlated with their offspring's voting behavior (15, 16). Finally, in an effort to trace the pathway through which genes influence political participation, we test whether genes confound the relationship between educational attainment and voter turnout (because they separately influence both education and turnout) as well as assess how much of the relationship between the education-linked genes and turnout is mediated by education, cognitive ability, and personality traits.

Using three genetically-informative samples from the United States and one from Sweden which combined include more than 50,000 individuals, we test whether an individual-level index aggregating the effect of genes associated with educational attainment, referred to as a polygenic score (17), predicts voter turnout. We find that the educational attainment polygenic score (EA PGS) is significantly related to self-reported and validated measures of voting. This relationship is significantly stronger in second-order elections (midterm elections

Significance Statement

The strong correlation between education and voting is among the most robust findings in social science. We show that genes associated with the propensity to acquire education are also associated with higher voter turnout. A within-family analysis suggests education-linked genes exert direct effects on voter turnout but also reveals evidence of genetic nurture in second-order elections. Our findings have important implications for the study of political inequality. Scholars have argued that parental education is the main driver of the reproduction of political inequality across generations. By separating the effect of genes from parental nurturing, our findings suggest that the roots of individual-level political inequality run deeper than family background.

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in the US and EU Parliament elections in Swedish) in which information is likely to be harder to obtain or less desirable (18, 19) compared to first-order elections (presidential elections in the US and national parliament elections in the Sweden). In addition, we find that the effect of the EA PGS and voting in second-order elections is stronger among younger voters. Taken together, this suggests that the political environment may moderate the genetic influence on voting. Our within-family analysis suggests that education-linked genes exert a significant direct effect in both first- and second-order elections, but we also find evidence of genetic nurture in second-order elections. Finally, after controlling for the EA PGS, the effect of education shrinks by between 8% and 17% signaling genes associated with education partially confound the relationship between education and turnout. Our mediation analysis suggests that educational attainment and cognitive ability combine to account for between 41% and 63% of the relationship between the EA PGS and voter turnout.

Results

To conduct our analysis, we use individual-level information from the National Longitudinal Study of Adolescent to Adult Health (Add Health), the Minnesota Twin and Family Study (MTFS), the Wisconsin Longitudinal Study (WLS), and the Swedish Twin Registry (STR). All four studies collected measures of self-reported and/or validated voter turnout as well as made available to researchers polygenic scores for educational attainment. Relevant summary statistics for each sample are reported in the Appendix Table A1.

Table 1 presents our baseline estimates of the association between the EA PGS and the three different measures of voter turnout - self-reported voting and validated measures of turnout in first-order (presidential elections in the US samples and national parliament elections in the Swedish sample) and second-order (midterm elections in the US samples and European parliament elections in the Swedish sample) elections. Self-reported turnout has been standardized to have a mean equal to 0 and a standard deviation equal to 1. First-order and second-order election turnout are measured on the unit interval scale.

Looking first at column 1, a one standard deviation increase in the EA PGS is associated with about a sixth of a standard deviation increase in self-reported voting in the Add Health and MTFS samples. Turning to the results for validated turnout in columns 2 and 3, the effect of the EA PGS is larger in second-order elections that in first-order elections; the effect is twice as large in the MTFS parent and WLS samples and more than four times as large in the MTFS twin and STR samples. In Appendix Table A4 we show that the relative difference in polygenic score effect size decreases when using a generalized linear model instead of a linear probability model. However, with the exception for the MTFS parents, the pattern of statistically significant larger EA PGS effects in second-order elections is discernible irrespective of modeling choice.

In order to put the magnitude of these effects in perspective, in Appendix Table A3 we estimate the effect of years of schooling, one of the strongest documented predictors of voter turnout (2), in each sample. The effect of the EA PGS on voter turnout reported in Table 1 is between 55% and 70% of the corresponding effect of years of schooling.

Table 1. EA PGS and Voting, Baseline results

	Self-reported voting	First-order voting	Second-order voting
Add Health			
EA PGS	0.153***		
	(0.013)		
Δ R^2	0.023		
Average birth year	1979		
Observations	5,633		
MTFS twins			
EA PGS	0.178***	0.011*	0.052***
	(0.025)	(0.005)	(0.008)
ΔR^2	0.028	0.002	0.018
Average birth year	1979	1983	1983
Observations	2,264	3,013	3,035
MTFS parents			
EA PGS		0.011***	0.028***
		(0.002)	(0.004)
ΔR^2		0.009	0.017
Average birth year		1953	1953
Observations		3,448	3,452
WLS			
EA PGS		0.014***	0.027***
		(0.004)	(0.004)
ΔR^2		0.002	0.006
Average birth year		1939	1939
Observations		7,042	7,042
STR			
EA PGS		0.018***	0.080***
		(0.001)	(0.004)
ΔR^2		0.007	0.034
Average birth year		1967	1968
Observations		39,333	39,633

Notes: Self-reported voting and the EA PGS are standardized (mean=0, s.d.=1) within each sample. First-order (presidential in the US and National in Sweden) and second-order (midterm in the US and EP in Sweden) election turnout are measured as average turnout across all the elections for which we have information for the individuals. All models include controls for gender, birth year, and the first ten principal components of the genetic-relatedness matrix. Standard errors, shown in parentheses, allow for clustering at the family level. ***/**/*, indicates significance at the .1/1/5% level.

In addition to the estimated effects, we also report the incremental R^2 (ΔR^2), or the increase in the coefficient of determination accounted for by the EA PGS. To put the amount of variation explained by the EA PGS in perspective, Figure 1 compares the incremental R^2 for the EA PGS to years of education as well as other factors identified by political behavior scholars to be strong predictors of voter turnout: parental education and income (15), cognitive ability (20, 21), and personal income (22). Figure 1 illustrates that the polygenic score's explanatory power is on par with that of personal income, parental income, and parental education and accounts for about half as much variation as years of education.

It should be noted that in Figure 1 the EA PGS, as well as other predictors of voter turnout, explain less of the variation in validated turnout in the WLS sample than the MTFS and STR samples. This may be due to the fact that the older WLS subjects are at a point in their lives where voting has become an

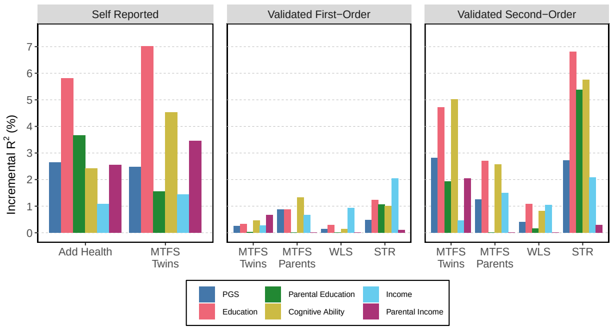

Fig. 1. Incremental R^2 for the EA PGS compared to other predictors of voter turnout. The height of each bar represents the increase in the coefficient of determination (R^2) when the EA PGS is added as a covariate to a regression of voter turnout on a set of baseline controls that includes gender, birth year, and 10 principal components of the genetic relatedness matrix. Parental income and education are not available for the MTFS parents. The income measure for Add Health and the MTFS twins is personal income before taxes and for the MTFS parents is household income before taxes. For the WLS sample, the figure reports personal net worth rather than income since it is more appropriate measure of financial resources for older individuals in the sample, many of whom are retired. For the STR sample we use annual register information on gross total wage income and income from business to calculate average income between age 25 and 65.

ingrained habit (23) meaning that individual- and contextual-level factors become less influential in determining turnout (24). Further, among older citizens, factors such as health (25) and social isolation (26, 27) become more prominent in determining whether or not to vote. In the Appendix (Table A5 and Figure A2) we make use of the the wide and approximately uniform age distribution in the STR sample and show that the estimated effects and predictive power of both the EA PGS and years of education on validated voter turnout are significantly stronger among younger individuals.

To check the representativeness of our samples we show, in Appendix Table A6, that the amount of variation in validated turnout accounted for by education in the MTFS and WLS samples are similar to what we find based on the Cooperative Congressional Election Study, a US survey based on a very large national representative sample. We also show that the results obtained in the STR sample are comparable to corresponding estimates based on individual-level population data.

We next check the degree to which the EA PGS confounds the relationship between education and turnout. A recent discordant twin study based on a similar Minnesota sample found that approximately half of the effect of education on political participation was due to genetic factors and/or family environment (28). In Appendix Table A12, we show that controlling for the EA PGS reduces the effect of education by on average about 12% across the four samples. While these results suggest only a modest amount of confounding, it is important to remember that the EA PGS does not capture all of the genetic propensity to acquire education. When more precise polygenic scores become available in the future, it is possible that the effect of education falls by closer to 30% to 40% (29).

We also test whether genes associated with educational attainment influence voter turnout via education and cognitive ability. Cognitive ability is likely to be a mediator given that it has been shown to be associated with the EA PGS (30), is strongly related to voter turnout (20, 21), and both have been shown to be influenced by shared genetic factors (9, 10). As shown in Figure 1, voter turnout is strongly related to both years of schooling and cognitive ability in all four samples. In Figure 2, we present results from a mediation analysis (31, 32) for the two traits (the full regression results are presented in Appendix Tables A13 and A14). We acknowledge that since we cannot account for potential alternative mediators, this analysis should be considered descriptive rather than causal (33).

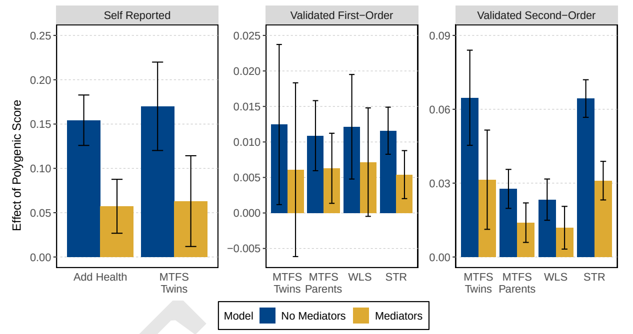

Fig. 2. Mediation analysis results for self-reported and validated turnout. The height of each bar represents the estimated effect of the polygenic score on turnout and the error bars represent 95% confidence intervals. The model with mediators includes years of education and cognitive ability. Both models include controls for gender, birth year, and the first ten principal components of the genetic-relatedness matrix.

