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Supplemental information

Stability of polygenic scores across

discovery genome-wide association studies

Laura M. Schultz, Alison K. Merikangas, Kosha Ruparel, Sébastien Jacquemont, David C. Glahn, Raquel E. Gur, Ran Barzilay, and Laura Almasy

Supplemental Methods

Pre-imputation quality control (QC) and imputation were done separately for each of the fifteen genotyping array batches that comprise the Philadelphia Neurodevelopmental Cohort (PNC) dataset. Due to the substantial variation in SNPs contained on the arrays and the numbers of samples genotyped on each array (Table S1), we imputed each array batch separately to the 1000 Genomes Mixed/Other reference panel rather than assigning ancestry prior to imputation. The fifteen batches were merged by chromosome after imputation, and post-imputation QC was run on the merged chromosome files.

Genetic ancestry was inferred by KING¹ from the principal components (PCs) derived using multi-dimensional scaling (MDS) of the hard-call dataset that was produced with PLINK 1.9 after concatenating the post-imputation-QC chromosome files. Each array batch included samples from more than one ancestry group (Table S2), thus validating our decision to not impute the array batches to specific ancestry panels.

After splitting the dataset into European-American (EUR) and African-American (AFR) cohorts, we ran a second round of unprojected MDS for each cohort separately. The first ten PCs were later regressed out of the standardized polygenic scores (PGS) to correct for both population structure and array batch effects. Batch effects, which were captured by PC2, were especially pronounced for the AFR samples that were genotyped on array_01 and array_07 (Figure S1). There were no obvious batch effects visible in the second-round PC plot for the EUR samples (Figure S2).

We further analyzed the PNC array batch effects by running a series of logistic-regression GWAS with a single array as a dummy "case" and the other arrays as dummy "controls" within the EUR and AFR subgroups. We only used arrays that had been used to genotype at least 100 samples as "cases." For the AFR subgroup, these arrays included array 01, array 03, array 04, array 05, array 06, and array 08; the arrays for the EUR subgroup that were run as "cases" were array 03, array 04, array 05, array 06, and array 09. The GWAS were run in PLINK 1.9 both including and not including the first 10 second-round ancestry PCs as covariates so that we could confirm that including the PCs would be an adequate control for array batch effects. *P*-values were generated using Fisher's exact test. We used the R package qqman² to produce Manhattan and Q-Q plots from the Bonferroni-adjusted *p*-values.

As expected, the most dramatic GWAS results were observed for AFR array 01 (Figure S3). The logistic association model without ancestry PC covariates had many "significant" SNPs, seen as many tall peaks on the Manhattan plot (Figure S3-A) and dramatic curvature on the Q-Q plot (Figure S3-B). When the first 10 PCs were included as covariates, no significant peaks remained in the Manhattan plot (Figure S3-C), and the Q-Q plot did not deviate substantially from the straight line (Figure S3-D). The GWAS results from the other arrays yielded similar Manhattan and Q-Q plots when 10 within-ancestry PCs were included as covariates. Taken together, these results indicated that regressing out the first 10 within-ancestry PCs from our polygenic scores (PGS) would adequately control for any array batch effects.

The ABCD dataset was genotyped exclusively on the Affymetrix NIDA SmokeScreen array. As such, QC and imputation were done on a single dataset. Table S3 shows the ABCD SNP and sample counts before and after the pre-imputation QC. Within-ancestry PCs were computed for the AFR (Figure S4) and EUR (Figure S5) subsets of the ABCD dataset.

PRS-CS 3 requires a single GWAS sample size as an input. Given that most of our discovery GWAS were meta-GWAS that were comprised of individual studies that varied in terms of their sample sizes and the SNPs they included, the effective sample size often varied considerably between SNPs. To account for this reality, we examined the distribution of SNP sample sizes in R and excluded SNPs that had sample sizes that were less than half of the maximum SNP sample size. Of the remaining SNPs, the median SNP sample size was used as the PRS-CS GWAS sample size input.

As an example, consider the Freeze 2 EUR PTSD GWAS produced by the Psychiatric Genomics Consortium (PGC).⁴ This meta-GWAS includes 9,766,174 SNPs with effective sample sizes that range from 17,559.4 to 70,237.5 (Figure S6-A). Given that PRS-CS uses only those SNPs that overlap with both the relevant LD panel and the dataset, we started by retaining only the 1,116,862 SNPs that were present in the EUR LD panel. These SNPs also had effective sample sizes ranging from 17,559.4 to 70,237.5 (Figure S6-B). After we removed SNPs with effective sample sizes that were less than 35,000, the remaining 1,113,044 SNPs had effective sample sizes that ranged from 38,250.5 to 70,237.5 (Figure S6-C), with a median of 70,237.5. This median value was truncated to 70,237 and used as the GWAS sample size when we ran PRS-CS. We made similar sample size determinations for the other discovery GWAS.

