

**Supplementary Online Materials**

**OSCA: a tool for omic-data-based complex trait analysis**

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## Supplementary Note 1: Simulating phenotypes from DNAm data

### Simulation scenario 1: Simulating a phenotype with effects from a set of causal probes (on the odd chromosomes)

We used the DNAm data from the LBC cohort after quality control (**Methods**). The DNAm probes were adjusted for age, sex, experimental batches, and smoking status. The phenotype was simulated based on the following model

$$\mathbf{y} = \mathbf{X}\mathbf{b} + \mathbf{e} \quad (1)$$

where  $\mathbf{y}$  is a vector of phenotypes,  $\mathbf{X}$  is a matrix of standardised DNAm measures for 1,319 individuals and a set of causal probes (randomly sampled from all probes on the odd chromosomes),  $\mathbf{b}$  is a vector of the effects of the causal probes, and  $\mathbf{e}$  is a vector of residuals. The probe effects were generated from a standard normal distribution, and the elements in  $\mathbf{e}$  were generated from  $N(0, \sigma_{\mathbf{Xb}}^2(\frac{1}{\rho^2} - 1))$  with  $\sigma_{\mathbf{Xb}}^2$  being the empirical variance of the elements in vector  $\mathbf{Xb}$  and  $\rho^2$  being the proportion of phenotypic variance explained by the causal probes. We simulated the phenotype with 100 causal probes with  $\rho^2 = 0.5$  (per-probe  $\rho^2 = 0.005$ ), and repeated the simulation 100 times with the causal probes resampled in each simulation replicate. We also tested the robustness of the models under two additional settings, i.e., 10 causal probes with  $\rho^2 = 0.2$  (per-probe  $\rho^2 = 0.02$ ) and 1000 causal probes with  $\rho^2 = 0.4$  (per-probe  $\rho^2 = 0.004$ ).

In each simulation replicate, we tested the associations between the simulated phenotype and all the probes using different methods. The genome-wide significance level was set to  $2.19\text{e-}07$  based on a Bonferroni correction for 228,694 tests.

### Simulation scenario 2: Simulating a phenotype with effects from cell types but no direct effects from the probes

We used the DNAm data and cell counts measured for five primary blood cell types in the LBC cohort to simulate a phenotype based on the following model

$$\mathbf{y} = \mathbf{C}\boldsymbol{\beta} + \mathbf{e} \quad (2)$$

where  $\mathbf{y}$  is a vector of phenotypes,  $\mathbf{C}$  is a matrix of standardised cell counts for 1,319 individuals and 5 cell types,  $\boldsymbol{\beta}$  is a vector of the effects of the cell types, and  $\mathbf{e}$  is a vector of residuals. The cell type effects were generated from a standard normal distribution, and the elements of  $\mathbf{e}$  were generated from  $N(0, \sigma_{\mathbf{C}\boldsymbol{\beta}}^2(\frac{1}{R_{\text{CTCs}}^2} - 1))$  with  $\sigma_{\mathbf{C}\boldsymbol{\beta}}^2$  being the empirical variance of all the elements in vector  $\mathbf{C}\boldsymbol{\beta}$  and  $R_{\text{CTCs}}^2$  being the proportion of

phenotypic variance explained by CTCs. Given the observed variance explained by 5 cell types (i.e., neutrophils, lymphocytes, monocytes, eosinophils and basophils) that varied from 0 to  $\sim 0.05$  for 4 real traits (i.e., BMI, height, lung function and walking speed) in LBC (**Supplementary Table 10**), we used a range of parameter values for  $R_{CTCs}^2$  in the simulation, i.e., 0.005, 0.01, 0.02, 0.03, 0.04 and 0.05. We repeated each simulation scenario 1000 times (we ran more simulation replicates in this case to get a more precise estimate of power). In addition, we also simulated extreme cases with  $R_{CTCs}^2 = 0.1, 0.3, 0.5$  and  $0.7$ . In each simulation replicate, we performed the association tests using different methods and used a genome-wide significance level of  $2.19e-07$  based on a Bonferroni correction for 228,694 tests.

We also applied the method to simulate a phenotype with 100 replicates based on 22 experimental batches (i.e., 22 plates) in lieu of the 5 cell types with  $R_{batch}^2$  ranging from 0.005 to 0.7. Note that in this case the DNAm probes were adjusted for age, sex, sample position on the chip, CTCs and smoking status.

### **Simulation scenario 3: Simulating a phenotype with effects from both causal probes and cell types**

In this scenario, we used the LBC data to simulate a phenotype based on the model below

$$\mathbf{y} = \mathbf{C}\boldsymbol{\beta} + \mathbf{X}\mathbf{b} + \mathbf{e} \quad (3)$$

where all the parameters and variables have been defined above. The five cell types explained 5% of variance of the simulated phenotype and the 100 causal probes (randomly sampled from all probes on the odd chromosomes) explained 50% of the variance. The simulation was repeated 100 times with causal probes resampled in each simulation replicate.

We also applied the method to simulate a phenotype with 100 replicates based on 100 causal probes (explaining 50% of the variance) and 22 experimental batches (explaining 5% of the variance). In this case, the DNAm probes were adjusted for age, sex, sample position on the chip, CTCs and smoking status.

### **Simulations to evaluate OSCA-OREML**

We simulated a phenotype based on model (1), i.e.  $\mathbf{y} = \mathbf{X}\mathbf{b} + \mathbf{e}$ . In this simulation, we did not limit the causal probes on the odd chromosomes but allowed them to be sampled at random across the whole genome. We simulated the phenotype in 2 scenarios, 1) the

null model (i.e.,  $\mathbf{Xb} = \mathbf{0}$ ), 2) the alternative model ( $m$  causal probes randomly sampled from all the probes with  $m = 1, 50$  or  $500$  and the corresponding  $\rho^2 = 0.1, 0.2$  or  $0.5$ ) using the method described above. Each DNA methylation probe in LBC was adjusted for age, sex, experimental batches, smoking status and CTCs. We repeated each simulation 500 times to obtain the mean and standard deviation of the OREML estimate over repeated sampling.

## Supplementary Note 2: A brief summary of the feature selection strategy used in FaST-LMM-EWASher

FaST-LMM-EWASher is an MLM-based EWAS method which tests the association of a probe with a trait conditioning on the random effects of a set of selected probes. The main analysis pipeline implemented in FaST-LMM-EWASher can be summarised as following:

1. Read the DNAm and phenotype data.
2. Remove probes with small and large mean beta values.
3. Compute the principal components for the individuals using the DNAm data.
4. Run MLM-based association analyses iteratively with increasing number of PCs (from 0 to 10) fitted as covariates. In each iteration, a feature selection process is conducted to select probes to be fitted as the random effects in the MLM (not including the probes in <50Kb distance from the probe in question). The iteration proceeds until the genome inflation factor is smaller than 1 or the number of PCs is 10.

The algorithm to select the random-effect probes can be described as

- 1) Split the sample into 10 sub-samples of the same size
- 2) For each sub-sample
  - a. Use the target sub-sample as the test set and a pool of all the other sub-samples as the training set.
  - b. Run linear regression analysis in the training set.
  - c. Define a vector with fixed numbers, i.e.,  $\mathbf{v} = [1, 101, 201, 301, 401, 501, 601, 701, 801, 901, 2000, 3000, 4000, 5000, 6000, 7000, 8000, 9000]$
  - d. For each number in the vector  $\mathbf{v}$  above, take the top  $v_i$  probes ranked by the linear regression p-values in the training set to predict the phenotype in the test set.
  - e. Calculate SSE and the log likelihood from regressing the phenotype against the predictor in the test set.
- 3) Calculate the mean values of SSE and log likelihood across the 10 sub-samples for  $v_i$ .
- 4) Select a number in vector  $\mathbf{v}$  (denoted by  $v_{max}$ ) that shows the largest mean log likelihood or the smallest mean SSE.
- 5) Select the top  $v_{max}$  probes from linear regression analysis in the whole sample.