Consistent with a mediated relationship, Figure 2 shows that the effect of the EA PGS on voter turnout shrinks considerably when controlling for educational attainment and cognitive ability. This is the case across all four samples. The amount mediated differs depending on the measure of turnout; educational attainment and cognitive ability account for approximately 63% of the effect of the EA PGS on self-reported voting, 47% of the effect on voting in first-order elections, and 50% of the effect on voting in second-order elections. While this analysis suggests that the genetic propensity to acquire education is mediated by educational attainment and cognitive ability, it also suggests there are EA PGS mechanisms influencing voter turnout that are unrelated to education and cognitive ability as there are still significant and sizeable effects of the EA PGS on the three outcomes. Another possible mediator is personality given that the EA PGS is correlated with personality traits (34, 35), a growing literature has demonstrated personality traits to be important for turnout (36), and personality and turnout have been shown to be influenced by shared genetic factors (9, 10). In Appendix Tables A15 - A19, we present results from regression models in which we include different measures of personality traits included in the four samples as additional controls. The inclusion of these variables does not reduce the estimated effect of the EA PGS any further.

Having demonstrated a relationship between the EA PGS and voter turnout, we next assess the extent to which this relationship is due to direct genetic effects (effects of individuals' education-linked genes on their voting behavior) versus indirect effects via genetic nurture. As evidence of the latter, there are moderate (and significant) correlations between i) the offspring EA PGS and parental education, ii) parental education and offspring education, and iii) offspring education and offspring turnout in all four samples used in this study.[*] Additionally, the EA PGS effects may still be confounded by population stratification despite the fact that the previous analysis restricted the samples to individuals of European descent and include controls for a set of principal components of the genetic-relatedness matrix.

In order to identify potential bias, we restrict our analysis to sibling pairs. Since this restriction dramatically reduces the size of each sample, we pool the US samples having similar outcome measures in order to increase power.[†] Table 2 displays the results based on the pooled US samples (as well as estimates based on each of the samples) and the STR sample. As a point of comparison, the first column for each outcome represents the OLS effect in these restricted samples and the second column shows estimates from models in which we include fixed effects for each sibling pair. That is, in the latter models we only use the within-family variation in order to account for both genetic nurture effects that are related to common family environment and any remaining confounding due to population stratification and assortative mating.

Comparing the OLS and FE estimates, there is no indication of any confounding due to genetic nurturing, population stratification, or assortative mating for voting in first-order elections. The effect of the EA PGS on self-reported turnout is smaller based on the fixed effects model compared to the OLS analysis. However, the estimates are not precise enough to draw any definitive conclusions regarding the existence of confounding. Looking instead at the results for voting in second-order elections, there is evidence of bias due to confounding, especially in the STR sample. The FE estimate for the STR sample is less than half the magnitude of the OLS estimate and (given the sample of more than 8,000 siblings) both are precisely estimated. While less precisely estimated, the OLS and FE results based on the MTFS twins display the same pattern; the nearly significant ($p = 0.055$) OLS estimate becomes negative and insignificant in the fixed effects model. In Appendix Tables A7 and A8, we show by comparing results from an OLS regression controlling for parental education with those from the fixed effects model that genetic nurturing is likely the source of most of the bias. In Appendix Tables A9 through A11 we present further evidence on genetic nurturing effects by showing that parental and sibling polygenic scores are related to second-order election turnout also after controlling for own EA PGS.

Conclusions

Based on the political participation of more than 50,000 US and Swedish citizens, we find a significant association between education-linked genes and both self-reported voting as well as validated turnout across a total of 23 different elections. Further, the polygenic score for education has predictive power comparable to well-studied correlates of voting such as parental education and personal income.

Both in the US and Sweden, we find that genes associated with educational attainment play a more influential role in explaining voting in second-order compared to first-order elections. Second-order elections are generally considered by voters, parties, and the media to be less important than first-order presidential or national elections (18). Thus, citizens typically have to navigate a more information-poor electoral environment, making it more challenging to participate. More educated citizens are relatively more likely to vote in these elections (19) since they are better equipped to overcome the costs of acquiring information. We also observe a stronger effect of the EA PGS among the younger Swedish twins. Perhaps among older citizens, experience and habit reduce the importance of the genetic propensity for traits that reduce the cost of participation. More research is necessary, but these results suggest genes and the political environment both combine to influence political participation.

Our findings corroborate a recent Danish study of voter turnout (13), however our novel within-family analyses based on a large number of sibling pairs and mediation analysis provide a more nuanced picture of this relationship. Since models based on unrelated individuals are vulnerable to environmental confounding (14), the significant within-family estimates we report provide the first solid evidence of a direct relationship between education-linked genes and voter turnout in both first- and second-order elections.[‡] For second-order elections, the within-family estimates also reveal evidence of confounding. For the Swedish sample, the effect of the EA PGS in the fixed effects model is half the size of the estimate from a naive OLS model and our follow-up analysis suggests that much of this confounding is due to genetic nurture. Political behavior scholars have long held that well-educated parents influence their children's civic development by providing the resources necessary to enable them to be well educated, thus facilitating their political engagement, as well as to create family environments that foster political interest and impart skills necessary to be politically active (16). However, recent work has shown that education-linked genes influence the type of environments parents choose for their children, which in turn impacts their children's educational attainment (39–44). Our findings suggest that these genes are also influencing voter behavior via family environment.

The availability of detailed information on subjects' educational attainment, cognitive ability, personality traits also allowed us to test potential pathways through which education-linked genes influence turnout. While our mediation analysis suggests that these genes likely influence turnout via educational attainment and cognitive ability, surprisingly, a large fraction of this genetic influence was not mediated by these two factors. This underlines the importance of testing potential mechanisms rather than making assumptions based solely on theory or past empirical evidence; genes associated with educational attainment may influence complex traits like voting through a number of different pathways. A wealth of studies show the EA PGS is predictive of traits related to voter turnout, and thus suggest potential mediators to be explored in future research. They include socioeconomic status (35, 41, 45–47), wealth (48), labor market outcomes (47, 49, 50), geographic mobility and migration (35, 51, 52),

[*] The bivariate correlations ($p < 0.001$ in all cases) between i) offspring polygenic score and parental education are equal to 0.294 (Add Health), 0.201 (MTFS twins), 0.239 (MTFS parents), 0.154 (WLS) and 0.245 (STR); ii) parental education and offspring education: 0.400 (Add Health), 0.314 (MTFS twins), 0.794 (MTFS parents), 0.325 (WLS), and 0.786 (STR); iii) offspring education and offspring self-reported voting: 0.273 (Add Health) and 0.291 (MTFS twins), 0.239; iv) offspring education and offspring first-order voting: 0.113 (MTFS twins), 0.138 (MTFS parents), 0.076 (WLS), and 0.114 (STR); and v) offspring education and offspring second-order voting: 0.201 (MTFS twins), 0.157 (MTFS parents), 0.112 (WLS), and 0.227 (STR).

[†] For self-reported voting, we have pooled the MTFS and the Add Health samples and for first-order (presidential) and second-order (midterm voting), we pooled the MTFS and WLS samples.

[‡] Since any genetic differences between full siblings are random, within-family estimates are typically given a causal interpretation (14). However, recent theoretical work (37, 38) has argued that estimates from within-family models may still be biased due to environmental confounding.

Table 2. EA PGS and voting - OLS and fixed effects models

	Self-reported voting		First-order voting		Second-order voting	
	OLS	FE	OLS	FE	OLS	FE
Pooled US results						
EA PGS	0.172***	0.107*	0.016***	0.022**	0.028***	0.017
	(0.029)	(0.048)	(0.004)	(0.009)	(0.005)	(0.011)
ΔR^2	0.026	0.007	0.003	0.003	0.006	0.001
Observations	1,492	1,492	3,934	3,934	3,943	3,943
Add Health						
EA PGS	0.151***	0.068				
	(0.040)	(0.066)				
ΔR^2	0.020	0.003				
Observations	788	788				
MTFS twins						
EA PGS	0.202***	0.174*	0.018*	0.023	0.023	-0.036
	(0.043)	(0.073)	(0.008)	(0.015)	(0.012)	(0.022)
ΔR^2	0.035	0.019	0.006	0.000	0.004	0.006
Observations	704	704	1,005	1,005	1,014	1,014
WLS						
EA PGS			0.015***	0.021	0.029***	0.033**
			(0.005)	(0.011)	(0.006)	(0.012)
ΔR^2			0.003	0.002	0.008	0.005
Observations			2,929	2,929	2,929	2,929
STR						
EA PGS			0.017***	0.015***	0.074***	0.034***
			(0.002)	(0.003)	(0.004)	(0.006)
ΔR^2			0.006	0.003	0.028	0.004
Observations			16,386	16,386	16,520	16,520

Notes: Self-reported voting and the EA PGS are standardized (mean=0, s.d.=1) within each sample. First-order (presidential in the US and National in Sweden) and second-order (midterm in the US and EP in Sweden) election turnout are measured as average turnout across all the elections for which we have information for the individuals. All models include controls for gender, birth year, and the first ten principal components of the genetic-relatedness matrix. Standard errors, shown in parentheses, allow for clustering at the family level. ***/**/*, indicates significance at the .1/1/5% level.

and mate choice (53, 54). Health outcomes may be another possible mediator; recent work found that cognitive and physical well-being predict voter turnout (25) and (34) showed that educational attainment is genetically linked with psychiatric and physical traits.

Our findings also contribute to the study of political inequality created by structured differences in access to political resources (1, 15, 55, 56). (15) argue that parental education is the main driver of the reproduction of political inequality across generations. However, most studies of the inter-generational transmission of political participation fail to separate the effect of genes from parental nurturing. We show that genes are nearly as predictive as parental education for self-reported and validated voting. Thus, inheriting genes beneficial for educational attainment makes individuals more likely to vote. Taken together, our findings suggest that the roots of individual-level political inequality run deeper than family background. It is important to note, though, that since the GWAS used to construct the EA PGS consisted of individuals of European ancestry, the EA PGS cannot yet shed any light on group differences in political participation (15).[§]

Finally, it is important to point out that the EA PGS does not fully capture the genetic propensity to acquire education; it accounts for between 11% and 13% of the variation in educational attainment (30) while heritability based on all genotyped SNPs has been shown to be approximately 20% (57) and a meta-analysis of twin studies reported that about 40% of the variation in educational attainment can be attributed to genetic factors (58). Thus, our results likely represent a lower bound on the effect of genes associated with educational attainment on voter turnout. Ongoing larger GWA studies of educational attainment will provide us with more accurate polygenic scores in the near future.

Methods

Samples and Measures. We use data from four different samples to examine the relationship between the EA PGS and voter turnout: the Minnesota Twin Family Study, the National Longitudinal Study of Adolescent to Adult Health, the Wisconsin Longitudinal Study, and the Swedish Twin Registry. Please see the Appendix for detailed information about each of the

[§]For example, (30) show that the EA PGS did a poor job of predicting educational attainment in a sample of African Americans.

samples and the measures we use as well as how to access the data.