UK Biobank Experiment

To explore the impact of GWAS sample size on our PGS results, we ran an experiment using imputed genotype data for the UK Biobank that we obtained under data use application 40980. As illustrated in Figure S7, we identified 276,107 unrelated white British subjects who had both imputed genotype data and also a measured standing height phenotype (Data-Field 50), and we

then randomly assigned these samples into seven groups as shown. The non-overlapping Groups A and B were each used to produce a "medium-large" height GWAS (both *N* = 134,000). Groups C and D were sub-sampled from Groups A and B, respectively, and each used to produce a "medium" height GWAS (both *N* = 75,000). Groups E and F were sub-sampled from Groups C and D, respectively, and each used to produce a "small" height GWAS (both *N* = 10,000). Groups A and B were merged to form Group AB, which was used to produce a "large" height GWAS (*N* = 268,000). The remaining 8,107 subjects with height phenotypes comprised the test set for whom we computed PGS using all seven GWAS. All GWAS were computed using the PLINK 2 --linear function with sex, age at height measurement, and the first 20 ancestry PCs supplied by the UK Biobank as covariates. The subject characteristics for each GWAS group and the test set are summarized in Table S16, and the mean χ^2 computed by LDSC for each height GWAS is provided in Table S17. Table S18 provides the number of genome-wide significant SNPs ($P < 5 \times 10^{-8}$) for each of the seven discovery GWAS that were included among the 1,113,490 SNPs that were used for PRS-CS computations (i.e., the set of SNPs that were jointly present in the test data set, the discovery GWAS, and the PRS-CS EUR LD panel). We also used LDSC to compute the genetic correlation between each pair of height GWAS (Table S19).

We used PRS-CS to compute seven height PGS for each sample in the test set (i.e., a PGS was computed from each of the seven discovery GWAS) as described in the main Methods section of our paper. We standardized the PGS and then corrected for batch effects and stratification by regressing the first 20 UKBB-supplied ancestry PCs out of the standardized PGS. We then calculated the correlation between each pair of corrected height PGS (Table S20). We also used each set of standardized PGS to predict height in an additive linear regression model that included sex, age at height measurement, and the first 20 ancestry PCs as covariates. We calculated the coefficient of determination (R^2) for each model as a measure of how well the PGS predicted height, and we also ran a partial F-test for each model to assess the effect of adding the standardized PGS to a base model that included sex, age at height measurement, and the first 20 ancestry PCs as predictors of height (Table S21).

Supplemental Data

Figure S1. Within-ancestry PC2 vs. PC1 for the AFR subset of PNC with samples color coded by their genotyping array batch. PC2 captures an array batch effect that is most pronounced for array_01 and array_07.

Figure S2. Within-ancestry PC2 vs. PC1 for the EUR subset of PNC with samples color coded by their genotyping array batch.

Figure S3. Illustration of PNC batch effects for AFR array 01. The plots are limited to 9,809,388 biallelic SNPs. (A) The Manhattan plot showed many highly significant SNPs when the ancestry PCs were not included as covariates. (B) When PCs were not included as covariates, the Q-Q plot deviated substantially from the expected straight line. (C) When 10 PCs were included as covariates, no significant peaks remained in the Manhattan plot. (D) With 10 PCs included as covariates, the Q-Q plot of observed -log₁₀(p) versus expected -log₁₀(p) largely followed the expected straight line.

Figure S4. Within-ancestry PC2 vs. PC1 for the AFR subset of the ABCD dataset.

Figure S5. Within-ancestry PC2 vs. PC1 for the EUR subset of the ABCD dataset.

Figure S6. GWAS sample size determination for the PTSD Freeze 2 EUR meta-GWAS. (A) This meta-GWAS contained 9,766,174 SNPs with effective sample sizes that ranged from 17,559.4 to 70,237.5. (B) The 1,116,862 SNPs that were present in the PRS-CS EUR LD panel had this same range of effective sample sizes. (C) Filtering to retain only LD-selected SNPs with effective sample sizes of at least 35,000 resulted in 1,113,044 SNPs with effective sample sizes between 38,250.5 and 70,237.5. The median effective SNP sample size of 70,237.5 for these filtered SNPs was truncated to 70,237 and used as the GWAS sample size in PRS-CS.

Table S1. PNC sample and SNP counts by genotyping array before and after pre-imputation QC.

