sociological science

Supplement to:

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Online Supplement 1. Construction of Dependent Variables

This supplement provides additional information on how we constructed the dependent variables capturing highbrow/lowbrow/popular cultural tastes and participation. In the survey, we asked respondents about their interest/frequency of participation in 12 cultural activities. Table A1 summarizes descriptive statistics for the 12 indicators.

Table A1. Descriptive Statistics for Indicators of Cultural Taste and Participation. Means and Standard Deviations

	Cultural Taste[a]			Cultural Participation[b]		
Cultural activity:	Mean	SD	*N*	Mean	SD	*N*
Cinema	3.904	1.061	1,199	2.610	0.877	1,196
Opera	1.786	1.069	1,194	1.078	0.315	1,198
Musical	2.883	1.359	1,199	1.331	0.529	1,196
Flea market/cattle show	2.780	1.283	1,198	1.603	0.710	1,187
Ballet	2.114	1.248	1,197	1.143	0.403	1,198
Play	2.831	1.269	1,198	1.329	0.582	1,192
Classical concert	2.126	1.237	1,194	1.145	0.412	1,193
Rock/pop concert	3.716	1.202	1,197	1.422	0.572	1,197
Stand-up comedy	3.630	1.291	1,195	1.774	0.837	1,188
Techno etc. concert	2.490	1.352	1,191	1.264	0.583	1,195
Art museum	2.681	1.277	1,196	1.655	0.786	1,189
Amusement park	3.782	1.155	1,197	1.748	0.738	1,189

Note: [a] 1-5 scale, [b] 1-4 scale. We treat "Don't know" answers as missing values.

We use polychoric correlations between the 12 indicators for each dimension (taste and participation) and Principal Component Analysis (PCA) to identify latent variables that capture underlying dimensions of cultural tastes and participation. As shown in Table A2 below, the PCA identifies three latent variables for cultural tastes and three latent variables for cultural participation capturing (1) highbrow, (2) lowbrow, and (3) popular culture. The highbrow dimension loads on expressing a stronger taste for/more often participating in highbrow culture, for example, opera and classical concerts, while the lowbrow dimension loads on, for example, amusement parks and flea markets. The popular dimension loads on expressing a taste for/participating in rock/pop concerts and stand-up comedy shows; i.e., mostly performing arts. Combined, the three latent variables explain 64 percent of the shared variance between the 12 indicators of cultural interests, while the three latent variables for cultural participation explain 52 percent of the shared variance between the indicators of cultural participation. In the empirical analyses, we use standardized predicted scores for each of the six latent variable as dependent variables.

Table A2. Results from PCAs of Cultural Taste and Participation. Rotated Factor Loadings

	Cultural Taste			Cultural Participation		
Cultural activity:	Highbrow	Lowbrow	Popular	Highbrow	Lowbrow	Popular
Cinema		0.561	0.418		0.532	
Opera	0.870			0.813		
Musical	0.651	0.558		0.486	0.501	
Flea market/cattle show		0.671			0.439	
Ballet	0.850			0.744		
Play	0.822			0.724		
Classical concert	0.784			0.745		
Rock/Pop			0.752		0.537	0.369
Stand-up comedy		0.554	0.648			0.830
Techno etc. concert			0.834			0.874
Art museum	0.740			0.647		
Amusement Park		0.798			0.671	
% Explained variance	0.358	0.179	0.105	0.286	0.102	0.136

Notes: Factor loadings < 0.35 not shown. Rotated factor loadings (Oblique Oblimin).

Online Supplement 2. Correlations between Dependent Variables

Table A3. Bivariate Correlations Between Indicators of Cultural Taste, Participation, and Omnivorousness in Music and Reading

	Taste			Participation			Omnivorousness	
	Highbrow	Lowbrow	Popular	Highbrow	Lowbrow	Popular	Music	Reading
Taste								
Highbrow	1							
Lowbrow	0.19***	1						
Popular	0.10***	0.11***	1					
Participation								
Highbrow	0.59***	-0.11***	-0.01	1				
Lowbrow	0.23***	0.43***	0.12***	0.22***	1			
Popular	0.21***	-0.07**	0.46***	0.19***	0.16***	1		
Omnivorousness								
Music	0.28***	-0.04	0.19***	0.17***	0.00	0.20***	1	
Reading	0.41***	0.12***	0.03	0.26***	0.12***	0.08*	0.20***	1

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Online Supplement 3. Assumptions in the ACE model

The ACE model relies on a set of assumptions to decompose the total variance in a dependent variable into components attributable to shared genes (A), shared environments (C), and individual experiences (E; Plomin et al. 2014). In this supplement, we describe these assumptions and their substantive implications.