Polygenic Score Prediction. To test our hypothesis that genes associated with educational attainment influence voter turnout, we use an index, referred to as a *polygenic score*, of an individual's genetic predisposition for educational attainment. A PGS maximizes the predictive power for a trait by using information from a well-powered genome-wide association study (GWAS) (17). The standard approach of a GWAS is to run K separate regressions of a trait y on the K genotyped SNPs:

$$y_i = \mu_k + \beta_k x_{ik} + \epsilon_{ik} \quad [1]$$

for $k = 1, ..., K$ where x_{ik} ($x \in \{0, 1, 2\}$) is the number of minor alleles individual i has for SNP k.

To create a PGS, a GWAS is conducted in a discovery sample and the estimated effects of the SNPs ($\hat{\beta_k}$) are subsequently used as a weights in the aggregation of SNPs in a target sample of interest:

$$PGS_i = \sum_{k=1}^{K} \hat{\beta}_k x_{ik}, \quad [2]$$

The polygenic scores for educational attainment we use were made available to researchers by the four studies (described in greater detail below) we analyze as part of our study. All of the scores were constructed in the same manner by the Social Science Genetic Association Consortium (https://www.thessgac.org/) and were made available to researchers as part of the their Polygenic Index Repository (59).[¶] For a more detailed discussion of the polygenic score framework, please refer to the Appendix.

Empirical Framework. As a starting point for our analysis, we analyze the EA PGS in the following simple regression framework:

$$y_i = \beta_0 + \beta_1 PGS_i + C_i \beta_C + \epsilon_i \quad [3]$$

where y_i is a measure of voter turnout for individual i; PGS_i is the polygenic score of educational attainment; C_i is a vector of control variables; and ϵ_i is an i.i.d. error term. The control variables include fixed effects for each birth cohort (i.e. birth year), a dummy indicator for being male, and the top ten principal components of the covariance matrix of the individuals' genotypic data to mitigate the risk of population stratification.

In equation 3, β_1 provides us with an estimate of the effect of the EA PGS on voter turnout. However, this estimate may be biased due to population stratification, assortative mating, genetic nurturing. Since our samples are comprised of families including biological siblings, we are able to estimate sibling fixed effect models that eliminate all three sources of potential bias. For a more detailed discussion of the empirical framework, please refer to the Appendix.

[¶] The educational attainment polygenic score is constructed using the results of a published GWAS of educational attainment based on over 1,100,000 subjects (30). Information about the construction of the EA PGS can be found in (59).

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Supplementary Information for

A Polygenic Score for Educational Attainment Partially Predicts Voter Turnout

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1. Polygenic Scores and Framework

Polygenic Score Prediction To test our hypothesis that genes associated with educational attainment influence voter turnout, we use an index, referred to as a *polygenic score*, of an individual's genetic predisposition for educational attainment. More precisely, a PGS is a specified linear combination of a very large number, typically several million, of single nucleotide polymorphisms (SNPs).* A PGS maximizes the predictive power for a trait by using information from a well-powered genome-wide association study (GWAS) (1). The standard approach of a GWAS is to run K separate regressions of a trait y on the K genotyped SNPs:

$$y_i = \mu_k + \beta_k x_{ik} + \epsilon_{ik} \tag{1}$$

for $k = 1, ..., K$ where x_{ik} ($x \in \{0, 1, 2\}$) is the number of minor alleles individual i has for SNP k.

To create a PGS, a GWAS is conducted in a discovery sample and the estimated effects of the SNPs ($\hat{\beta_k}$) are subsequently used as a weights in the aggregation of SNPs in a target sample of interest:

$$PGS_i = \sum_{k=1}^{K} \hat{\beta_k} x_{ik}, \tag{2}$$

Equation (2) illustrates the importance of using the results from a well-powered GWAS to construct the score; since there is measurement error associated with the estimates ($\hat{\beta_k}$), the more precise the estimates, which is a function of the GWAS sample size, the more faithfully the score captures the total additive genetic predisposition of a trait (2).

The polygenic scores for educational attainment we use were made available to researchers by the four studies (described in greater detail below) we analyze as part of our study. All of the scores were constructed in the same manner by the Social Science Genetic Association Consortium (https://www.thessgac.org/) and were made available to researchers as part of the their Polygenic Index Repository (**?**).†

Empirical Framework As a starting point for our analysis, we analyze the EA PGS in the following simple regression framework:

$$y_i = \beta_0 + \beta_1 PGS_i + C_i \beta_C + \epsilon_i \tag{3}$$

where y_i is a measure of voter turnout for individual i; PGS_i is the polygenic score of educational attainment; C_i is a vector of control variables; and ϵ_i is an i.i.d. error term. The control variables include fixed effects for each birth cohort (i.e. birth year), a dummy indicator for being male, and controls for what is known as population stratification.‡ Population stratification refers to genetic differences between population subgroups corresponding to environmental differences that are in actuality causally related to a trait or outcome of interest (4). As a result, the failure to account for these genetic differences may lead to a spurious association between the EA PGS and voter turnout. Following the standard practice in the genetics literature, we restrict our samples to individuals of European ancestry as well as include the top ten principal components of the covariance matrix of the individuals' genotypic data as controls in all of our regression analyses (5).

In equation (3), β_1 provides us with an estimate of the effect of the EA PGS on voter turnout. However, this estimate may be biased for three reasons. First, the inclusion of control variables may not fully eliminate population stratification. Second, bias may result from assortative mating; the fact that individuals with similar (or dissimilar) traits mate with one another more frequently than would be expected under a pattern of random mating. The third source of potential bias is due to the fact that children inherit genes associated with educational attainment from their parents as well as experience the family environment their parents provide for them. Both of these factors may influence their voting behavior, but β_1 is intended to capture only the former. However, there is mounting evidence that genes associated with parental educational attainment influence their children's education via the family environments they create for them (6–12), a phenomenon known as "genetic nurturing" (6), resulting in a confounding of the EA PGS and family environment. Given the established links between parental education and child political engagement (13–15), this suggests that β_1 may include both the direct effect of the EA PGS as well as the effect of genetic nurturing.

Since our samples are comprised of families including biological siblings, we are able to estimate sibling fixed effect models that eliminate bias due to population stratification, assortative mating, and environmentally mediated parental genetic effects (16). Further, by comparing the results from the sibling fixed effect models to the between-family model with an additional control for parental education, we are able to test for the existence genetic nurturing (11).

The estimated effect of the EA PGS on voter turnout in a sibling fixed effect model comes from sibling-pair differences in the alleles they inherit from their parents (e.g. one sibling inherits more alleles associated with educational attainment than the other). Since Mendel's law of segregation dictates that (at a given locus) the alleles parents pass along to children are randomly

* DNA is made up of subunits called nucleotides (adenine (A), cytosine (C), thymine (T), and guanine (G)). At the vast majority of the approximately 3 billion locations, called loci, across the human genome the nucleotide sequence does not vary between individuals but at a small fraction of loci they do. The different versions at those loci are called alleles and for most of those loci there are only two possible alleles, one for each nucleotide base that occurs. The major allele refers to the allele that has the highest frequency in a given population whereas the less common allele is called the minor allele. When individuals differ in terms of a single nucleotide pair, it is known as a single nucleotide polymorphism (SNP). Since an individual inherits half of her DNA from each parent, one allele in each SNP is transmitted from the mother and the other is transmitted from the father. With two alleles, for each SNP there are three possible combinations: An individual may carry 0, 1, or 2 minor alleles.

† The educational attainment polygenic score is constructed using the results of a published GWAS of educational attainment based on over 1,100,000 subjects (3). Information about the construction of the EA PGS can be found in (**?**).

‡ Since our samples are made up of family members, we use cluster-robust standard errors at the family level to take the grouping structure into account.

determined, scholars typically interpret the estimated effect as a (direct) causal genetic effect (16). However, recent theoretical work (17, 18) has argued that estimates from within-family models may still be biased due to environmental confounding.

Finally, genes cannot influence voter turnout directly; there must be intervening factors linking the two. Educational attainment and cognitive ability are obvious candidates, given that the EA PGS was constructed to maximally capture the genetic propensity to acquire education and has been shown to also be a good predictor of cognitive ability (3, 19) combined with the fact that both are important determinants of voter turnout (20–30).

2. Samples and Measures

In the next section we describe in detail the four data sets we use, in particular reporting the evidence each provides on political participation.

A. The Minnesota Twin and Family Study. The Minnesota Twin and Family Study (MTFS) is a population-based multi-wave longitudinal study of same-sex twins and their parents from the Upper Midwest and is collected by the Minnesota Center for Twin and Family Research (MCTFR) (31). The MTFS twin sample is comprised of two age cohorts, one in which subjects were 11 years old at the time of their initial assessment and the other in which subjects were 17 years old. The younger cohort was born between 1977-1994 and the older cohort was born between 1972-1979.

We use two measures of voter turnout in the twin sample. The first is based on the twins' response (at approximately age 29) to whether the statement *I vote in national or state elections* is "not true at all", "not very true", "pretty true", or "very true" (coded as 1-4). In addition, we matched MTFS twins and parents to Minnesota voter records to obtain measures of voting participation. Using vote history information, we construct measures of presidential voting based on the 1996, 2000, 2004, 2008, 2012, and 2016 elections ($N_{twins} = 3,013$, $N_{parents} = 3,448$) and midterm voting based on the 1994, 1998, 2002, 2006, 2010, 2014, and 2018 elections ($N_{twins} = 3,035$, $N_{parents} = 3,452$).

The MTFS also contains information on twins' and parents' educational attainment (years of schooling) and performance on the Wechsler Adult Intelligence Scale-Revised (WAIS-R) (32). We use the two subtests designed to measure verbal comprehension to construct a measure of verbal IQ for twins at approximately age 17.[§]

B. National Longitudinal Study of Adolescent to Adult Health. The National Longitudinal Study of Adolescent to Adult Health (Add Health) is a nationally representative multi-wave longitudinal study of a nationally representative sample of adolescents in grades 7-12 in the United States, during the 1994-95 school year (33). Among other topics, Add Health includes data on the respondents' social, economic, political, psychological, and physical well-being. In Wave I of the Add Health study, researchers created a sample of sibling pairs based on a screening of a sample of 90,118 adolescents. These pairs include all adolescents that were identified as twin pairs, full-siblings, half-siblings, or unrelated siblings raised together. Genome-wide DNA information is available from the subset of respondents who contributed saliva samples during the fourth wave of data collection in 2008.

To measure turnout behavior, we use self-reported voting based on the subjects' response (between ages 25 and 34) to the question *How often do you usually vote in local or statewide elections?* where the responses are "never", "sometimes", "often", or "always" ($N = 5,633$). We utilize subjects' (between ages 25 and 34) and parents' (at the time of joining the study) self-reported educational attainment and results from the Peabody Picture Vocabulary Test (PVT). The PVT was administered to subjects between the ages 12 and 21 and is intended to measure verbal intelligence.