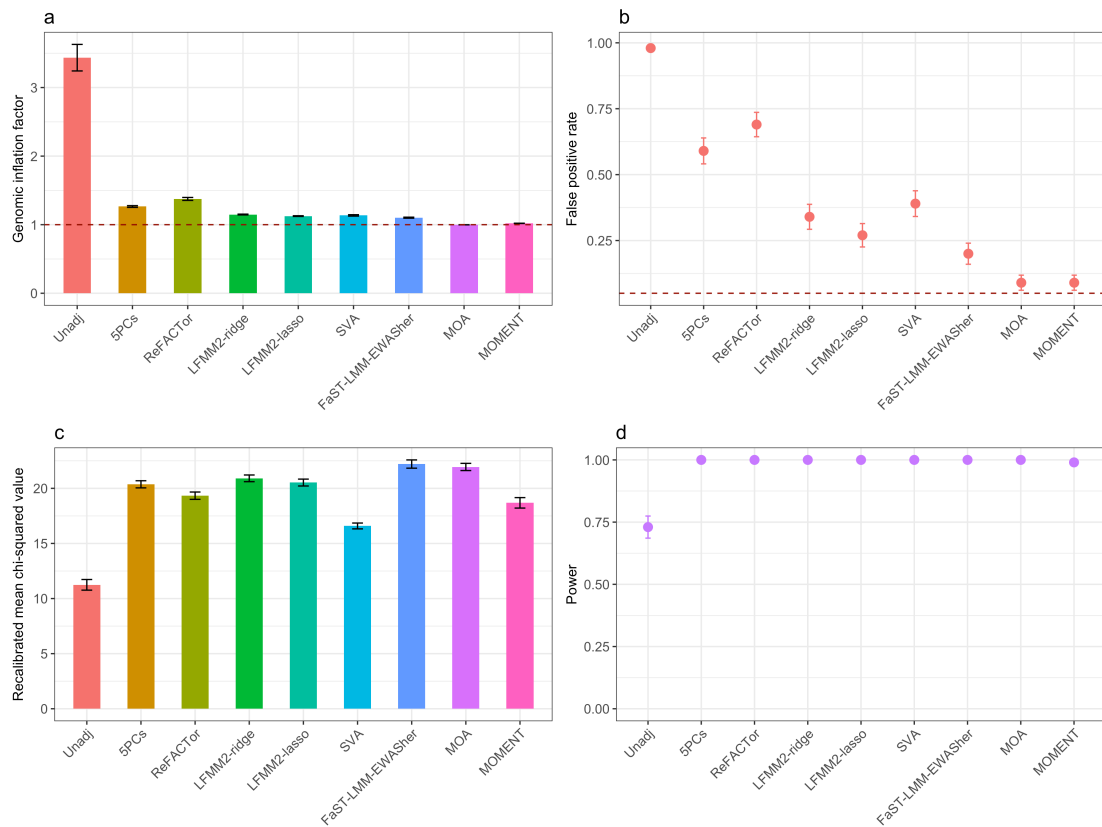
### **Supplementary Note 3: Quality control of the DNA methylation data in LBC**

A total of 3,191 whole blood samples from 3 waves were assayed with the Illumina HumanMethylation450 Bead Chips at 485,512 CpG sites across the genome. We removed 146 duplicated samples or samples for which >5% of the probes with intensity detection (against negative probes on the array) p-value >0.01. We also removed probes with intensity detection p-value >0.01 in >5% of the samples and probes on the sex chromosomes. We further excluded probes encompassing SNPs annotated in dbSNP and probes identified as potentially cross-hybridizing. A total of 3,018 samples and 307,360 probes were retained for analysis (**Supplementary Table 11**).

#### Supplementary Note 4: Key features of OSCA

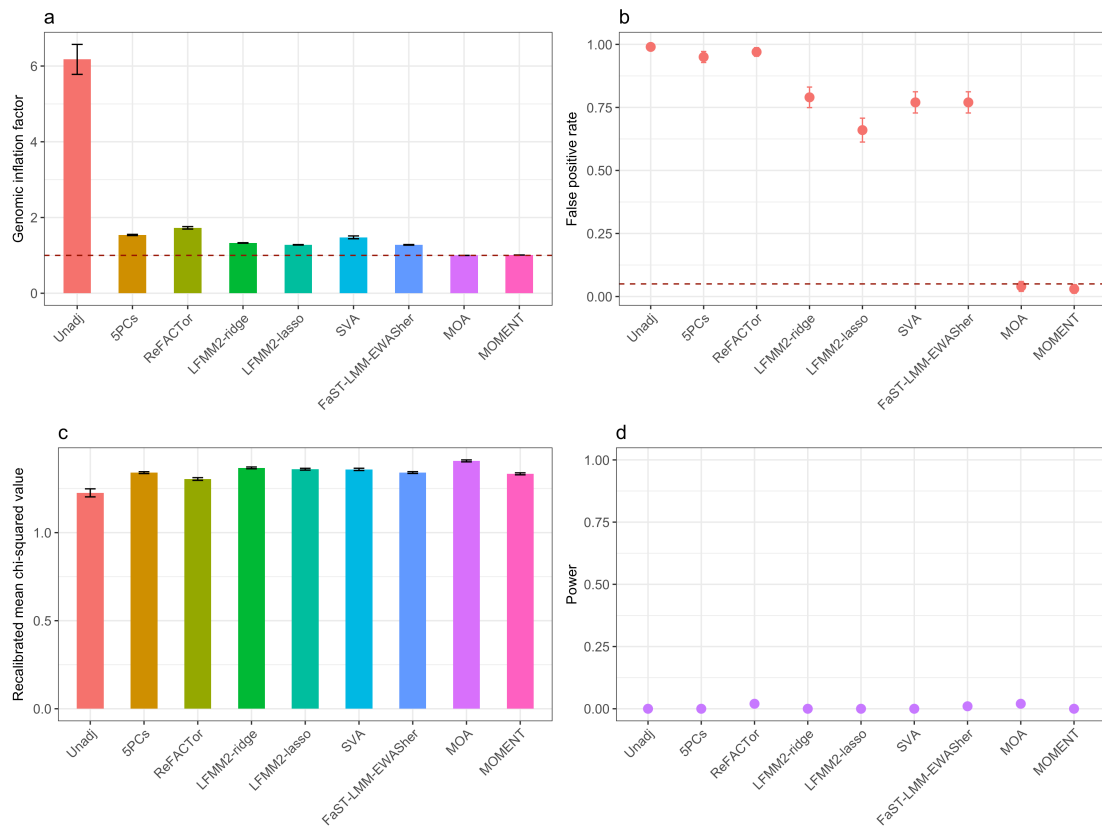
We have mentioned in the main text the two primary applications of OSCA (OSCA-MOMENT and OSCA-OREML). Here, we listed a number of additional key features of OSCA (**Supplementary Figure 27**).

- Genetic association analysis based on linear regression for molecular traits, also known as omic-data-based quantitative trait locus (xQTL) analysis. The xQTL analysis is computationally intensive because of the large number of traits (e.g., tens of thousands of traits for gene expression and hundreds of thousands of traits for DNA methylation). To speed up the analysis, OSCA parallelises the analysis to array jobs and uses multi-threading to utilise multiple CPUs in one job. For analyses with a number of covariates, OSCA has an option to accelerate the computation by pre-adjusting the phenotype and omic measures by the covariates. The xQTL output (i.e., the summary statistics) are stored in the SMR BESD format [1], greatly alleviating the storage burden and also facilitating the follow-up analyses using SMR.
- Omic-data-based phenotype prediction. We have implemented in OSCA the omic-data-based best linear unbiased predictor (OBLUP) [2] to compute the joint effects of all measures of an omic profile, which can subsequently be used to predict the phenotypes of individuals in an independent sample. Note that the OBLUP analysis needs to be performed in conjunction with OREML. We will implement Lasso and Elastic net based prediction approaches and multi-component OBLUP in OSCA in the near future.
- Simulating phenotype based on omic data (see the **Supplementary Note 1** for the simulation method).
- Meta-analysis of xQTL summary statistics from multiple cohorts with or without sample overlap. OSCA estimates sample overlap between pairwise cohorts using summary statistics of the non-significant SNPs and performs a meta-analysis account for sampling covariance among the estimates from multiple cohorts by a generalised least squares approach [3]. If all the cohorts are independent, the method is equivalent to the conventional inverse-variance-weighted meta-analysis approach [4].
- Data storage. For the efficiency of data management, we store the omic data in binary format (BOD file format) in OSCA, which is more efficient to read and write compared to text format, and save the xQTL output in SMR BESD format as mentioned above. We also provide functions that support the conversion between a BOD file and a plain text file.

