

**Supplementary Table 2: Descriptions of cohorts for simulations with population stratification**

Supplementary table 1 describes the seven PGC Schizophrenia control cohorts used for simulation with population stratification. All cohorts were genotyped on the Illumina Omni Express array; only unaffected individuals (controls) and directly genotyped SNPs post-QC (between approximately 600,000 and 700,000 SNPs, depending on cohort) were retained for simulations. In total genotypes for 9,135 individuals were incorporated into the simulations with pure population stratification



**Supplementary Table 3a: Performance of genomic control and LD Score regression intercept in simulations with continental-scale population stratification**

This table compares the performance of  $\lambda_{GC}$  and the LD Score regression intercept in simulations with continental-scale population stratification. In each simulation, individuals from population 1 were labeled cases and  $N_2$  individuals from population 2 were labeled controls. We then computed association statistics for variants in the intersection of the subset of HapMap 3 variants used for LD Score regressions on real data (Online Methods) and variants on the Illumina Omni Express array (approx. 450,000 variants in each simulation).

The conclusion is that the LD Score regression intercept gives approximately the same answer as  $\lambda_{GC}$ in simulations with pure population stratification, and so would be appropriately conservative if used as a correction factor.

\* The mean and SD are computed with the umeb/swe6 outlier removed.



**Supplementary Table 3b. Correlation between LD Score and FST in simulations with continental-scale population stratification**

Column descriptions. Population 1 and population 2 are the two populations involved in the simulations. Signed R-squared is the squared Pearson correlation coefficient between  $F_{ST}$  (between the two populations in the simulation) and LD Score multiplied by the negative one if the (nonsquared) correlation is negative.



**Supplementary Table 3c Heritability and intercept for a confounded GWAS with continentalscale population stratification**

This table puts the slopes from the simulations with continental-scale population stratification on an interpretable scale by transforming all parameters to the scale of a GWAS with 100,000 samples and mean chi-square of 1.5, where all inflation in the mean chi-square comes from population stratification. All estimates of h2(1kG) use M=15 million. For comparison, the aggregate LD Score estimator of h2(1kG),  $\widehat{h^2} = \frac{M(\overline{\chi^2}-1)}{\overline{N}\overline{\ell}}$ , which is representative of heritability estimators that are highly susceptible to population stratification, would give a heritability estimate of **0.68** in all cases, assuming mean LD Score = 110. The reason why the LD Score regression slope is not equal to zero is likely because linked selection introduces a small correlation between LD Score and  $F_{ST}$ . The conclusion is that in a worst-case scenario (pure population stratification), LD Score regression misattributes on average a small proportion of stratification to heritability, but nevertheless performs many times better than existing estimators (upward bias of 0.017 for LD Score regression vs. approximately 0.68 for other methods).



**Supplementary Table 4a: Performance of genomic control and LD Score regression intercept in simulations with national-scale population stratification**

This table compares the performance of  $\lambda_{GC}$  and the LD Score regression intercept in simulations with national-scale population stratification. We LD-pruned the SNPs so that no SNPs on the same chromosome had  $R^2$   $>$  0.02, then computed the top three principal components. We then used these principal components as phenotypes and computed association statistics for the same set of variants as in the simulations described in supplementary table 2.

The conclusion is that the LD Score regression intercept gives approximately the same answer as  $\lambda_{GC}$ in simulations with pure population stratification, and so would be appropriately conservative if used as a correction factor.



**Supplementary Table 4b. Correlation between LD Score and FST in simulations with national-scale population stratification**

Column descriptions. Population is the population and PC is the principal component used to simulate population stratification in the simulations and population 2. Signed R-squared is the squared Pearson correlation coefficient between  $F_{ST}$  (between the two populations in the simulation) and LD Score multiplied by the negative one if the (non-squared) correlation is negative.



**Supplementary Table 4c: Heritability and intercept for a confounded GWAS with nationalscale population stratification**

This table is similar to supplementary table 2c it puts the slopes from the simulations with nationalscale population stratification on an interpretable scale by transforming all parameters to the scale of a GWAS with 100,000 samples and mean chi-square of 1.5 where all inflation in the mean chi-square comes from population stratification along the relevant principal component. As in supplementary table 4, the aggregate estimator would give a h2(1kG) estimate of 0.68, which is similar to the result that one would obtain with Haseman-Elston regression or linear mixed models (using M=15 million). The conclusions are similar to supplementary table 4.