C. Wisconsin Longitudinal Study. The Wisconsin Longitudinal Study (WLS) is a long-term multi-wave longitudinal study of a random sample of 10,317 men and women who graduated from Wisconsin high schools in 1957 (34). Survey data was collected from the original respondents in several waves between between 1957 and 2011 and from a selected sibling between 1977 and 2011. The WLS data cover, among other things, social background, labor market experiences, family characteristics, psychological characteristics, and social and political participation. In the 2011 round of survey collection, the respondents also provided biological specimens (saliva samples) for DNA analysis.

The WLS contains validated turnout for several elections based on Wisconsin voter records. We use turnout in the 2008 and 2012 presidential and 2006 and 2010 midterm elections as outcomes in the empirical analysis. The WLS also contains educational attainment reported in 2004 when the subjects were on average 64 years old and performance on the Henmon-Nelson Test of Mental Ability that was administered to the subjects while in high school and collected by the WLS from state records.

D. Swedish Twin Registry. The Swedish Twin Registry (STR) began in the 1950s and contains nearly all twins born in Sweden since 1886. The total sample contains more than 170,000 twins (35). In this study we will use the subset of the twins that were successfully genotyped. We have matched this sample to validated turnout data from the European Parliament elections in 2009 and 2019 and the national elections in 1970, 1994, 2010, and 2018.[¶] For our measure of cognitive ability, we used social security numbers to match the men in the STR sample to conscription data provided by the Military Archives of Sweden.[‖] (37) discusses the history of psychometric testing in the Swedish military and provides evidence that the measure of cognitive ability is a good measure of general intelligence. Years of schooling was imputed from information obtained from administrative data contained in the national registers on educational level and type of education.

[§] Scholars have argued that verbal ability is more important for political participation than overall cognitive ability (20, 24, 26).

[¶] The turnout data is available thanks to a recent a recent effort to scan and digitize election roles from a number of elections. (36) provide a detailed description of the procedures used to scan and digitize these election rolls. Extensive quality checks suggest that the digitized information on electoral participation conforms with actual voting behavior in at least 99.7% of the cases.

[‖] All men in our sample were required by law to participate in military conscription around the age of 18.

3. Summary Statistics

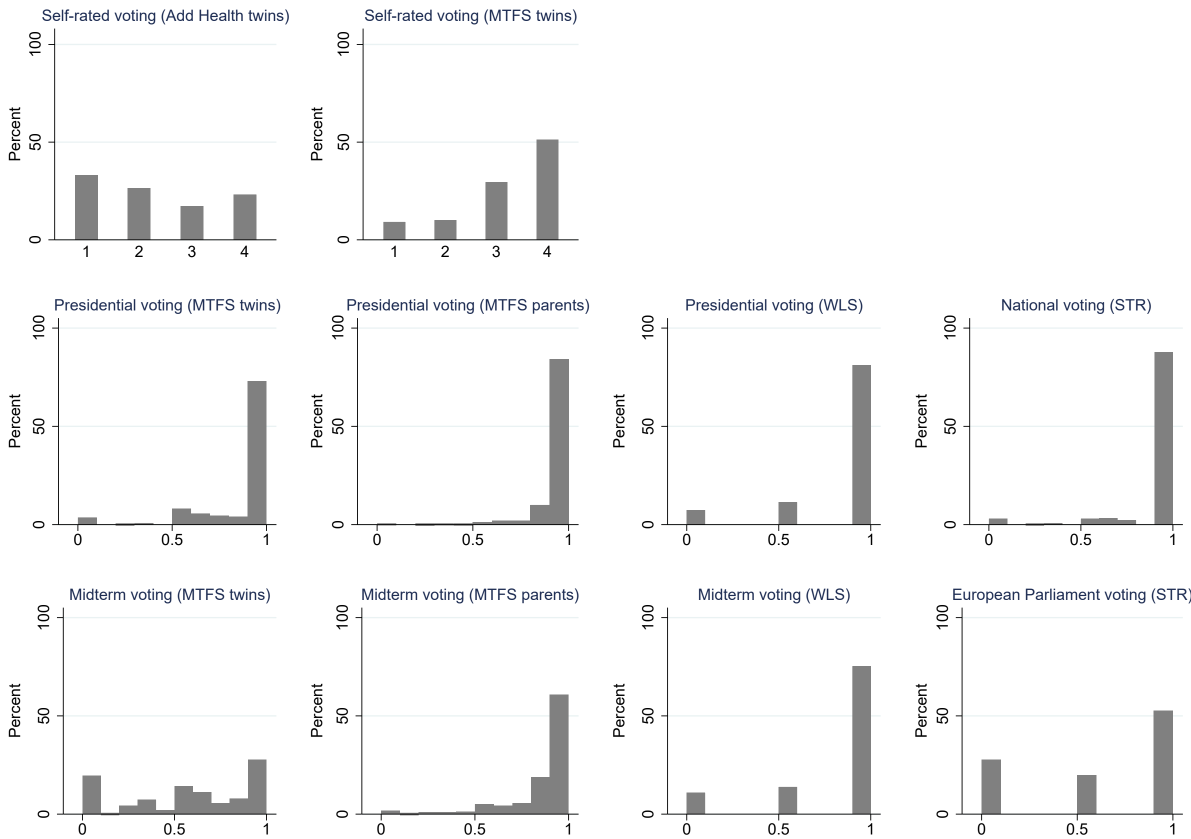
Table A1 presents summary statistics for the four samples. The indicators for presidential, midterm, national and EP votes are measured as averages across all available elections (0-1). The distributions for each measure of turnout are presented in Figure A1. Males are slightly underrepresented in all samples. The last two rows display the incremental explanatory power associated with the EA PGS when using years of education (EA) and cognitive ability (IQ) as outcomes. The magnitude of the estimates indicate that variation in the score accounts for large fractions of the variance in educational attainment and cognitive ability in all three samples.

Table A1. Summary Statistics

	MTFS Twins	MTFS Parents	Add Health	WLS	STR
Self-Reported Turnout	3.228		2.307		
	(0.964)		(1.157)		
Presidential Vote	0.878	0.959		0.869	
	(0.240)	(0.112)		(0.293)	
Midterm Vote	0.571	0.875		0.822	
	(0.364)	(0.209)		(0.334)	
National Vote					0.933
					(0.205)
EP Vote					0.624
					(0.430)
Years of Education	17.29	15.74	15.65	15.79	14.66
	(2.754)	(3.081)	(2.844)	(3.141)	(3.963)
Birth Year	1982.1	1953.4	1979.0	1939.4	1971.3
	(5.698)	(6.680)	(1.771)	(4.104)	(23.65)
Male	0.474	0.459	0.389	0.476	0.458
	(0.499)	(0.498)	(0.488)	(0.499)	(0.498)
ΔR^2_{EA}	0.078	0.070	0.130	0.055	0.059
ΔR^2_{IQ}	0.137	0.098	0.079	0.068	0.074

Notes: Means and number of standard deviations (in parentheses) for some key variables. Self-reported turnout is measured on a 1-4 scale. Presidential, midterm, national, and EP election turnout are measured as average turnout across all the elections for which we have information for the individuals.

Fig. A1. Turnout Measure Distributions Across Samples



Notes: Distribution of self-reported voting (1-4 scale) in the Add Health and MTFS samples and average validated turnout across all presidential and midterm elections for which we have information for the individuals in the MTFS and WLS samples and all national and EP elections for which we have information for individuals in the STR sample.

4. Accessing the Data

We use restricted individual level information obtained from each of the studies. As part of our contractual agreement with each study, we agreed not to disseminate the data to other individuals. However, researchers can access the restricted data directly from each study. Details on how to access restricted data for each sample can be found at:
MTFS: https://mctfr.psych.umn.edu/
Add Health: https://www.cpc.unc.edu/projects/addhealth/documentation/restricteduse
WLS: https://www.ssc.wisc.edu/wlsresearch/data/
STR: https://ki.se/en/research/swedish-twin-registry-for-researchers
https://www.scb.se/en/services/ordering-data-and-statistics/ordering-microdata/

5. MTFS Vote Matching

We matched MTFS subjects (twins and parents) to Minnesota registration records provided by Minnesota Secretary of State's office. Subjects were matched to voter records obtained in November 2007, July 2008, January 2009, December 2010, March 2013, March 2015, and March 2017. Matching was done using the CRAN package *fastLink* (38) using the settings based on the fastLink technical reports. Our matching process utilized available information collected by the MTFS on first name, middle initial, last name, birth year, phone number, house number, street name, and zip code. We were able to match 85% of the MTFS subjects for which we had address information and birth year. We only retain subjects for the analysis that matched the voter records so our measure of turnout for the MTFS is among registered voters.

Using vote history information provided in the records, we construct a measure of voting in each election. If a registered voter is reported as having participated in an election based on any of the 7 voter files we analyze, they are assigned a 1 for that election. If they were eligible to participate in an election based on the registration date reported in the voter file immediately preceding or immediately following the election (e.g. the 2015 and 2017 voter files for the 2016 election) but are not reported as having participated, they are assigned a zero.

6. Coding of Education

Educational attainment is based on highest completed degree following the coding schemes provided in (39) and (3). The STR sample includes register information on educational attainment according to the Swedish standard classification of education (SUN1969 and SUN2000). The SUN codes are readily transferable into ISCED1997 first-digit codes which are subsequently mapped to years of education according to the following scheme: $0 = 1$ year of education; $1 = 7$ years; $2 = 10$ years; $3 = 13$ years; $4 = 15$ years; $5 = 19$ years; and $6 = 22$ years. For the three US samples the conversion from highest self-reported degree into years of education is displayed in Table A2.

Table A2. Conversion of Highest Completed Degree to Years of Education

Degree	Years of Education
MTFS Twins	
Did not complete high school	10
Completed high school or GED program	13
Completed post high school vocational training or trade school program	15
Completed community college program	19
Attended four year college or university	19
Completed four year college or university program	19
Completed professional or graduate program	20
MTFS Parents	
Less than high school	10
High school or GED	13
Business or technical certificate	15
Associates / some college	19
BA / BS	19
Professional / graduate	20
Add Health	
8th grade or less	7
Some high school	10
High school graduate	13
Some vocational/technical training (after high school)	15
Completed vocational/technical training (after high school)	15
Some college	15
Completed college (bachelor's degree)	19
Some graduate school	19
Completed a master's degree	19
Some graduate training beyond a master's degree	19
Some post baccalaureate professional education	19
Completed a doctoral degree	22
Completed post baccalaureate professional education	22
WLS	
Completed 7 years of school	10
Completed 8 years of school	10
Completed 9 years of school	10
Completed 10 years of school	13
Completed 11 years of school	13
Less than one year of college	13
One year of college	15
Associates degree, 2 years of college	19
Three or more years of college	19
Bachelor's degree	19
Master's degree	19
Two-year master's	19
Professional degrees, one or more years post	22
Phd, MD	22
Post doctorate education	22

7. Auxiliary Results and Robustness Checks

In this section we provide some details on the auxiliary results and robustness checks briefly discussed in the main text.