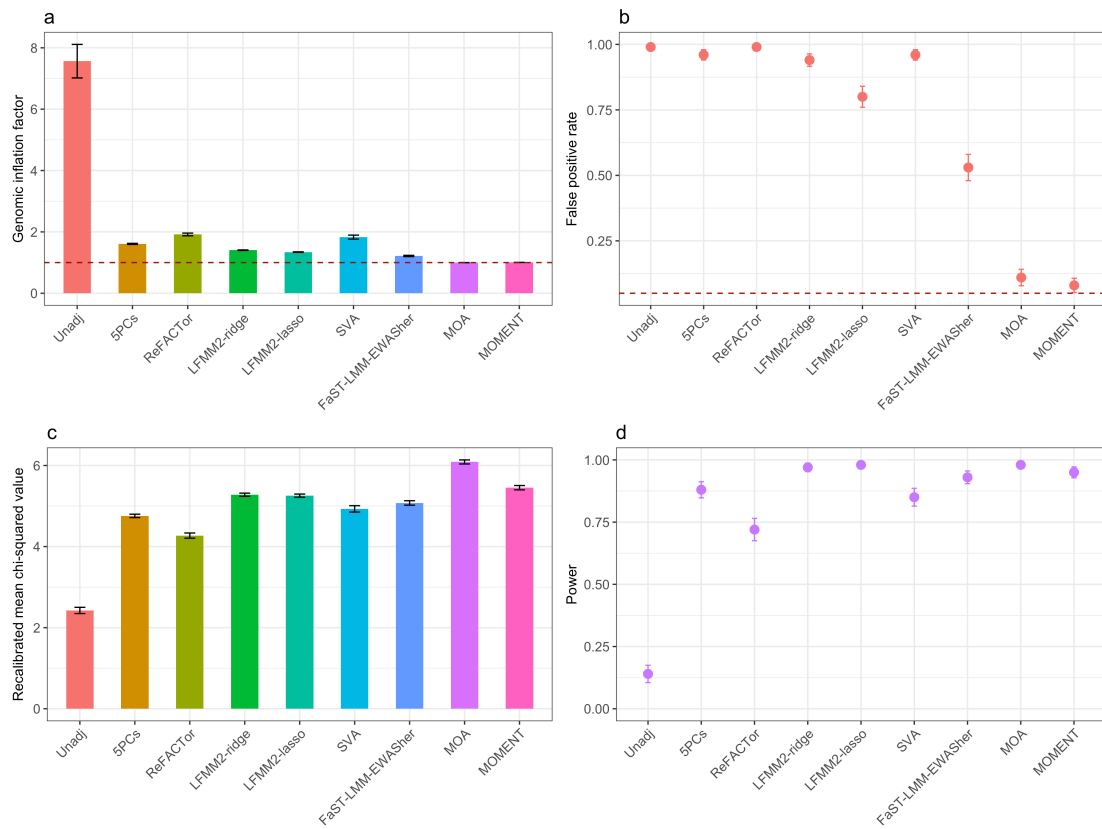


**Supplementary Figure 1** Power and false positive rate for the MWAS methods in simulation scenario 1 (phenotypes simulated based on effects from 10 causal probes). (a) Each column represents the mean of genomic inflation factor from a method across 100 simulation replicates with an error bar representing +/- SE of the mean. (b) Each dot represents the false positive rate of a method (with an error bar representing +/- the SE), calculated as the proportion of simulations with one or more null probes detected at the genome-wide significance level. (c) Each column represents the mean of the mean chi-squared values of 10 causal probes from a method across 100 simulation replicates with an error bar representing +/- SE of the mean. (d) Each dot represents the power of a method (with an error bar representing +/- the SE), computed as the proportion of causal probes detected at a genome-wide significance level based on the calibrated chi-squared values in 100 simulation replicates.

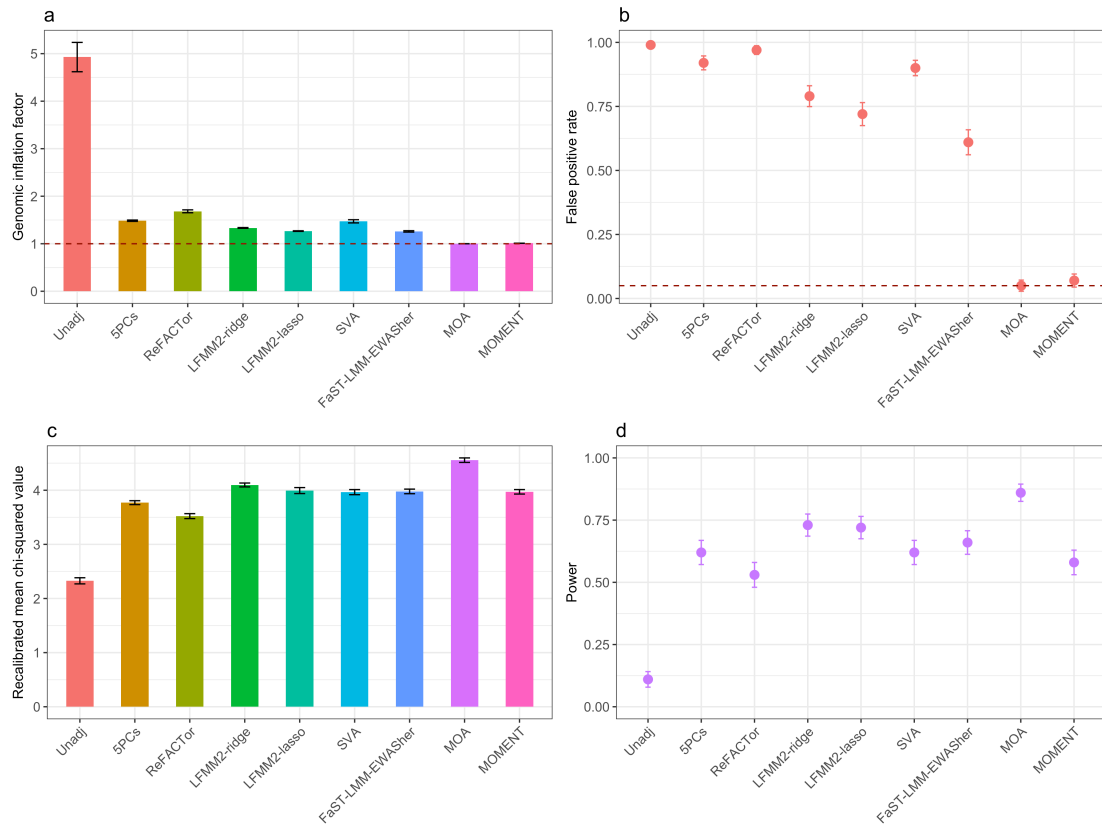




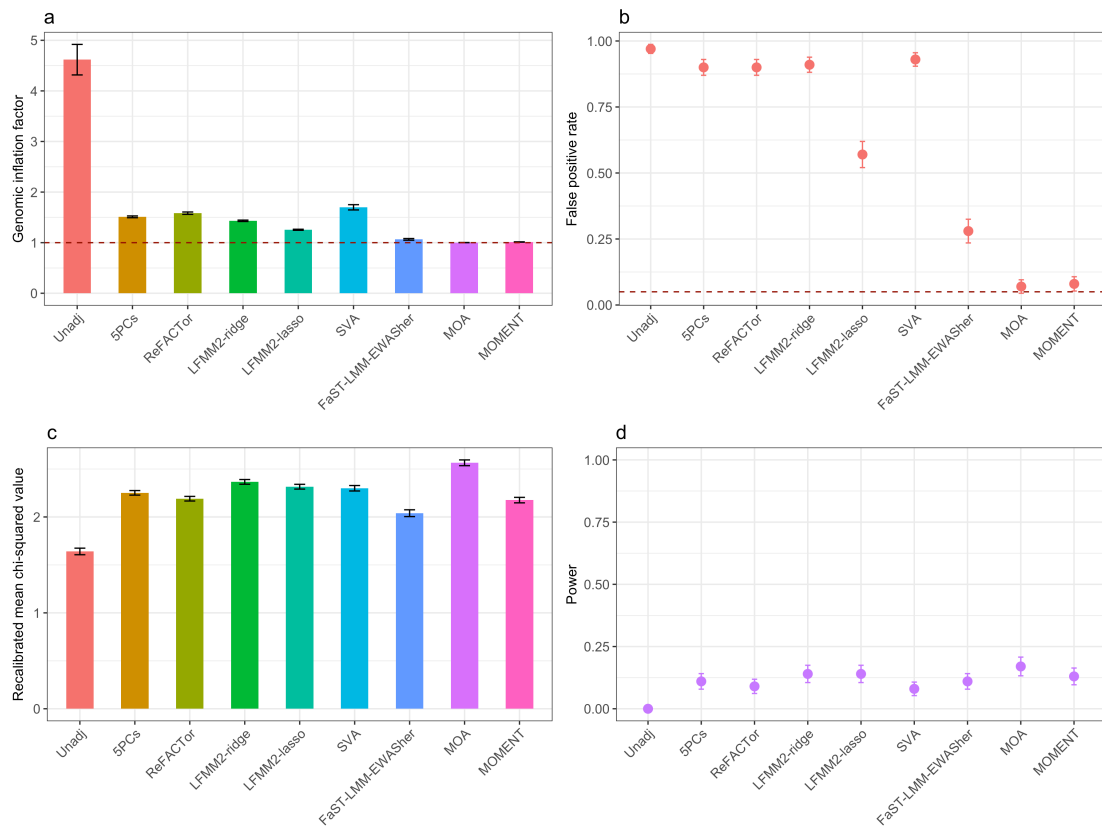
**Supplementary Figure 2** Power and false positive rate for the MWAS methods in simulation scenario 1 (phenotypes simulated based on effects from 1000 causal probes). See **Figure 1** for details of the labels.



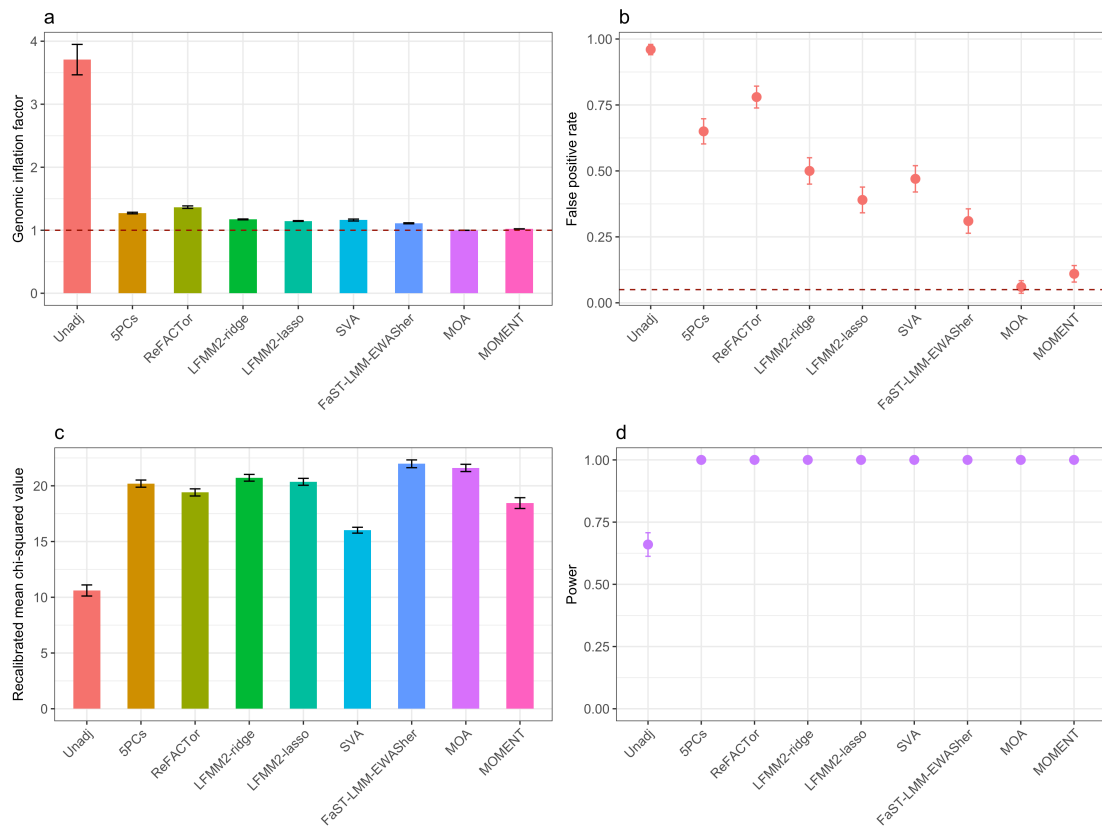
**Supplementary Figure 3** Power and false positive rate for the MWAS methods in simulation scenario 3 (phenotypes simulated based on effects from 100 causal probes and 5 CTCs). See **Figure 1** for details of the labels.