**Supplementary Table 5: Simulations with both bias and polygenicity**



Column descriptions. The column labeled bias identifies the source of bias, either cryptic relatedness (from the Framingham Heart Study) or population stratification (from introducing an environmental stratification term correlated with the first PC of the WTCCC2 data). Intercept is LD Score regression intercept, with the standard deviation (SD) across five simulations in parentheses. Null  $\bar{\chi}^2$ is the mean  $\chi^2$  among SNPs on the opposite halves of chromosomes from causal SNPs, with SD across five simulations in parentheses. Since null SNPs are not in LD with causal SNPs, the mean  $\chi^2$ among null SNPs precisely quantifies the mean inflation in  $\chi^2$ -statistics that results from bias. Null  $\bar{\chi}^2$ /Intercept is equal to the mean  $\chi^2$  among null SNPs divided by the LD Score regression intercept, with the SD across five simulations in parentheses. Null  $\bar{\chi}^2$ /Intercept should be approximately equal to one if the LD Score regression intercept is accurately estimating the mean inflation in test statistics that results from bias.



## **Supplementary Table 6: Simulations with Ascertained Binary Phenotypes**

This table displays results from simulations with ascertained binary phenotypes following the liability threshold model. In all simulation replicates, the true heritability (of liability, in the population) was 0.8, the effective number of independent SNPs (defined as  $M_{eff} := M/\overline{\ell}$ ) was 10,000 and the proportion of cases in the sample was 0.5. All SNPs were causal, with effect sizes (precisely, pernormalized genotype effects on liability) drawn *i.i.d.* from a normal distribution. Each entry in the table represents 20 simulation replicates. The column labeled  $\widehat h^2_l$  lists the estimated heritability of liability in the population from the LD Score regression slope. The column labeled intercept lists LD Score regression intercepts. There was no population stratification in these simulations, so the intercept should be close to one. The columns  $\lambda_{GC}$  and  $\overline{\chi}^2$  list the genomic control inflation factor and mean  $\chi^2$  computed from a perfectly LD-pruned set of variants.

<b>Exponent</b>	Intercept (SD)	$\overline{\chi}^2$ (SD)
$-3$	1.007(0.013)	1.011(0.008)
$-2$	1.006(0.014)	1.013(0.008)
$-1$	1.003(0.014)	1.023(0.009)
$-0.5$	1.001(0.013)	1.037(0.009)
$-0.25$	1.000(0.012)	1.048(0.008)
$\bf{0}$	0.998(0.011)	1.059(0.007)
0.25	0.997(0.011)	1.070(0.006)
0.5	0.996(0.011)	1.079(0.006)
1	0.994(0.012)	1.091(0.007)
$\overline{2}$	0.991(0.013)	1.101(0.009)
3	0.989(0.013)	1.105(0.010)

**Supplementary Table 7: Simulations with frequency-dependent genetic architecture**

Supplementary table 5 describes simulations in which per-normalized genotype effects (precisely, if X denotes a matrix of genotypes normalized to mean zero and variance one, the per-normalized genotype effects are a vector  $\beta$  such that  $X\beta$  is equal to the additive genetic component of the phenotype) for 10,000 randomly chosen causal variants were drawn from  $N(0, (p(1-p))^x)$ , where  $\dot{p}$  is MAF and  $\dot{x}$  is the entry in the column labeled exponent. To prevent singleton and doubleton variants from having extreme effects for large negative values of *x*, we drew the effect sizes for variants with MAF < 1% from  $N(0,0.0099^x)$ . Our model holds when  $x=0$ , which corresponds to moderate negative selection on the phenotype in question, similar to a typical disease phenotype.  $x=1$ is an appropriate model for a selectively neutral phenotype. Values of *x* outside the range [0,1] represent extreme genetic architectures. Standard errors are empirical standard errors across 10 replicates with randomly chosen causal variants and effect sizes.



**Supplementary Table 8a: Summary Statistic Metadata, Quantitative Trait**

Column descriptions. All columns are self-explanatory, except the column labeled N counts the number of individuals in the discovery phase of the GWAS, not including replication samples. The column labeled public indicates whether the summary statistics are publicly available for download (see URLs).

## **Supplementary Table 8b: Summary Statistic Metadata, Case/Control**



Column descriptions. All columns are self-explanatory, except the columns labeled cases and controls note the number of cases and controls in the discovery phase of the GWAS, not including replication samples. The column labeled public indicates whether the summary statistics are publicly available for download (see URLs)

\* These summary statistics may be meta-analyzed with Immunochip data, which is not appropriate for LD Score regression.

\*\* This figure counts only European samples. The full GWAS includes several thousand Asian samples, which were excluded from the LD Score regression, because the 1000 Genomes European

LD Score is not representative of LD patterns in Asian populations.

\*\*\* Here cases are individuals with college education, controls those without.

## **Supplementary Table 9: Simulation with intergenic GC correction**



This table describes a simulation with 1000 Swedish samples and ~700,000 best-guess imputed genotypes on chromosome 1. We simulated phenotypes by assigning causal effects to only SNPs within coding exons on chromosome 1. We then computed association statistics for variants within 100 kB of a gene, more than 100 kB from a gene and for null SNPs on chromosome 2. Because of long-range linkage disequilibrium, lambda (i.e.,  $\lambda_{GC}$ ) is significantly elevated for intergenic SNPs even though there is no bias in the test statistics, as can be seen from the fact that the test statistics of null SNPs are not inflated.