A. Baseline Results. Table A3 present estimates of the effect of the polygenic score for education (columns 1, 3 and 5) and years of schooling (columns 2, 4 and 6) on our three measures of voter turnout. Both the EA PGS and the years of schooling are standardized (within each sample) to have a mean = 0 and s.d = 1.

Table A3. Education and Voting, Baseline Results

	Self-reported voting		First-order voting		Second-order voting	
Pooled US results						
EA PGS	0.156***		0.012***		0.029***	
	(0.012)		(0.003)		(0.003)	
Education		0.284***		0.017***		0.042***
		(0.012)		(0.002)		(0.003)
R^2	0.031	0.081	0.030	0.032	0.094	0.102
ΔR^2	0.023	0.074	0.002	0.005	0.008	0.016
Observations	7,897	7,897	10,383	10,383	10,339	10,339
STR						
EA PGS			0.017***		0.080***	
			(0.001)		(0.002)	
Education				0.028***		0.120***
				(0.001)		(0.002)
R^2			0.019	0.027	0.063	0.088
ΔR^2			0.007	0.015	0.034	0.059
Observations			39,234	39,234	39,532	39,532

Notes: Self-reported voting, the polygenic score and education (years of schooling) are standardized (mean=0, s.d.=1) within each sample. First-order (presidential in the US and National in Sweden) and second-order (midterm in the US and EP in Sweden) election turnout are measured as average turnout across all the elections for which we have information for the individuals. All models include controls for gender, birth year and sample fixed effects, and the first ten principal components of the genetic-relatedness matrix. Standard errors, shown in parentheses, allow for clustering at the family level. ***/**/*, indicates significance at the .1/1/5% level.

As expected, educational attainment is strongly associated with voter turnout (21–24, 40). Moreover, similar to the results for the relationship between the EA PGS and turnout, the estimates suggest that the influence of schooling is stronger in lower turnout second-order elections. More importantly for our purpose is the fact that the effect of the EA PGS is sizeable also in comparison to the influence of years of schooling. The estimated impact of a one standard deviation increase in the EA PGS amounts to about two-thirds of the corresponding effect of educational attainment.

B. Heterogeneity across Election Type and Birth Cohort. In the main text we use ordinary least squares (OLS) to estimate the effect of the polygenic score on voter turnout. However, given that two of our outcome variables - validated turnout in first- and second-order elections - are measured as fractions bounded between 0 and 1 the OLS estimates may lead to problems analogous to the drawbacks of the linear model for binary data: the predicted values from the linear probability model can fall outside the 0-1 range; the effects of any explanatory variable should be expected to be non-linear and non-additive; and the variance should be expected to decrease when the mean of the outcome approaches 0 or 1.

To account for this Table A4 report results from both linear probability models (LPM) estimated using OLS and generalized linear models (GLM) with a logit link and assuming a binomial distribution of the response variable (41). Average marginal effects based on the GLM estimates, which are directly comparable to the coefficient estimates from the OLS models displayed in the odd columns, are presented within brackets.

Two things should be noted with these results. First, the average marginal effects are very similar to the corresponding OLS estimates. Second, the relative difference in effect size between first- and second-order elections is more pronounced for the OLS estimates compared to the GLM estimates. This should be expected since the GLM estimator is dependent on the mean value of the outcome while the OLS estimator is not. In our case the average turnout in first-order elections is closer to unity in all samples. However, with the exception for the MTFS parents the pattern of larger EA PGS effects in second-order elections is discernible irrespective of modeling choice. Moreover, the effect size differences across first- and second order elections are statistically significant ($p < 0.05$) in both the OLS models and the GLM.[**]

In the main text we note that the EA PGS as well as other predictors of voter turnout seem to be more weakly related to and account for less of the variation in validated voter turnout, especially in second order elections, in the older MTFS parent and WLS samples compared to the younger MTFS twin and STR samples (see Table 1 and Figure 1). In this Appendix

[**] We test the difference in effect size across the two outcome variables using seemingly unrelated regression models.

Table A4. EA PGS and Voting - Fractional Logit Models

	First-order voting		Second-order voting	
	LPM	GLM	LPM	GLM
Pooled US results				
EA PGS	0.012***	0.139***	0.033***	0.207***
	(0.002)	(0.024)	(0.003)	(0.019)
		[0.013***]		[0.033***]
Average turnout	0.894	0.894	0.779	0.779
Observations	13,503	13,503	13,529	13,529
MTFS twins				
EA PGS	0.011*	0.098*	0.050***	0.213***
	(0.005)	(0.047)	(0.008)	(0.032)
		[0.010*]		[0.050***]
Average turnout	0.878	0.878	0.571	0.571
Observations	3,013	3,013	3,035	3,035
MTFS parents				
EA PGS	0.011***	0.272***	0.029***	0.267***
	(0.002)	(0.050)	(0.004)	(0.033)
		[0.011***]		[0.028***]
Average turnout	0.959	0.959	0.875	0.875
Observations	3,448	3,448	3,452	3,452
WLS				
EA PGS	0.014***	0.124***	0.027***	0.186***
	(0.004)	(0.032)	(0.004)	(0.029)
		[0.014***]		[0.027***]
Average turnout	0.869	0.869	0.821	0.821
Observations	7,042	7,042	7,042	7,042
STR				
EA PGS	0.017***	0.284***	0.080***	0.354***
	(0.001)	(0.018)	(0.002)	(0.011)
		[0.018***]		[0.080***]
Average turnout	0.933	0.933	0.625	0.625
Observations	39,333	39,333	39,633	39,633

Notes: The EA PGS is standardized (mean=0, s.d.=1) within each sample. First-order (presidential in the US and National in Sweden) and second-order (midterm in the US and EP in Sweden) election turnout are measured as average turnout across all the elections for which we have information for the individuals. All models include controls for gender, birth year, and the first ten principal components of the genetic-relatedness matrix. Standard errors, shown in parentheses, allow for clustering at the family level. Marginal effects are shown in brackets. ***/**/*, indicates significance at the .1/1/5% level.

we make use of the wide and approximately uniform birth year distribution in the STR sample to test if the educational attainment and the EA PGS exert a stronger influence on the turnout of younger citizens compared to older ones.

Table A5 displays results from models including an interaction term between the EA PGS and birth year (columns 1 and 3) and between own EA and birth year (columns 2 and 4). The birth year variable is mean adjusted implying that the main effect in each model can be interpreted as the effect of the EA PGS/own EA at for a person of average age. Furthermore, the interaction coefficients (and standard errors) are mutliplied by a factor 10. That is, the interaction coefficients show the increase in EA PGS/own EA effect on voter turnout from decreasing age (increasing birth year) by 10 years.

It is evident that the effect of the EA PGS and own EA on voting in both first- and second order elections is significantly stronger among younger individuals in the STR sample. In order to account for potential ceiling effects due to the fact that older individuals on average vote more often than younger ones we re-estimated the interaction models using the GLM estimator discussed above. The results from these models are presented in the lower panel of Table A5. The pattern of results obtained from the GLM models are very similar to the corresponding OLS results.

Finally, in Figure A2 we display results from rolling regressions to illustrate how the association between the EA PGS/own EA and voter turnout changes across birth year. For each birth-year estimate we include the target birth year and the ten preceding and succeeding birth cohorts in the sample. The estimates show that both the effect and predictive power (incremental R^2) of the EA PGS/own EA on the two measures of validated turnout increase approximately linearly with birth year.

Table A5. Heterogeneity Across Birth Year

	First-order voting		Second-order voting	
OLS				
EA PGS	0.018***		0.080***	
	(0.001)		(0.002)	
EA PGS× Birth Year	0.003***		0.008***	
	(0.001)		(0.001)	
EA		0.038***		0.140***
		(0.002)		(0.003)
EA× Birth Year		0.010***		0.020***
		(0.001)		(0.001)
Observations	39,333	39,236	39,633	39,532
GLM				
EA PGS	0.279***		0.356***	
	(0.017)		(0.011)	
EA PGS× Birth Year	0.025***		0.030***	
	(0.008)		(0.005)	
EA		0.608***		0.627***
		(0.024)		(0.013)
EA× Birth Year		0.126***		0.080***
		(0.010)		(0.006)
Observations	39,333	39,236	39,633	39,532

Notes: The polygenic score and years of education are standardized (mean=0, s.d.=1). First-order (National) and second-order (EP) election turnout are measured as average turnout across all the elections for which we have information for the individuals. The birth-year variable used in the interaction term is mean adjusted and the interaction estimate (and standard error) is multiplies by 10. All models include controls for gender, birth year and sample fixed effects, and the first ten principal components of the genetic-relatedness matrix. Standard errors, shown in parentheses, allow for clustering at the family level. ***/**/*, indicates significance at the .1/1/5% level.