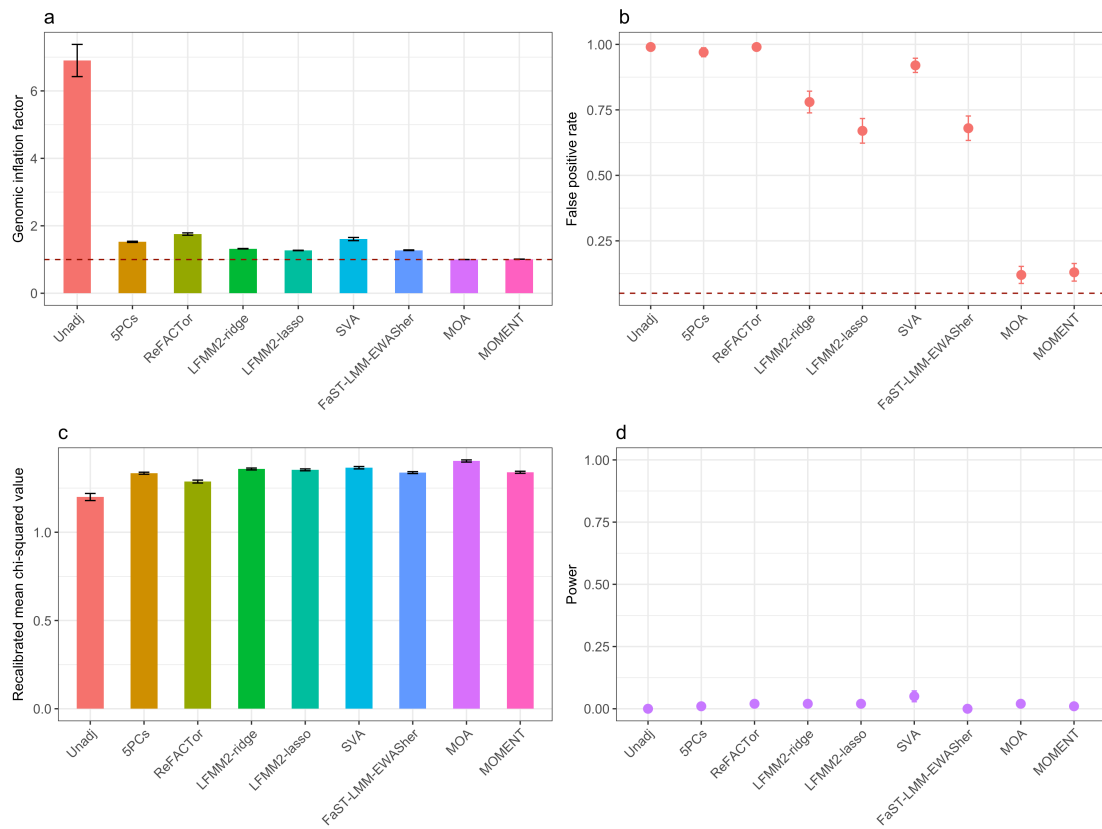
**Supplementary Figure 4** Power and false positive rate for the MWAS methods in simulation scenario 3 (phenotypes simulated based on effects from 100 causal probes and 5 CTCs) with LBC1936. See **Figure 1** for details of the labels.



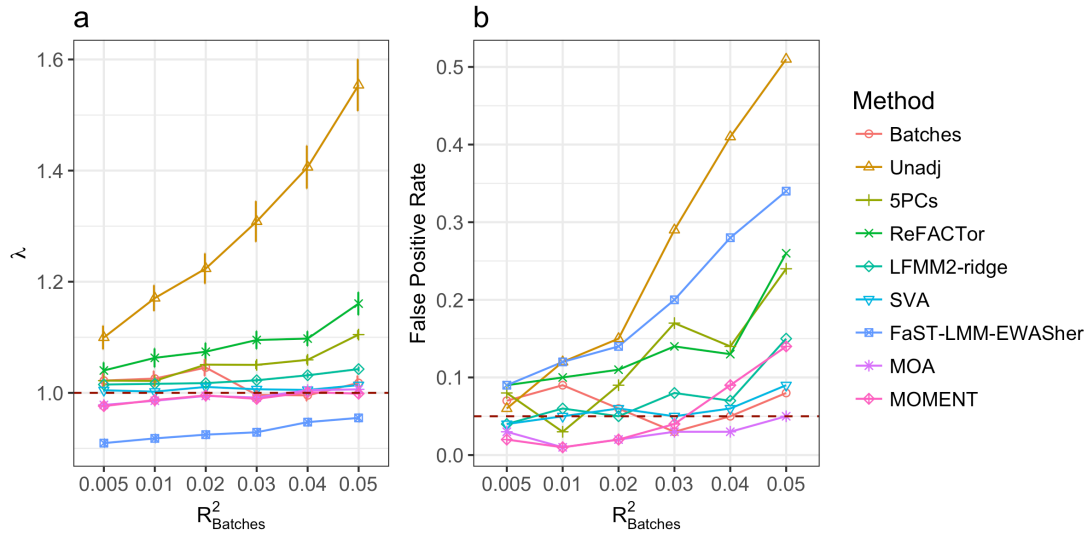
**Supplementary Figure 5** Power and false positive rate for the MWAS methods in simulation scenario 3 (phenotypes simulated based on effects from 100 causal probes and 5 CTCs) with LBC1921. See **Figure 1** for details of the labels.



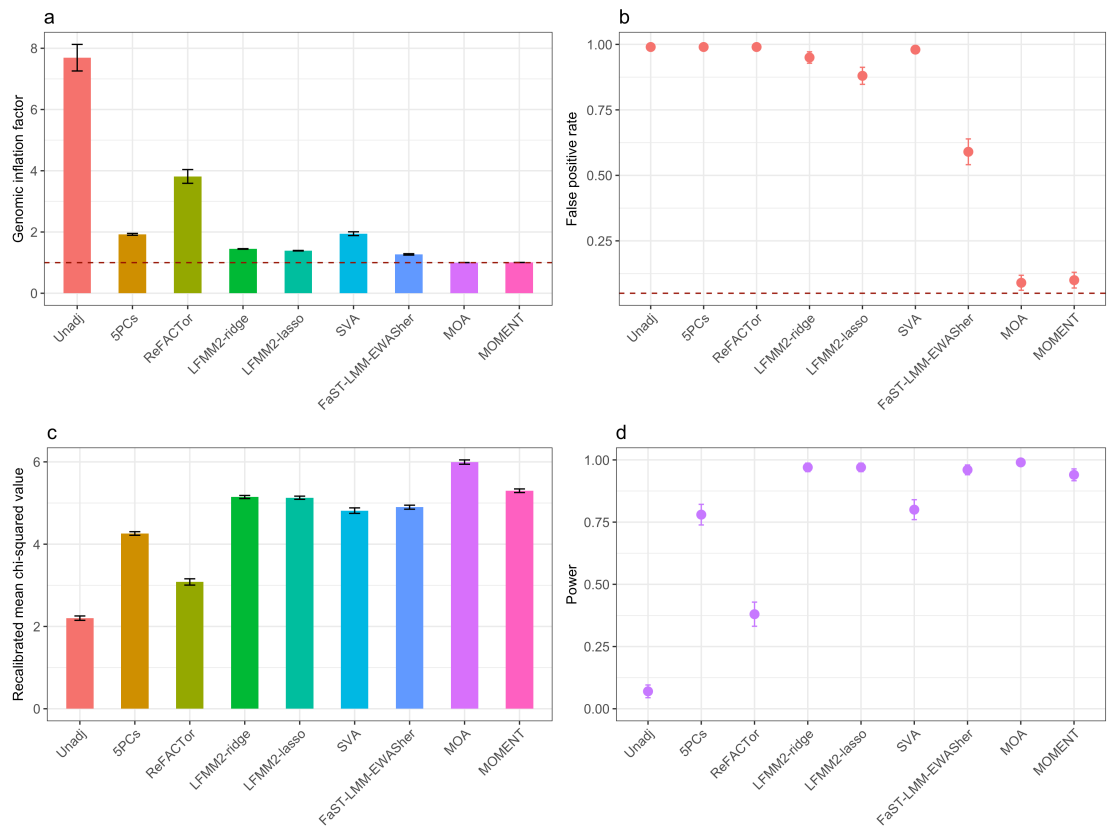
**Supplementary Figure 6** Power and false positive rate for the MWAS methods in simulation scenario 3 (phenotypes simulated based on effects from 10 causal probes and 5 CTCs). See **Figure 1** for details of the labels.