The first assumption is that MZ and DZ twins have the same degree of similarity in their environments, so that excess similarity between MZ twins can be attributed to the greater proportion of shared genes. This is the *Equal Environment Assumption* (EEA). Violation of EEA, for example if MZ twins are treated more similarly than DZ twins, leads to overestimation of A in the ACE model. Moreover, we assume similar (if any) *intersibling effects* between MZ and DZ twin pairs, i.e., twins with different zygosity treat each other in similar ways. Violations of this assumption, for example if MZ twins have a greater influence on each other than DZ twins do, attenuate the DZ correlation and thus induces upward bias in A at the expense of C. Since the EEA is central in twin models, it has been rigosously tested and found to be credible across a wide range of outcomes (e.g., Conley et al. 2013; Felson 2014). Consequently, we have no reason to assume that it presents a problem in our analysis.

The second assumption is that *genetic effects are additive*; i.e., they “add up” rather than interact in creating variation in the dependent variable. Research shows that violations of this assumption do not lead to large biases in ACE estimates for complex traits such as education, occupation, and income (Mills, Barban and Tropf 2020).

The third assumption is that there are *no gene-environment interactions*; i.e., the effect of genetic factors do no depend on environmental factors. As we argue in the paper, there is now widespread agreement that this assumption does not hold. However, rather than fixing violations of this assumption by means of statistics (Purcell 2002), recent research actively explores gene-environment interactions and their substantive implications (e.g., Baier and Lang 2019; Erola et al. 2021). In the discussion section (“third takeaway from our analysis”), we discuss results from supplementary analyses in which we estimate the ACE models separately in high- and low-SEP families (using SEP as a proxy for heterogeneity in environmental factors). As we write, we find no evidence that genes matter more/less in low-SEP families compared to in high-SEP families. Obviously, results might be different in other contexts.

The fourth assumption is that there is *no genetic assortative mating with regard to the dependent variable*. No genetic assortative mating justifies the assumption that, on average, DZ twins are 50 percent genetically similar with regard to the dependent variable. Violation of this assumption means that DZ twins are more than 50 percent genetically similar, which results in the ACE model underestimating A and overestimating C. As we do not know the genetic correlation between parents’ cultural tastes and participation, we cannot address genetic assortative mating directly. However, in line with other research (Baier and Lang 2019) we can run sensitivity analyses in which we study changes in the estimated ACE components if we assume that DZ twins' genetic similarity is higher than 50 percent. We run sensitivity analyses with an assumed DZ similarity of 55 and 60 percent (and note that this sensitivity analysis is only relevant for dependent variables in which the C component is not zero). Table A3 summarizes results from analyses in which we find little evidence that (assumed) genetic assortative mating affects our substantive results.

Table A4. ACE Decompositions of Cultural Interests, Participation, and Omnivorousness, With Genetic Assortative Mating

Assumed DZ genetic similarity	0.50			0.55			0.60		
	A	C	E	A	C	E	A	C	E
Taste									
Highbrow	0.54	0.16	0.30	0.62	0.10	0.30	0.72	0	0.30
Lowbrow	0.30	0.33	0.37	0.33	0.29	0.37	0.38	0.25	0.37
Popular	0.29	0.23	0.48	0.52	0	0.43	0.35	0.15	0.46
Participation									
Highbrow	0.58	0.08	0.34	0.67	0	0.34	0.66	0	0.34
Lowbrow	0.63	0	0.37	0.64	0	0.39	0.62	0	0.40
Popular	0.54	0	0.46	0.52	0	0.45	0.51	0	0.47
Omnivorousness									
Music	0.46	0	0.54	0.45	0	0.53	0.44	0	0.54
Reading	0.43	0	0.57	0.41	0	0.57	0.40	0	0.58

Note: A = Shared genes, C = Shared environments, E = Individual experiences.

Online Supplement 4. Measurement Error

Measurement error induces bias in the ACE model. In this supplement, we discuss how measurement error might affect our results.

Random measurement error in the dependent variables leads to inflated estimates of E and, by implication, lower-bound estimates of A and C (Plomin et al. 2014). To reduce bias from random measurement error, we construct six out of eight dependent variables (those capturing highbrow/lowbrow/popular cultural tastes and participation) using multiple observed indicators and PCA. This approach (described in Online Supplement 1) reduces random measurement error by using several observed indicators to capture the same underlying construct. Consequently, we expect random measurement error not to matter too much in our ACE models for highbrow/lowbrow/popular cultural tastes and participation. However, our indices of omnivorousness in music and reading are more sensitive to bias from random measurement error because they are simple additive additive scales.

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