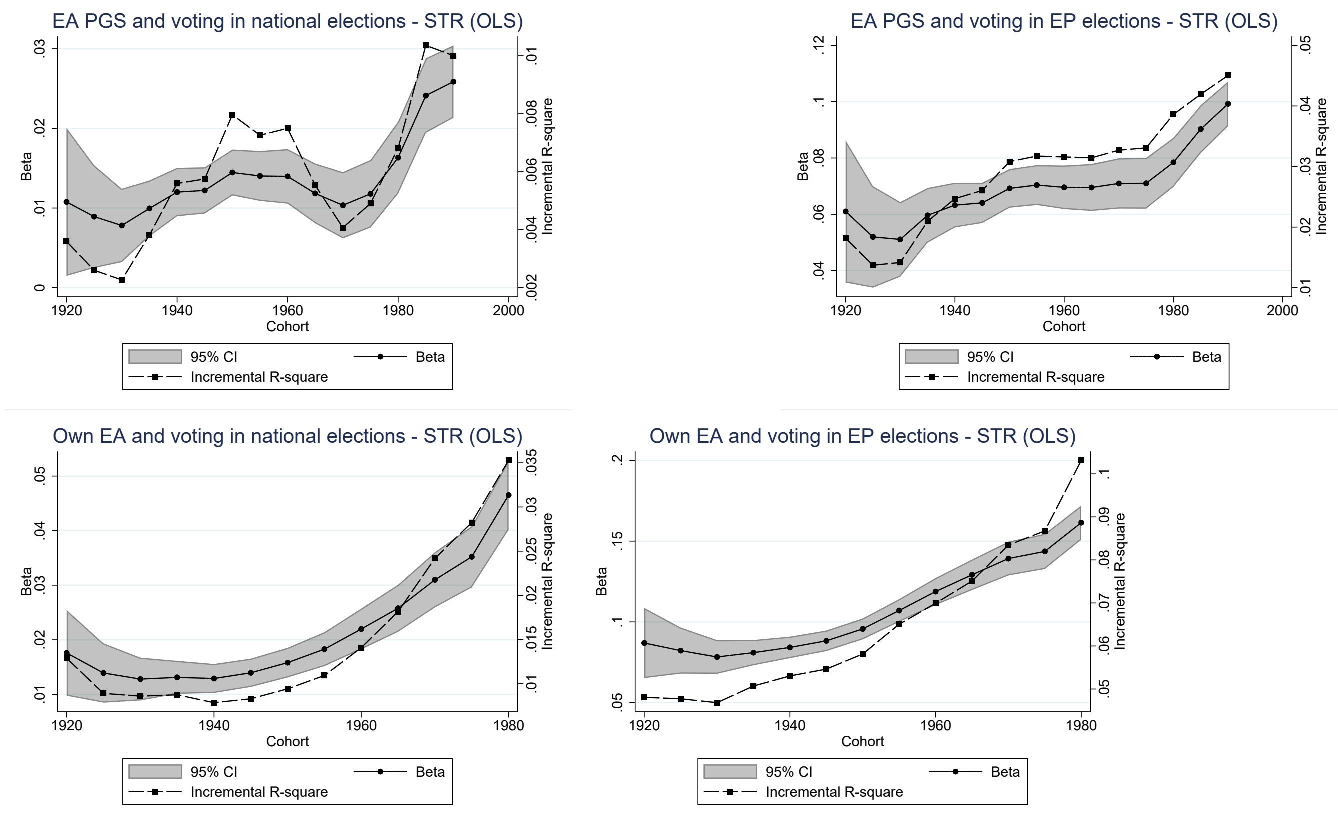
C. Representativeness. Table A6 presents the incremental R^2 for educational attainment in the Cooperative Congressional Election Study (CCES) and in the Swedish population. The CCES is a 50,000+ person national stratified sample survey administered by YouGov before and after each presidential and midterm election. For midterm and presidential elections, YouGov matches survey respondents to public voter files to determine whether a person has voted or not. Thus, we can use the CCES as a benchmark for the amount of variation in validated turnout accounted for by educational attainment.

The analysis is based on the CCES Common Content file including elections between 2006 and 2019 (n = 470,755). We analyze midterm and presidential elections separately. To measure educational attainment, CESS asks respondents for the highest level of education they have completed with response options “Did not graduate from high school", “High School Graduate", “Some college, but no degree", “2-year college degree", "4-year college degree", “Postgraduate degree (MA, MBA, MD, JD, PhD, etc.)". To be consistent with our analysis, we assigned years of education to each CESS respondent based to based on Table A2. More specifically, we assigned 10 years of education for those attending high school but not graduating, 13 years for graduating high school, 15 years for attending some college but not receiving a degree, 19 years for receiving a 2 or 4 year college degree, and 20 years for receiving a postgraduate degree. In addition to calculating the incremental R^2 for the entire sample, we also calculate it for sub-samples approximating the age ranges of the MTFS twin, MTFS parent, and WLS samples.

The lower panel present results from models based on individual-level register information for the Swedish population in birth cohorts born between 1913 and 2001 in order to mirror the age distribution in the STR sample. We use turnout information from the same elections as used for the STR sample. That is, voting in first-order elections is measured using turnout information in the 1970, 1994, 2010, and 2018 national parliament elections. For voting in second-order elections we use turnout from the 2009 and 2019 European parliament (EP) elections. The Swedish individual-level turnout data have been made available through digitization of the publicly available election rolls. The turnout data cover more than 90% of the electorate for the elections in questions, and previous research has shown that the digitization procedure being used provides highly reliable results (36).

The amount of variation in validated turnout accounted for by years of education in both the CCES and the Swedish population is similar to what we find based on the MTFS, WLS, and STR samples. Education matters more in second-order than first-order elections and its effect is weakest among older citizens, especially in first-order/presidential elections.

Fig. A2. Effects of EA PGS and Own EA Conditional on Birth Year



Note: Results from ten-year rolling regressions of i) turnout in national elections and the EA PGS (upper left panel); ii) turnout in EP elections and the EA PGS (upper right panel); iii) turnout in national elections and own EA (lower left panel); iv) and turnout in EP elections and own EA (lower right panel). The shaded areas display the 95% confidence intervals for the EA PGS/own EA effects. The dashed lines show the incremental R^2 from the rolling regressions.

Table A6. Representativeness

	First-order voting	Second-order First-voting
CCES		
Overall	0.010	0.021
	(206,267)	(151,890)
Birth years 1972 - 1994	0.010	0.032
	(47,564)	(58,006)
Birth years 1945 - 1965	0.013	0.020
	(67,354)	(93,330)
Birth years 1925 - 1945	0.004	0.014
	(22,544)	(32,870)
Swedish population data		
Overall	0.032	0.085
	(9,657,838)	(8,329,944)

Notes: Incremental R^2 is the difference in the coefficient of determination between a baseline model including fixed effects for birth year and a sex dummy and a model also including years of education. The sample sizes are in parentheses.

D. Genetic Nurture. In the main text we show that the estimated effect of the EA PGS on self-reported and second-order voting decreases in magnitude when controlling for family fixed effects. We argue that this pattern of results suggests confounding due to genetic nurture rather than population stratification or assortative mating. In this section we present further results corroborating this interpretation.

(6) demonstrate that an educational attainment polygenic score based on non-transmitted parental genes is significantly related to offspring education and that nearly 30% of the association between the polygenic score and education among offspring is accounted for by genetic nurture effects. These results were subsequently replicated by (7). Corroborating these findings, (8), (9), and (10) report that a parental education PGS is related to offspring education also when controlling for offspring's own PGS. Finally, (11) compare within- to between-family PGS predictions of education and cognitive traits and find that the between-family estimates are substantially greater. Much of this within- and between-family difference disappears when controlling for family socio-economic status, suggesting that a large share of the between-family PGS prediction is due to genetic nurture effects.

In Tables A7 and A8 we follow the approach used by (11) and present results from between-family models with and without control for parental education (measured as highest years of education among the two parents) and from within-family models. The logic here is to examine to what degree a plausible mediator in a genetic nurture scenario – parental education – accounts for the decrease in effect size when comparing the between-family estimates in column 1 (and 4 in Table A8) with the corresponding within-family estimates in column 3 (and 6 in Table A8).

For self-reported voting, the effect of the EA PGS decreases by approximately a third when controlling for parental education and parental education is positively and significantly related to voting in this model. Moreover, the estimate from the fixed effects model is similar to the parental-education adjusted OLS estimate in column 2. This suggests that the family environment as proxied by parental education, and not population stratification or assortative mating, is the main explanation for the decrease in coefficient estimate between the baseline OLS specification in column 1 and the fixed-effect specification in column 3. Turning to the validated turnout outcomes in Table A8, we can see that controlling for parental education only marginally affects the association between the EA PGS and first-order voting and that the fixed-effect estimates are similar to the corresponding OLS coefficients. The results for second-order voting are less clear-cut for the two smaller US sub-samples. However, for the pooled US sample and the much larger STR sample the pattern of estimates follows the one found for self-reported voting. The effect of the EA PGS shrinks in size and approaches the corresponding estimate from the within-family models in column 6 when controlling for parental education and parental education is strongly and significantly related to voting in second-order elections.

Table A7. EA PGS and Self-reported Voting - Controlling for Parental Education

	OLS	OLS	FE
Pooled US results			
EA PGS	0.172***	0.134***	0.113*
	(0.029)	(0.029)	(0.050)
Parental EA		0.174***	
		(0.033)	
Observations	1,426	1,426	1,426
Add Health			
EA PGS	0.152***	0.103*	0.075
	(0.042)	(0.041)	(0.070)
Parental EA		0.228***	
		(0.051)	
Observations	722	722	722
MTFS twins			
EA PGS	0.202***	0.163***	0.174*
	(0.042)	(0.043)	(0.073)
Parental EA		0.157***	
		(0.043)	
Observations	704	704	704

Notes: Self-reported voting, the EA PGS and parental education are standardized (mean=0, s.d.=1) within each sample. All models include controls for gender, birth year, and the first ten principal components of the genetic-relatedness matrix. Standard errors, shown in parentheses, allow for clustering at the family level. ***/**/*, indicates significance at the .1/1/5% level.

Table A9 displays results restricted to the MTFS twin sample. This enable us to more directly test for genetic nurture effects by entering both own and parental EA PGS in the regression models. To validate this approach the first panel presents estimates from a model using years of schooling as outcome. Corroborating previous studies (6–10) we can see that parental EA PGS is significantly associated with years of schooling also when controlling for own EA PGS. The results for the turnout

Table A8. EA PGS and Validated Voting - Controlling for Parental Education

	First-order voting			Second-order voting		
	OLS	OLS	FE	OLS	OLS	FE
Pooled US results						
EA PGS	0.016***	0.017***	0.021*	0.026***	0.017**	0.015
	(0.004)	(0.004)	(0.009)	(0.006)	(0.006)	(0.011)
Parental EA		-0.002			0.017**	
		(0.005)			(0.006)	
Observations	3,588	3,588	3,588	3,594	3,594	3,594
MTFS twins						
EA PGS	0.024**	0.024*	0.015	0.028*	0.020	-0.041
	(0.009)	(0.009)	(0.017)	(0.014)	(0.014)	(0.024)
Parental EA		0.002			0.040**	
		(0.009)			(0.015)	
Observations	704	704	704	768	768	768
WLS						
EA PGS	0.014**	0.015**	0.020	0.027***	0.026***	0.028*
	(0.005)	(0.005)	(0.011)	(0.006)	(0.006)	(0.012)
Parental EA		-0.003			0.012	
		(0.005)			(0.006)	
Observations	2,826	2,826	2,826	2,826	2,826	2,826
STR						
EA PGS	0.017***	0.012***	0.015***	0.074***	0.053***	0.034***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.006)
Parental EA		0.018***			0.084***	
		(0.002)			(0.004)	
Observations	16,380	16,380	16,380	16,515	16,515	16,515

Notes: The EA PGS and parental education are standardized (mean=0, s.d.=1) within each sample. First-order (presidential in the US and National in Sweden) and second-order (midterm in the US and EP in Sweden) election turnout are measured as average turnout across all the elections for which we have information for the individuals. All models include controls for gender, birth year, and the first ten principal components of the genetic-relatedness matrix. Standard errors, shown in parentheses, allow for clustering at the family level. ***/**/*, indicates significance at the .1/1/5% level.

outcomes are weaker, especially when using presidential voting as the outcome. Nevertheless, although insignificant, the estimated effects of parental EA PGS on self-reported are non-negligible in magnitude. Interestingly, the effects of both maternal and paternal EA PGS on midterm voting are statistically significant. Moreover, in line with a genetic nurture scenario the effect of own EA PGS decreases substantially when controlling for parental EA PGS.