**Supplementary Figure 7** Power and false positive rate for the MWAS methods in simulation scenario 3 (phenotypes simulated based on effects from 1000 causal probes and 5 CTCs). See **Figure 1** for details of the labels.

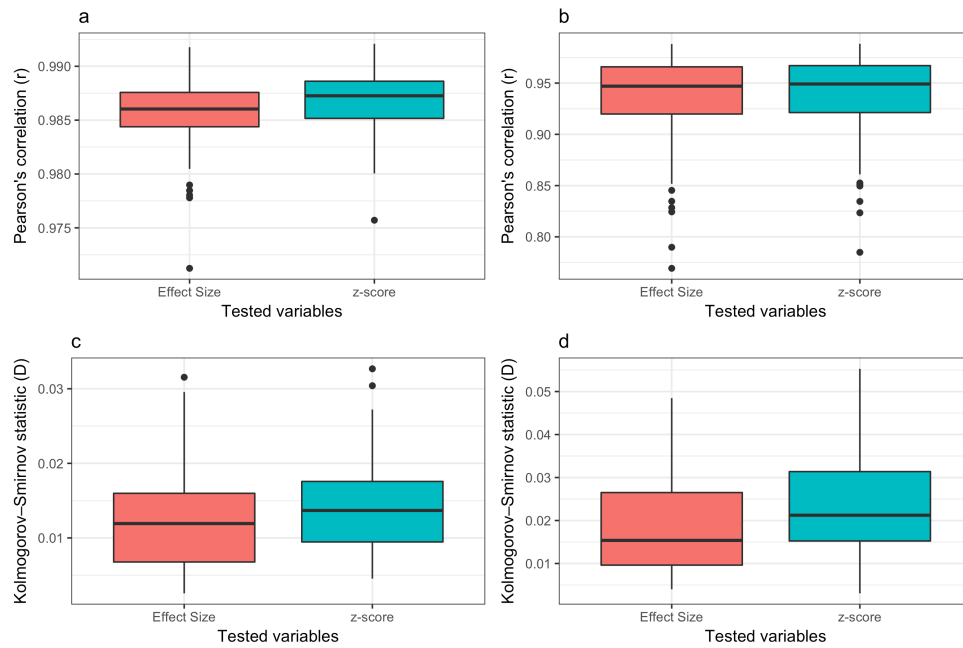


**Supplementary Figure 8** Genomic inflation factor and false positive rate for the MWAS methods in simulation scenario 2 (phenotypes simulated based on the effects of 22 batches without causal probes). Shown on the horizontal axis is the proportion of variance in the simulated phenotype explained by the batch effects ( $R^2_{\text{batch}}$ ). (a) Each dot represents the mean  $\lambda$  value from 100 simulation replicates given a specified  $R^2_{\text{batch}}$  value for a method with an error bar representing +/- the SE of the mean. (b) Each dot represents the false positive rate, calculated as the proportion of simulation replicates with one or more null probes detected at a genome-wide significance level.

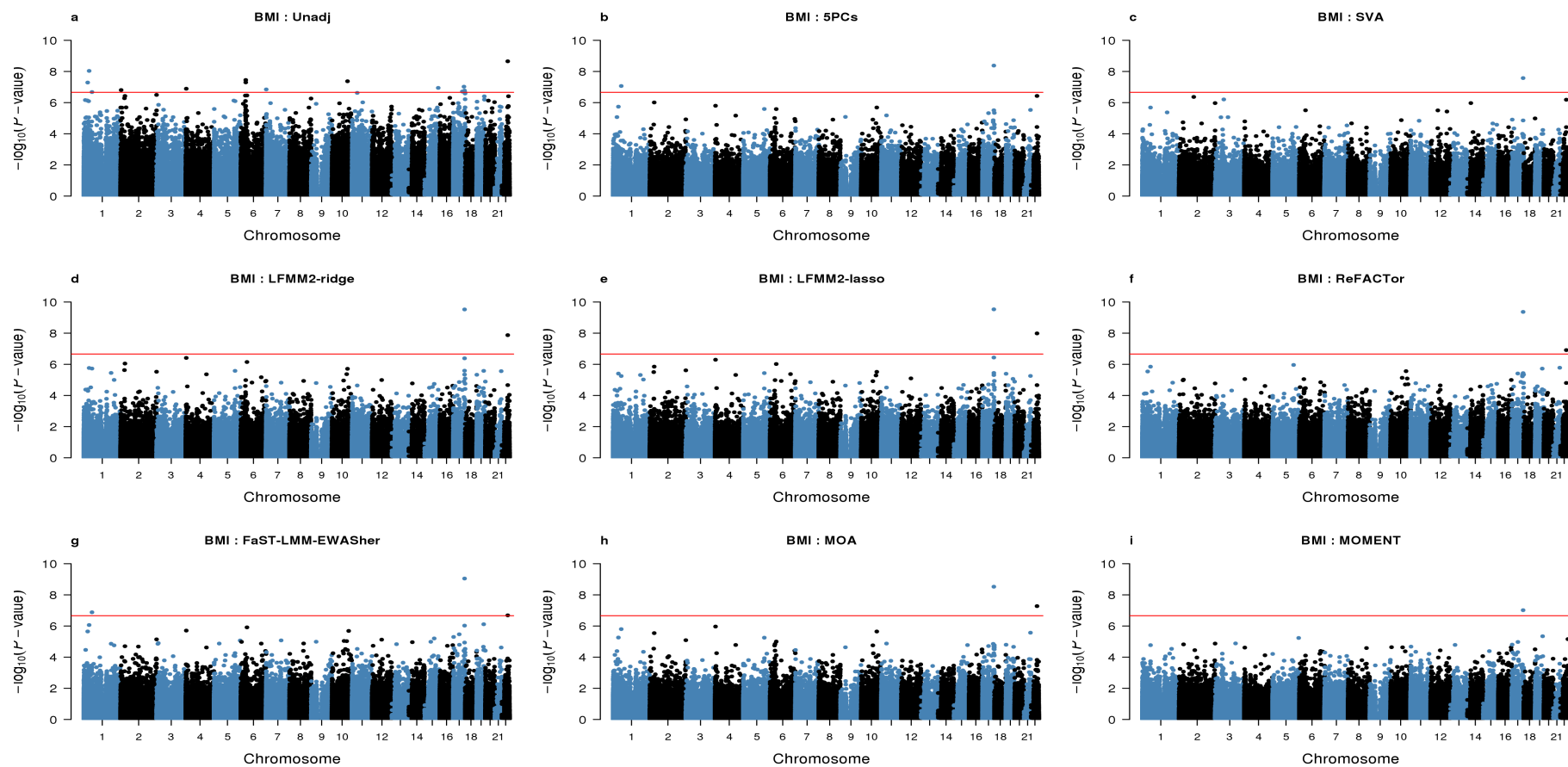


**Supplementary Figure 9** Power and false positive rate for the MWAS methods in simulation scenario 3 (phenotypes simulated based on effects from 100 causal probes and 22 batches). See **Figure 1** for details of the labels.