Array	AFR	EUR	Other	Total
array_01	693	8	18	719
array_02	63	$\overline{2}$	$\mathbf{1}$	66
array_03	1,341	2,157	291	3,789
array_04	177	341	34	552
array_05	623	1,137	133	1,893
array_06	112	1,354	188	1,654
array_07	29	Ω	3	32
array_08	101	102	15	218
array_09	9	7	$\mathbf{1}$	17
array_10	62	69	10	141
$array_11$	20	18	$\overline{2}$	40
$array_12$	19	8	$\overline{2}$	29
array_13	9	18	8	35
$array_14$	$\mathbf{1}$	16	$\mathbf{1}$	18
array_15	$\mathbf{1}$	$\overline{2}$	0	3
Total	3,260	5,239	707	9,206

Table S2. PNC ancestry by genotyping array.

Table S3. ABCD sample and SNP counts before and after pre-imputation QC.

Number of	Number of Number of		Number of
Samples	Samples	SNPs	SNPs
Pre-QC	Post-QC	Pre-QC	Post-QC
10,461	10,318	517,724	483,017

Table S4. PTSD PGS correlations for PNC EUR cohort when limited to one sample per family versus including all samples.

PNC, Philadelphia Neurodevelopmental Cohort; PTSD, post-traumatic stress disorder; PGS, polygenic score; EUR, European-American ancestry; GWAS, genome-wide association study; PGC; Psychiatric Genomics Consortium; *r*, Pearson correlation coefficient; *t*, linear association *t*-test statistic; *P*, two-tailed *P*-value on 4926 (or 5237) degrees of freedom.

Superscripts are the reference numbers for the discovery GWAS used to calculate PGS:

4 Nievergelt et al. (2019)**,** ⁵ Duncan et al. (2018).

PNC, Philadelphia Neurodevelopmental Cohort; PTSD, post-traumatic stress disorder; PGS, polygenic score; AFR, African-American ancestry; GWAS, genome-wide association study; PGC; Psychiatric Genomics Consortium; *r*, Pearson correlation coefficient; linear association *t*-test statistic, *P*, two-tailed *P*-value on 2952 (or 3258) degrees of freedom. Superscripts are the reference numbers for the discovery GWAS used to calculate PGS: 4 Nievergelt et al. (2019)**,** ⁵ Duncan et al. (2018).

PNC, Philadelphia Neurodevelopmental Cohort; PGS, polygenic score; AFR, African-American ancestry; GWAS, genome-wide association study; PTSD, post-traumatic stress disorder; T2D, type 2 diabetes; *r*, Pearson correlation coefficient; *t*, linear association *t*-test statistic; *P*, two-tailed *P*-value on 3258 degrees of freedom; NA, not applicable (analysis not run).

Superscripts are the reference numbers for the discovery GWAS used to calculate PGS:

⁴Nievergelt et al. (2019), ⁵Duncan et al. (2018), ⁶Mahajan et al. (2018), ⁷Chen et al. (2019), ⁸Marouli et al. (2017),
⁹Scott et al. (2017), ¹⁰Wood et al. (2014) 9 Scott et al. (2017), 10 Wood et al. (2014).

ABCD, Adolescent Brain and Cognitive Development Study; PGS, polygenic score; AFR, African-American ancestry; GWAS, genome-wide association study; PTSD, post-traumatic stress disorder; T2D, type 2 diabetes; *r*, Pearson correlation coefficient; *t*, linear association *t*-test statistic; *P*, two-tailed *P*-value on 1739 degrees of freedom; NA, not applicable (analysis not run).

Superscripts are the reference numbers for the discovery GWAS used to calculate PGS:

⁴Nievergelt et al. (2019), ⁵Duncan et al. (2018), ⁶Mahajan et al. (2018), ⁷Chen et al. (2019), ⁸Marouli et al. (2017),
ºScott et al. (2017), ¹⁰Wood et al. (2014) 9 Scott et al. (2017), 10 Wood et al. (2014).

PNC, Philadelphia Neurodevelopmental Cohort; PGS, polygenic score; EUR, European-American ancestry; GWAS, genome-wide association study; PTSD, post-traumatic stress disorder; T2D, type 2 diabetes; *r*, Pearson correlation coefficient; *t*, linear association *t*-test statistic; *P*, two-tailed *P*-value on 5237 degrees of freedom; NA, not applicable (analysis not run).

Superscripts are the reference numbers for the discovery GWAS used to calculate PGS:

⁴Nievergelt et al. (2019), ⁵Duncan et al. (2018), ⁶Mahajan et al. (2018), ⁷Chen et al. (2019), ⁸Marouli et al. (2017), ⁹Scott et al. (2017), ¹⁰Wood et al. (2014).

ABCD, Adolescent Brain and Cognitive Development Study; PGS, polygenic score; EUR, European-American ancestry; GWAS, genome-wide association study; PTSD, post-traumatic stress disorder; T2D, type 2 diabetes; *r*, Pearson correlation coefficient; *t*, linear association *t*-test statistic; *P*, two-tailed *P*-value on 5813 degrees of freedom.