In Tables A10 and A11 we report results from models restricted to sibling pairs and including both subjects' (ego) and siblings' (alter) EA PGS as predictors. The significant estimates for alter EA PGS in MTFS, Add Health and STR suggest the presence of genetic nurturing in educational attainment among siblings (42). With the exception for second-order voting in the STR sample the results displayed in Table A11 are less precise. Still, the estimated effects of alter EA PGS on self-reported and second-order voting in the pooled US sample are non-negligible in magnitude and indicate some degree of genetic nurturing. However, this fact does not mean that there is genetic nurture among siblings in all outcomes. For example, based on the Add Health sample (43) fail to detect any evidence of genetic nurture in body mass index (BMI) or waist circumference. Likewise, the results displayed in Table A11 show that sibling EA PGS is unrelated to first-order voter turnout in both the US and Swedish samples when controlling for ego EA PGS.

E. Confounding. Table A12 presents regression results testing whether the EA PGS confounds the relationship between education and voter turnout. More formally, we estimate the effect of education before and after controlling for EA PGS (the potential confounder). The estimated effect of education shrinks by between 10% and 20%.

F. Mediation. Tables A13 and A14 present the regression results used to construct Figure 2 in the main text. It should be pointed out that this simple mediation analysis framework rests on the assumption that we control for all the variables that are correlated with the mediators and turnout. Given the untenable nature of this assumption, the conditional coefficients should not be given a causal interpretation (44, 45).

Nevertheless, in line with previous research we note that both years of schooling and cognitive ability significantly predicts voter turnout (21–24, 27, 29, 40). Moreover, the direct effect of the EA PGS decreases by almost 50% or more when controlling for these potential mediators. This suggests that the genetic propensity to acquire education exerts an indirect effect on voting via educational attainment as well as cognitive ability.

Table A9. Parental and Own EA PGS in MTFS

Years of education		
Own EA PGS	0.747***	0.427***
	(0.078)	(0.106)
Maternal EA PGS		0.327***
		(0.084)
Paternal EA PGS		0.266**
		(0.090)
Observations	1,781	1,781
Self-reported voting		
Own EA PGS	0.170***	0.124***
	(0.027)	(0.035)
Maternal EA PGS		0.044
		(0.029)
Paternal EA PGS		0.043
		(0.031)
Observations	1,921	1,921
Presidential voting		
Own EA PGS	0.006	0.005
	(0.006)	(0.008)
Maternal EA PGS		-0.007
		(0.006)
Paternal EA PGS		0.008
		(0.007)
Observations	2,251	2,251
Midterm voting		
Own EA PGS	0.039***	0.010
	(0.009)	(0.012)
Maternal EA PGS		0.030**
		(0.010)
Paternal EA PGS		0.026*
		(0.010)
Observations	2,268	2,268

Notes: Self-reported voting and the polygenic scores are standardized (mean=0, s.d.=1) within each sample. Presidential and midterm election turnout are measured as average turnout across all the elections for which we have information for the individuals. All models include controls for gender and, birth year fixed effects, and the first ten principal components of the genetic-relatedness matrix. Standard errors, shown in parentheses, allow for clustering at the family level. ***/**/*, indicates significance at the .1/1/5% level.

However, it is also evident that there are EA PGS mechanisms influencing voter turnout that are unrelated to education and cognitive ability as there are still significant and sizeable effects of the polygenic score on the three outcomes.[††]

Finally, in Tables A15 through A19 we extend the analyses presented in Table A13 by controlling for different measures of personality traits available in our four samples. Both Add Health and WLS include measures on the five factor model of personality traits Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (46, 47). Extraversion is associated with being sociable, active, and assertive; Agreeableness with being altruistic, cooperative, and trusting; Conscientiousness with following norms and being organized; Openness with having broad interests and being imaginative; Neuroticism with being anxious and nervous. Previous studies have shown that the big five personality traits are related to both voting (48, 49) and the EA PGS (39). In Add Health the big five traits are measured using a condensed personality battery called the Mini-IPIP (50) elicited between age 25 and 34. In WLS we use a 29-item version (51) of the big five personality battery administered in 1993.

In the MTFS, subjects completed the 262 question Multidimensional Personality Questionnaire (MPQ) (52). The MPQ is comprised of three higher factors – Positive Emotionality, Negative Emotionality, and Constraint. Positive Emotionality reflects the tendency to be actively and pleasurably engaged with one's social and work environments; Negative Emotionality is characterized by perceptions of the world as threatening, problematic and distressing; and Constraint is primarily marked by self-restrictive caution, safety-consciousness and conventionality (52). The three higher factors of the MPQ are strongly related to personality traits as measured by the five factor model of personality (46, 47). Positive Emotionality is related to Extraversion, Negative Emotionality is similar to Neuroticism, and Constraint is related to Conscientiousness. The the three

[††] We assume here that the remaining effects of the polygenic score on the propensity to vote cannot be entirely accounted for by measurement errors in any or all of the variables used in the model or incorrect functional form specification.

Table A10. Ego and Alter EA PGS and Years of Schooling

MTFS		
Ego PGS	0.344***	0.276***
	(0.038)	(0.037)
Alter PGS	-	0.129***
	-	(0.039)
Observations	749	749
Add Health		
Ego PGS	0.392***	0.297***
	(0.038)	(0.036)
Alter PGS	-	0.194***
	-	(0.028)
Observations	714	714
WLS		
Ego PGS	0.253***	0.246***
	(0.019)	(0.019)
Alter PGS	-	0.014
	-	(0.020)
Observations	3,019	3,019
STR		
Ego PGS	0.211***	0.176***
	(0.008)	(0.007)
Alter PGS	-	0.063***
	-	(0.007)
Observations	17,585	17,585

Notes: Years of education and the polygenic scores and are standardized (mean=0, s.d.=1) within each sample. All models include controls for gender, birth year and sample fixed effects, and the first ten principal components of the genetic-relatedness matrix. Standard errors, shown in parentheses, allow for clustering at the family level. ***/**/*, indicates significance at the .1/1/5% level.

Table A11. Ego and Alter EA PGS and Voting

	Self-reported voting		First-order voting		Second-order voting	
Pooled US results						
Ego PGS	0.167***	0.148***	0.017***	0.019***	0.032***	0.026***
	(0.029)	(0.030)	(0.004)	(0.005)	(0.005)	(0.006)
Alter PGS		0.036		-0.004		0.011
		(0.029)		(0.005)		(0.006)
Observations	1,447	1,447	4,169	4,169	4,180	4,180
STR						
Ego PGS			0.017***	0.016***	0.074***	0.060***
			(0.002)	(0.002)	(0.004)	(0.004)
Alter PGS				0.001		0.025***
				(0.002)		(0.004)
Observations			16,185	16,185	16,318	16,318

Notes: Self-reported voting and the polygenic scores are standardized (mean=0, s.d.=1) within each sample. First-order (presidential in the US and National in Sweden) and second-order (midterm in the US and EP in Sweden) election turnout are measured as average turnout across all the elections for which we have information for the individuals. All models include controls for gender, birth year and sample fixed effects, and the first ten principal components of the genetic-relatedness matrix. Standard errors, shown in parentheses, allow for clustering at the family level. ***/**/*, indicates significance at the .1/1/5% level.

MPQ higher factors were all elicited at approximately 17 years old.

A subset of the STR individuals completed two survey batteries designed to measure personal control and extraversion. Personal control is measured using the Locus of Control Scale (LOC) battery (53). The LOC classifies individuals along a single dimension capturing the degree to which they feel like they control the outcome of events. Individuals with an internal locus of control feel they control their own destiny and believe outcomes they realize are the product of their own effort and skills. Those with an external locus of control believe that outcomes are outside of their control. A low score on the scale

Table A12. EA PGS and Voting - Confounding

	Self-reported voting		First-oder voting		Second-order voting	
Add Health						
EA	0.271***	0.247***				
	(0.012)	(0.013)				
EA PGS		0.063***				
		(0.014)				
Observations	5,633	5,633				
MTFS twins						
EA	0.331***	0.301***	0.019**	0.016**	0.094***	0.080***
	(0.028)	(0.029)	(0.006)	(0.006)	(0.010)	(0.010)
EA PGS		0.099***		0.008		0.050***
		(0.024)		(0.006)		(0.010)
Observations	2,264	2,264	1,894	1,894	1,902	1,902
MTFS parents						
EA			0.012***	0.010***	0.039***	0.033***
			(0.002)	(0.002)	(0.004)	(0.004)
EA PGS				0.008***		0.020***
				(0.003)		(0.004)
Observations			2,599	2,599	2,603	2,603
WLS						
EA			0.017***	0.015***	0.036***	0.033***
			(0.004)	(0.004)	(0.004)	(0.004)
EA PGS				0.008*		0.015***
				(0.004)		(0.004)
Observations			6,693	6,693	6,693	6,693
STR						
EA			0.021***	0.019***	0.107***	0.094***
			(0.001)	(0.001)	(0.002)	(0.002)
EA PGS				0.009***		0.045***
				(0.001)		(0.002)
Observations			28,671	28,671	28,329	28,329

Notes: Self-reported voting and the polygenic score are standardized (mean=0, s.d.=1) within each sample. First-order (presidential in the US and National in Sweden) and second-order (midterm in the US and EP in Sweden) election turnout are measured as average turnout across all the elections for which we have information for the individuals. All models include controls for gender and birth year fixed effects, and the first ten principal components of the genetic-relatedness matrix. Standard errors, shown in parentheses, allow for clustering at the family level. ***/**/*, indicates significance at the .1/1/5% level.

is associated with an internal locus of control and a high score with an external locus of control. External control is also strongly related to neuroticism and internal control with self-efficacy (54). We reverse-coded the LOC so that higher scores are associated with higher internal locus of control. To measure extraversion, the survey included the 16-item Adult Measure of Behavioral Inhibition (AMBI) battery (55). The AMBI is a subjective measure of general long-standing inhibition designed to capture how an individual responds to social novelty and risk stimuli (55). Higher scores on the AMBI reflect a proneness for social avoidance and introversion. We reverse-coded the AMBI so that higher scores are associated with extraversion.[‡‡]

With the exception for the WLS sample, in which all effects of the personality traits are insignificant, the results generally support previous studies on the relationship between the Big Five traits and political participation. Openness, Extraversion (Positive emotionality) and Conscientiousness (Constraint) are in general positively related to voter turnout whereas the effect of Neuroticism (Negative emotionality) is negative. More importantly, though, is the fact that the personality factors do not seem to account for any significant share of the overall effect of the EA PGS on voting. Controlling for the personality traits only marginally influence the estimated effects of the EA PGS.