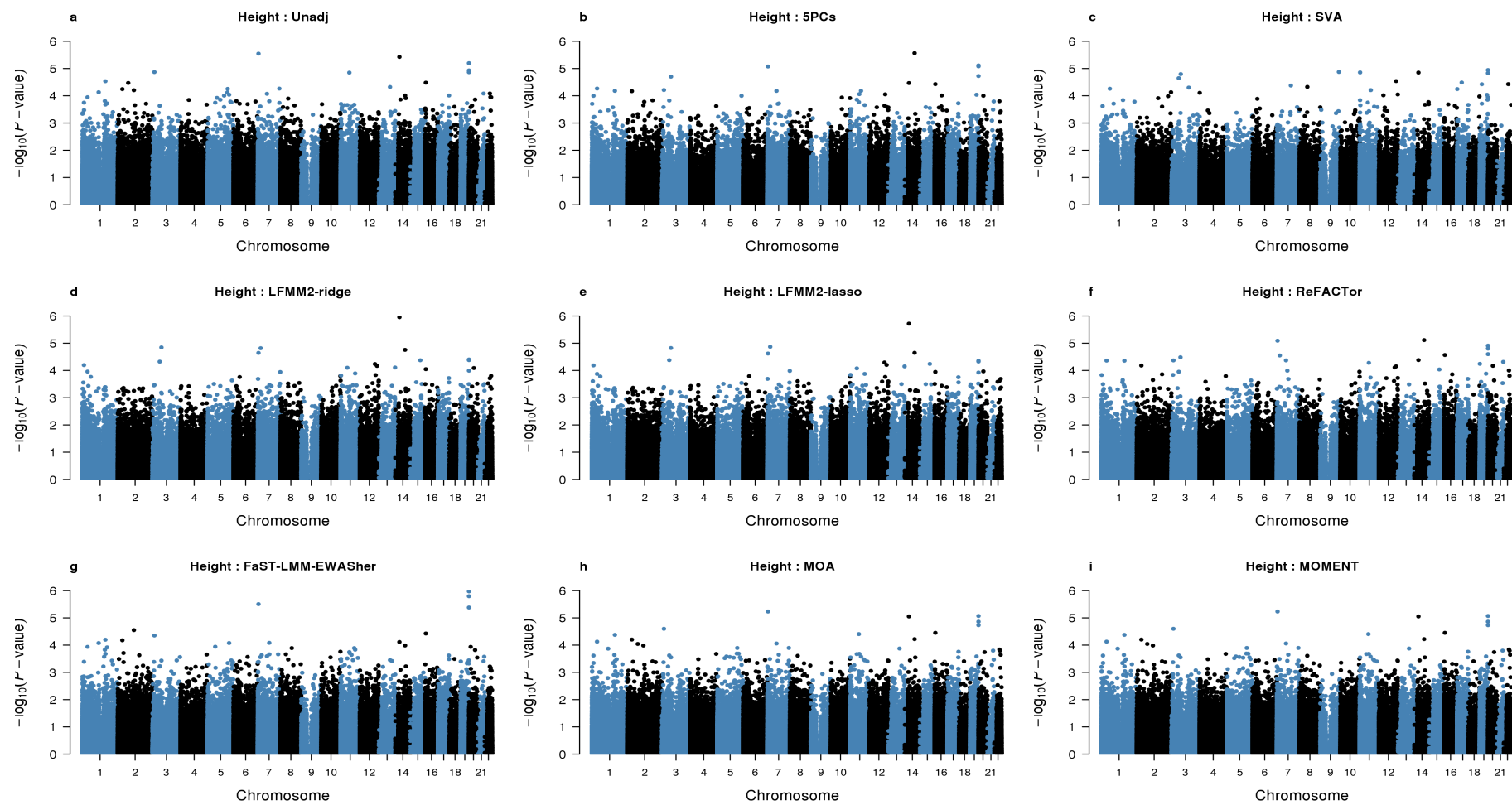




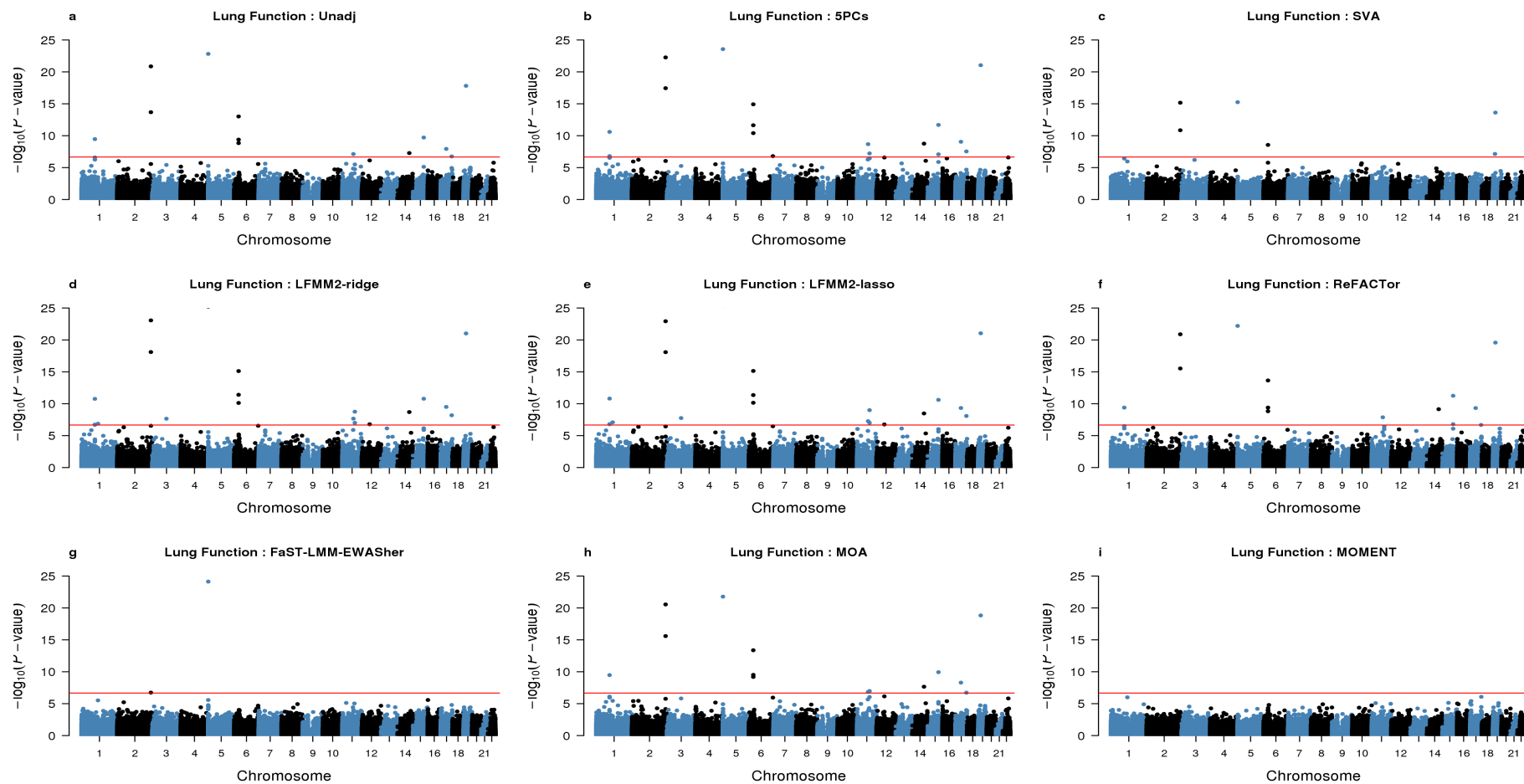
**Supplementary Figure 10** Comparison between the result from MOA/MOMENT analysis of the whole sample and that from a meta-analysis of summary statistics from MOA/MOMENT analyses of LBC1936 and LBC1921 across 100 simulation replicates. (a) Pearson correlation between the result from MOA of the whole sample and the meta-analysis of summary statistics from MOA. (b) Pearson correlation between the result from MOMENT of the whole sample and the meta-analysis of summary statistics from MOMENT. (c) Kolmogorov–Smirnov distance between the result from MOA of the whole sample and the meta-analysis of summary statistics from MOA. (d) Kolmogorov–Smirnov distance between the result from MOMENT of the whole sample and the meta-analysis of summary statistics from MOMENT.



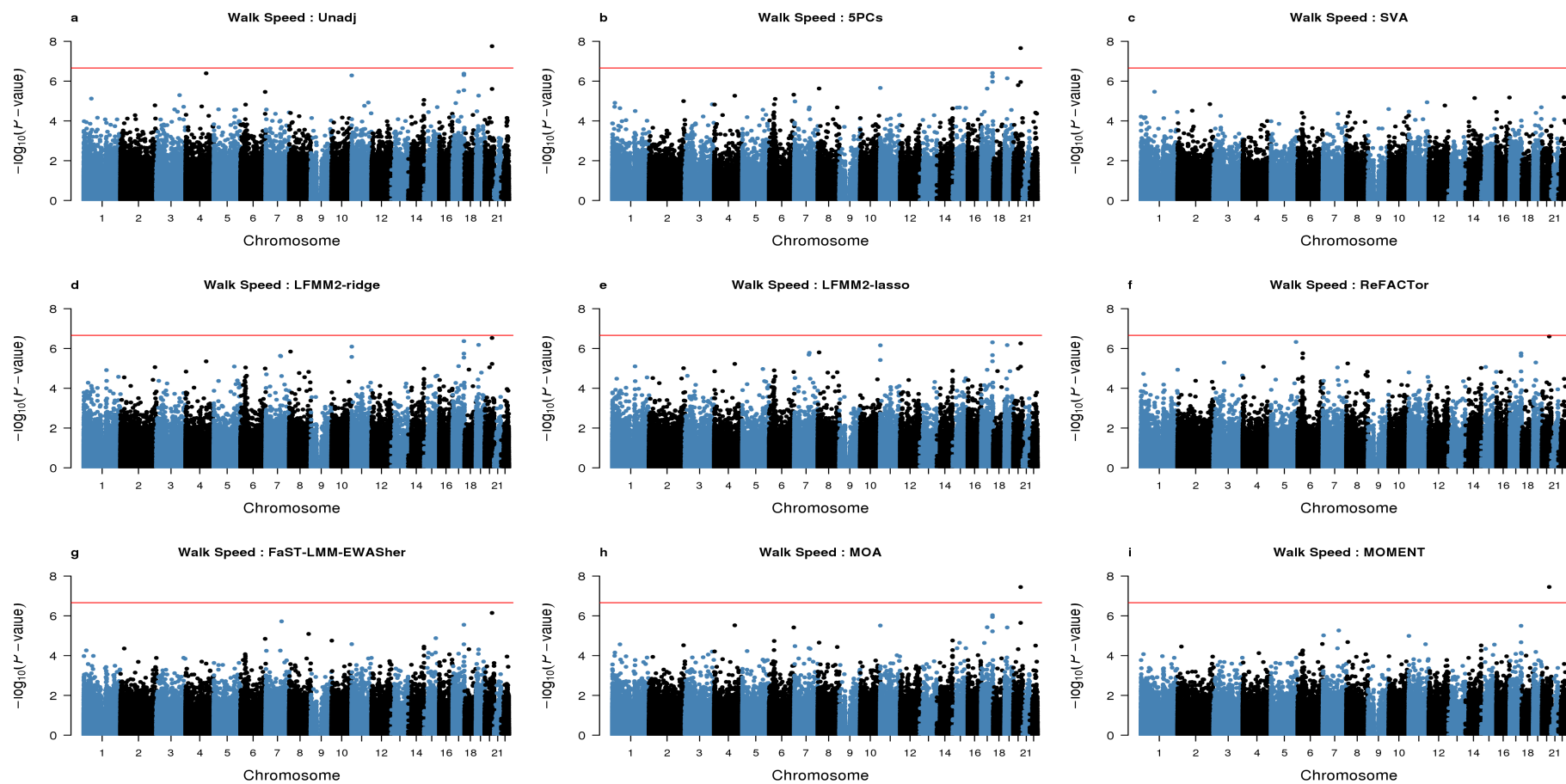
**Supplementary Figure 11** Manhattan plots of association p-values from 9 MWAS methods for BMI in LBC. The red horizontal line represents the genome-wide significance level.