Superscripts are the reference numbers for the discovery GWAS used to calculate PGS:

⁴Nievergelt et al. (2019), ⁵Duncan et al. (2018), ⁶Mahajan et al. (2018), ⁷Chen et al. (2019), ⁸Marouli et al. (2017),
ºScott et al. (2017), ¹⁰Wood et al. (2014) 9 Scott et al. (2017), 10 Wood et al. (2014).

PNC, Philadelphia Neurodevelopmental Cohort; AFR, African-American ancestry; *n*, number of subjects; PTSD, posttraumatic stress disorder; T2D, type 2 diabetes.

Superscripts are the reference numbers for the discovery GWAS used to calculate PGS:

⁴Nievergelt et al. (2019), ⁵Duncan et al. (2018), ⁶Mahajan et al. (2018), ⁷Chen et al. (2019), ⁸Marouli et al. (2017), ⁹Scott et al. (2017), ¹⁰Wood et al. (2014).

ABCD, Adolescent Brain and Cognitive Development Study; AFR, African-American ancestry; *n*, number of subjects; PTSD, post-traumatic stress disorder; T2D, type 2 diabetes.

Superscripts are the reference numbers for the discovery GWAS used to calculate PGS:

⁴Nievergelt et al. (2019), ⁵Duncan et al. (2018), ⁶Mahajan et al. (2018), ⁷Chen et al. (2019), ⁸Marouli et al. (2017), ⁹Scott et al. (2017), 10Wood et al. (2014).

PNC, Philadelphia Neurodevelopmental Cohort; EUR, European-American ancestry; *n*, number of subjects; PTSD, posttraumatic stress disorder; T2D, type 2 diabetes.

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⁴Nievergelt et al. (2019), ⁵Duncan et al. (2018), ⁶Mahajan et al. (2018), ⁷Chen et al. (2019), ⁸Marouli et al. (2017), ⁹Scott et al. (2017), 10Wood et al. (2014).

ABCD, Adolescent Brain and Cognitive Development Study; EUR, European-American ancestry; *n*, number of subjects; PTSD, post-traumatic stress disorder; T2D, type 2 diabetes.

Superscripts are the reference numbers for the discovery GWAS used to calculate PGS:

⁴Nievergelt et al. (2019), ⁵Duncan et al. (2018), ⁶Mahajan et al. (2018), ⁷Chen et al. (2019), ⁸Marouli et al. (2017), ⁹Scott et al. (2017), ¹⁰Wood et al. (2014).

LDSC, linkage disequilibrium score regression; PTSD, post-traumatic stress disorder; T2D, type 2 diabetes; SE, standard error estimate obtained via block jackknifing

*Genetic correlations >1 are a known issue with LDSC (https://github.com/bulik/ldsc/issues/89).

† The 75,000 individuals included in GWAS C were randomly sampled from the 134,000 individuals included in GWAS A, and the 10,000 individuals included in GWAS E were randomly sampled from those included in GWAS C. The same relationships exist for GWAS B, D, and F. GWAS AB was run using the 268,000 individuals who were included in GWAS A or GWAS B. The test set consists of 8,107 individuals who were not included in any GWAS.

LDSC, linkage disequilibrium score regression; SE, standard error estimate obtained via block jackknifing; h^2 , observed scale heritability; λ_{GC} , genomic control inflation factor

† LDSC was run using the SNPs that were jointly present in the GWAS and a EUR-ancestry LD reference panel. Partitioned LD scores with zero variance were excluded from the analysis.

Table S18. Number of genome-wide significant

SNPs included in PRS-CS calculations.

† These counts are the number of genome-wide SNPs present among the 1,113,490 LD-filtered SNPs that entered into the PRS-CS computations. We are defining genomewide significance as $P < 5 \times 10^{-8}$.

Table S19. LDSC genetic correlations computed for UKBB Height GWAS.

LDSC, linkage disequilibrium score regression

Standard errors in parentheses were estimated via block jackknifing.

*Genetic correlations >1 are a known issue with LDSC (https://github.com/bulik/ldsc/issues/89).

Table S21. Variance explained by PGS computed from each height discovery GWAS.

† This is the coefficient of determination for the additive linear model that includes sex, age at the time of height measurement, 20 ancestry PCs, and the standardized height PGS computed from the specified discovery GWAS as predictors of height. The *R*² for the base model was 0.5374; the base model was significant with *F*(22,8084) = 426.9, *P* $< 2.2 \times 10^{-16}$.

‡‡We are reporting the results for a partial-F test computed on 1 and 8083 degrees of freedom for the effect of adding the standardized polygenic score (PGS) to a base model that included sex, age, and the first 20 ancestry PCs as predictors.

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