[‡‡] The correlation between AMBI and the Extraversion-Introversion scale from the Eysenck Personality Questionnaire-Revised (EPQ-R; (56)) is 0.75 (55).

Table A13. EA PGS and Voting - Mediation Analysis

	Self-reported voting		Presidential voting		Midterm voting	
Add Health						
EA PGS	0.154***	0.057***				
	(0.015)	(0.016)				
EA		0.212***				
		(0.016)				
Cognitive Ability		0.108***				
		(0.024)				
Observations	4,665	4,665				
MTFS twins						
EA PGS	0.170***	0.063*	0.017**	0.006	0.065***	0.032**
	(0.025)	(0.026)	(0.006)	(0.006)	(0.010)	(0.010)
EA		0.241***		0.013*		0.062***
		(0.031)		(0.012)		(0.013)
Cognitive Ability		0.119***		0.009		0.049***
		(0.027)		(0.006)		(0.011)
Observations	2,106	2,106	1,771	1,771	1,778	1,778
MTFS parents						
EA PGS			0.011***	0.006*	0.028***	0.014***
			(0.003)	(0.003)	(0.004)	(0.004)
EA				0.005		0.022***
				(0.003)		(0.005)
Cognitive Ability				0.010***		0.024***
				(0.003)		(0.005)
Observations			2,569	2,569	2,573	2,573
WLS						
EA PGS			0.012***	0.007	0.023***	0.012**
			(0.004)	(0.004)	(0.004)	(0.004)
EA				0.014***		0.026***
				(0.004)		(0.005)
Cognitive Ability				0.006		0.021***
				(0.004)		(0.005)
Observations			6,361	6,361	6,361	6,361

Notes: Self-reported voting and the polygenic score are standardized (mean=0, s.d.=1) within each sample. Presidential and midterm election turnout are measured as average turnout across all the elections for which we have information for the individuals. All models include controls for gender and birth year fixed effects, and the first ten principal components of the genetic-relatedness matrix. Standard errors, shown in parentheses, allow for clustering at the family level. ***/**/*, indicates significance at the .1/1/5% level.

Table A14. EA PGS and Voting - Mediation Analysis - STR

	National voting		EP voting	
STR				
EA PGS	0.012***	0.005***	0.064***	0.031***
	(0.002)	(0.002)	(0.004)	(0.004)
EA		0.014***		0.073***
		(0.002)		(0.004)
Cognitive Ability		0.010***		0.053***
		(0.002)		(0.004)
Observations	10,972	10,972	10,912	10,912

Notes: The EA PGS is standardized (mean=0, s.d.=1). National and EP election turnout are measured as average turnout across all the elections for which we have information for the individuals (1970, 1994, 2010, and 2018 for the national elections; 2009 and 2019 for the EP elections). All models include controls for gender, birth year, and the first ten principal components of the genetic-relatedness matrix. Standard errors, shown in parentheses, allow for clustering at the family level. ***/**/*, indicates significance at the .1/1/5% level.

Table A15. EA PGS and Voting - Controlling for Personality in Add Health

	Self-reported voting	Self-reported voting	Self-reported voting
EA PGS	0.156***	0.060***	0.058***
	(0.015)	(0.016)	(0.016)
EA		0.207***	0.181***
		(0.016)	(0.017)
Cognitive ability		0.107***	0.085***
		(0.024)	(0.024)
Openness			0.052***
			(0.016)
Conscientiousness			0.010
			(0.014)
Extraversion			0.081***
			(0.015)
Agreeableness			0.032
			(0.017)
Neuroticism			-0.057***
			(0.015)
R^2	0.032	0.082	0.101
ΔR^2	0.024	0.003	0.003
Observations	4,597	597	597

Notes: Self-reported voting, the polygenic score, years of education, cognitive ability, and all personality variables are standardized (mean=0, s.d.=1). All models include controls for gender, parental education, and birth year and sample fixed effects, and the first ten principal components of the genetic-relatedness matrix. Standard errors, shown in parentheses, allow for clustering at the family level. ***/**/*, indicates significance at the .1/1/5% level.

Table A16. EA PGS and Voting - Controlling for Personality in MTFS (twins)

	Self-reported voting	Self-reported voting	Self-reported voting	Presidential voting	Presidential voting	Presidential voting	Midterm voting	Midterm voting	Midterm voting
EA PGS	0.160***	0.057*	0.055*	0.013*	0.007	0.007	0.065***	0.034***	0.033**
	(0.026)	(0.027)	(0.027)	(0.006)	(0.006)	(0.006)	(0.010)	(0.011)	(0.011)
EA		0.240***	0.209***		0.015*	0.016*		0.060***	0.052***
		(0.033)	(0.033)		(0.012)	(0.007)		(0.012)	(0.012)
Cognitive ability		0.111***	0.107***		0.007	0.008		0.048***	0.050***
		(0.029)	(0.027)		(0.006)	(0.007)		(0.011)	(0.011)
Positive emotionality			0.119***			-0.017***			-0.003
			(0.023)			(0.005)			(0.009)
Negative emotionality			-0.062*			-0.010			-0.007
			(0.024)			(0.006)			(0.009)
Constraint			0.008			0.004			0.028**
			(0.024)			(0.006)			(0.010)
R^2	0.036	0.101	0.122	0.024	0.029	0.038	0.076	0.121	0.113
ΔR^2	0.024	0.003	0.002	0.004	0.001	0.001	0.031	0.007	0.003
Observations	1,953	1,953	1,953	1,637	1,637	1,637	1,642	1,642	1,642

Notes: Self-reported voting, the polygenic score, years of education, cognitive ability, and all personality variables are standardized (mean=0, s.d.=1). Presidential and midterm election turnout are measured as average turnout across all the elections for which we have information for the individuals. All models include controls for gender, parental education, and birth year and sample fixed effects, and the first ten principal components of the genetic-relatedness matrix. Standard errors, shown in parentheses, allow for clustering at the family level. ***/**/*, indicates significance at the .1/1/5% level.

Table A17. EA PGS and Voting - Controlling for Personality in MTFS (parents)

	Presidential voting	**Presidential voting**	**Presidential voting**	**Midterm voting**	**Midterm** voting	**Midterm voting**
EA PGS	0.010***	0.006*	0.006*	0.027***	0.014***	0.013**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
EA		0.004	0.003		0.019***	0.019***
		(0.003)	(0.003)		(0.005)	(0.005)
Cognitive ability		0.011***	0.011***		0.024***	0.026***
		(0.003)	(0.003)		(0.005)	(0.005)
Positive emotionality			0.000			0.004
			(0.002)			(0.004)
Negative emotionality			-0.007**			-0.010*
			(0.002)			(0.005)
Constraint			0.005			0.013**
			(0.003)			(0.005)
R^2	0.059	0.068	0.073	0.110	0.135	0.140
ΔR^2	0.007	0.002	0.005	0.009	0.004	0.003
Observations	2,380	2,380	2,380	2,384	2,384	2,384

Notes: Self-reported voting, the polygenic score, years of education, cognitive ability, and all personality variables are standardized (mean=0, s.d.=1). Presidential and midterm election turnout are measured as average turnout across all the elections for which we have information for the individuals. All models include controls for gender, parental education, and birth year and sample fixed effects, and the first ten principal components of the genetic-relatedness matrix. Standard errors, shown in parentheses, allow for clustering at the family level. ***/**/*, indicates significance at the .1/1/5% level.

Table A18. EA PGS and Voting - Controlling for Personality in WLS

	Presidential voting	**Presidential voting**	**Presidential voting**	**Midterm voting**	**Midterm** voting	**Midterm voting**
EA PGS	0.010*	0.005	0.005	0.020***	0.009	0.009
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
EA		0.013**	0.014***		0.023***	0.023***
		(0.004)	(0.004)		(0.005)	(0.005)
Cognitive ability		0.008	0.009		0.023***	0.023***
		(0.004)	(0.005)		(0.005)	(0.005)
Openness			-0.005			0.000
			(0.005)			(0.005)
Conscientiousness			-0.002			-0.005
			(0.004)			(0.005)
Extraversion			0.002			-0.001
			(0.004)			(0.005)
Agreeableness			-0.003			0.000
			(0.005)			(0.005)
Neuroticism			0.005			-0.002
			(0.004)			(0.005)
R^2	0.013	0.016	0.016	0.017	0.029	0.029
ΔR^2	0.001	0.000	0.000	0.004	0.001	0.001
Observations	5,615	5,615	5,615	5,615	5,615	5,615

Notes: The polygenic score, years of education, cognitive ability, and all personality variables are standardized (mean=0, s.d.=1). Presidential and midterm election turnout are measured as average turnout across all the elections for which we have information for the individuals. All models include controls for gender, parental education, and birth year and sample fixed effects, and the first ten principal components of the genetic-relatedness matrix. Standard errors, shown in parentheses, allow for clustering at the family level. ***/**/*, indicates significance at the .1/1/5% level.

Table A19. EA PGS and Voting - Controlling for Personality in STR

	National voting	**National voting**	**National voting**	**EP voting**	**EP** voting	**EP voting**
EA PGS	0.010***	0.004	0.004	0.060***	0.028***	0.026***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.007)	(0.007)
EA		0.009***	0.008**		0.064***	0.058***
		(0.003)	(0.003)		(0.007)	(0.007)
Cognitive ability		0.011**	0.010**		0.053***	0.049***
		(0.003)	(0.003)		(0.007)	(0.007)
AMBI			0.008**			0.028***
			(0.003)			(0.006)
LOC			0.005*			0.023***
			(0.003)			(0.006)
R^2	0.013	0.023	0.027	0.030	0.089	0.098
ΔR^2	0.003	0.001	0.000	0.023	0.005	0.004
Observations	4,108	4,108	4,108	4,105	4,105	4,105

Notes: The polygenic score, years of education, cognitive ability, and all personality variables are standardized (mean=0, s.d.=1). National and EP election turnout are measured as average turnout across all the elections for which we have information for the individuals (1970, 1994, 2010, and 2018 for the national elections; 2009 and 2019 for the EP elections). All models include controls for gender, birth year, and the first ten principal components of the genetic-relatedness matrix. Standard errors, shown in parentheses, allow for clustering at the family level. ***/**/*, indicates significance at the .1/1/5% level.

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