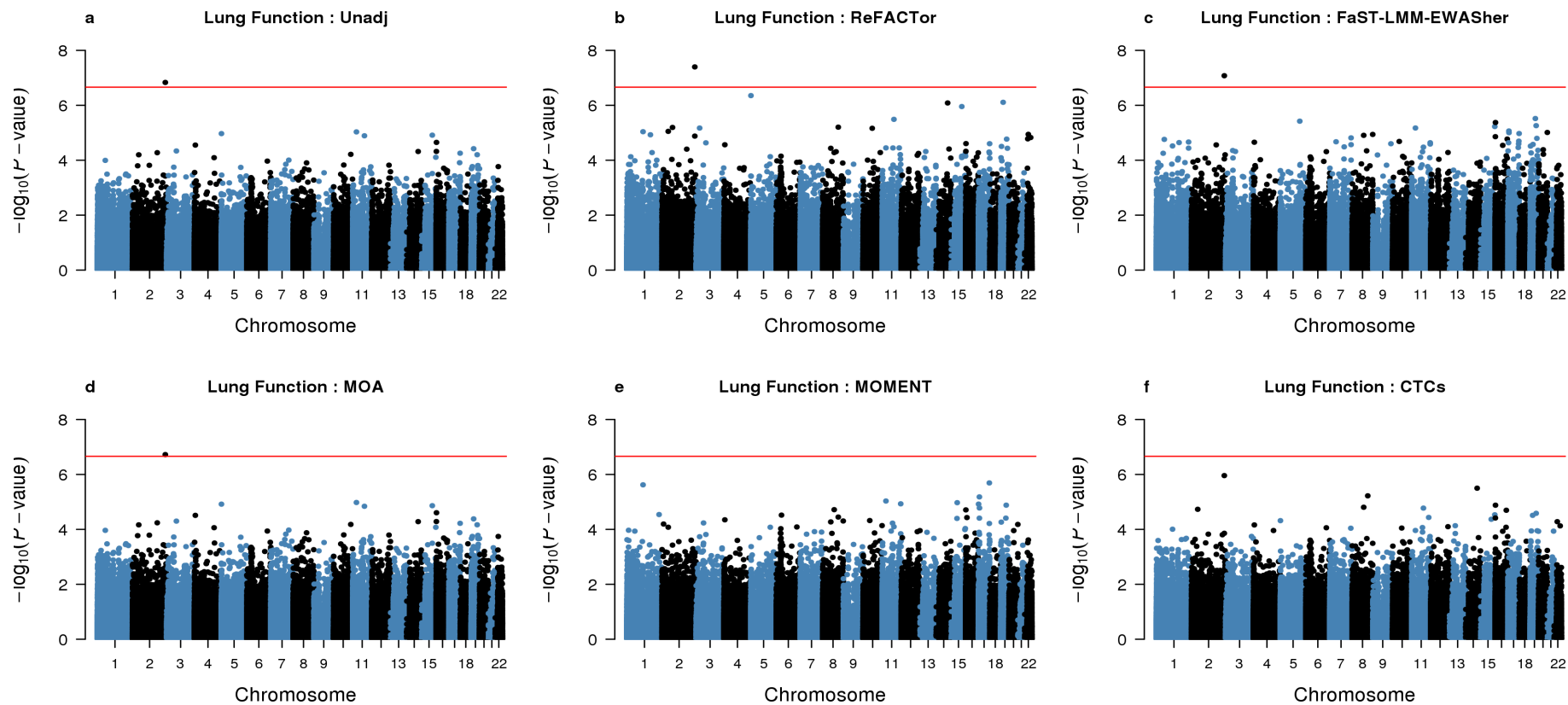
**Supplementary Figure 12** Manhattan plots of association p-values from 9 MWAS methods for height in LBC.



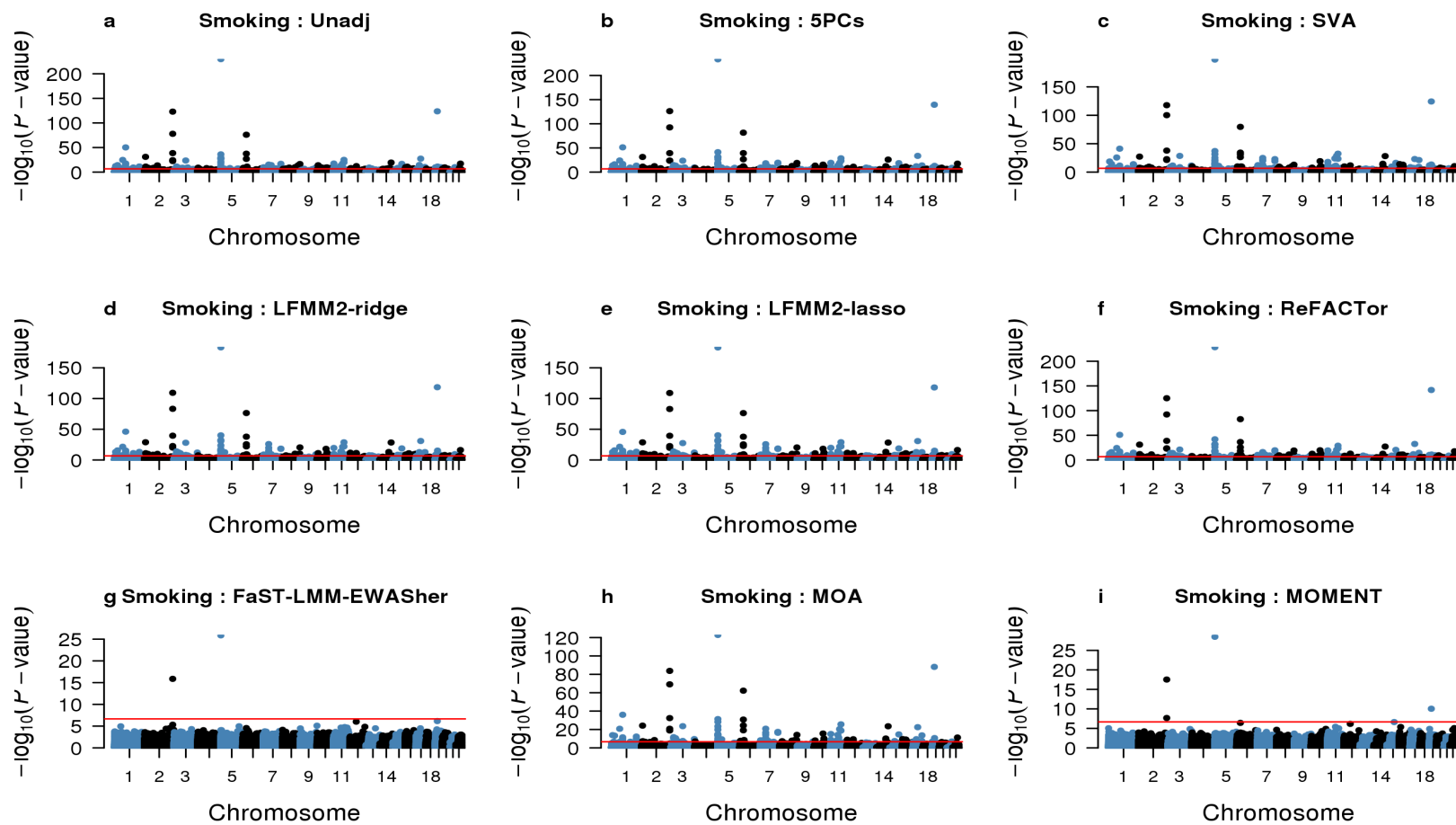
**Supplementary Figure 13** Manhattan plots of association p-values from 9 MWAS methods for lung function in LBC.



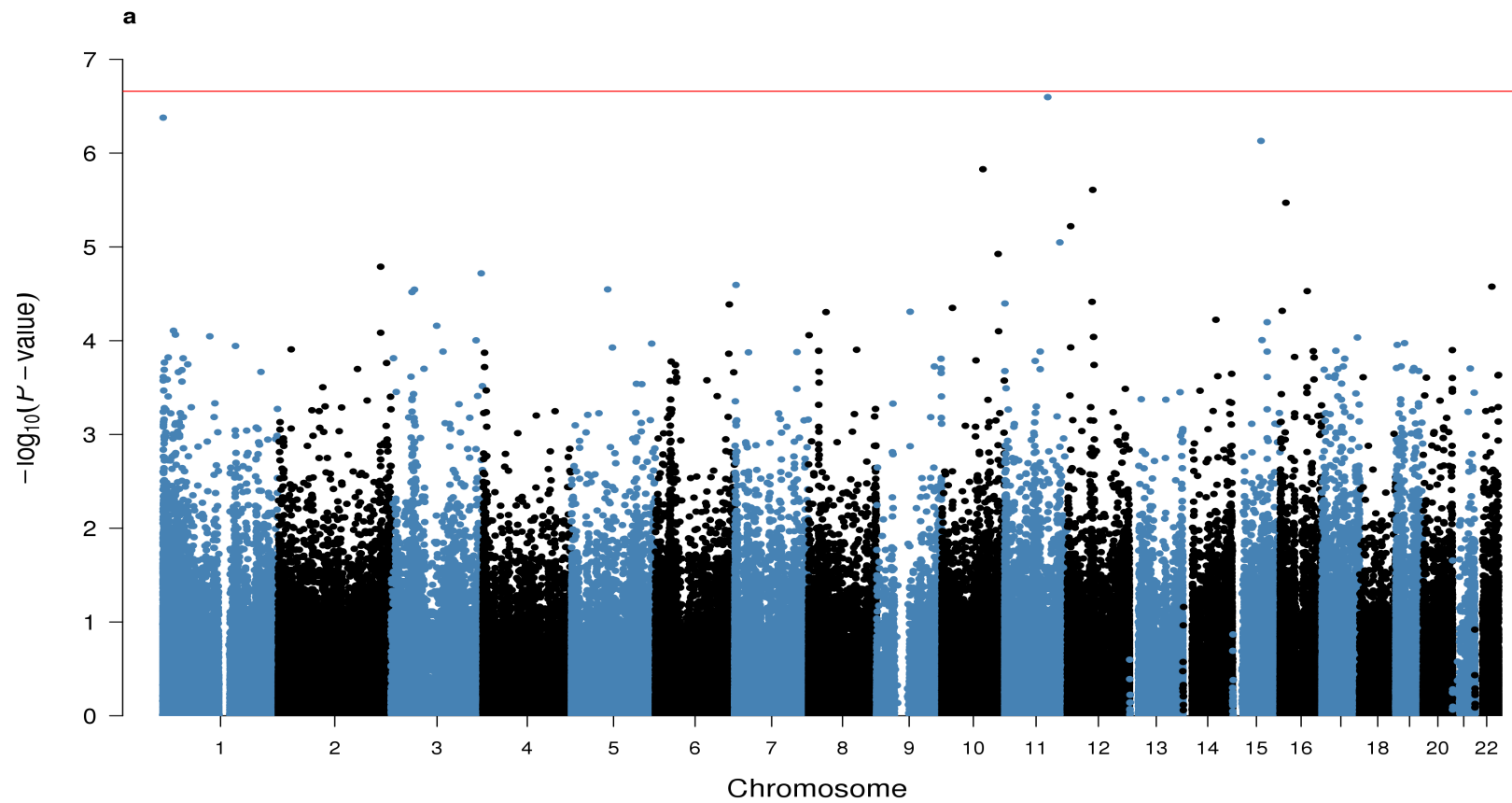
**Supplementary Figure 14** Manhattan plots of association p-values from 9 MWAS methods for walking speed in LBC.



**Supplementary Figure 15** Manhattan plots of association p-values from 6 MWAS methods for lung function with smoking status fitted as a fixed covariate in LBC.

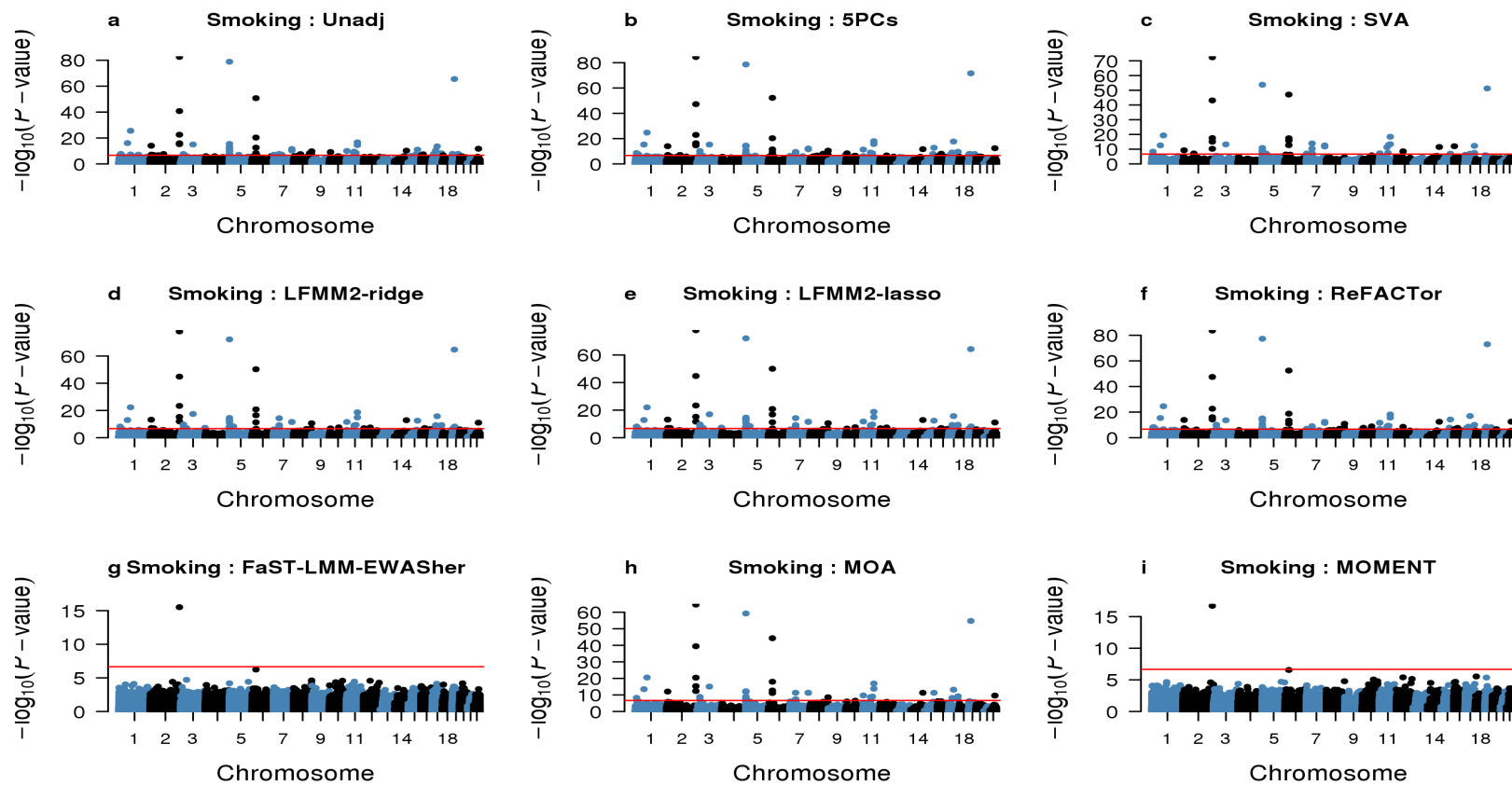


**Supplementary Figure 16** Manhattan plots of association p-values from 9 MWAS methods for a categorical phenotype of smoking status (coded as 0, 1 and 2 for non-smoker, former smoker and current smoker) in LBC.

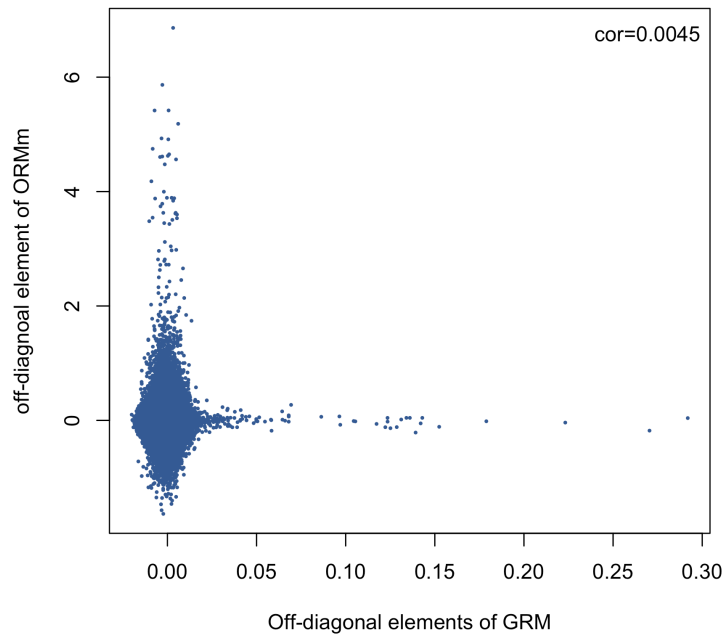


**Supplementary Figure 17** Manhattan plot of association p-values from MOA for a categorical phenotype (coded as 0, 1 or 2) of smoking status with the top 4 MOMENT signals fitted as fixed covariates.

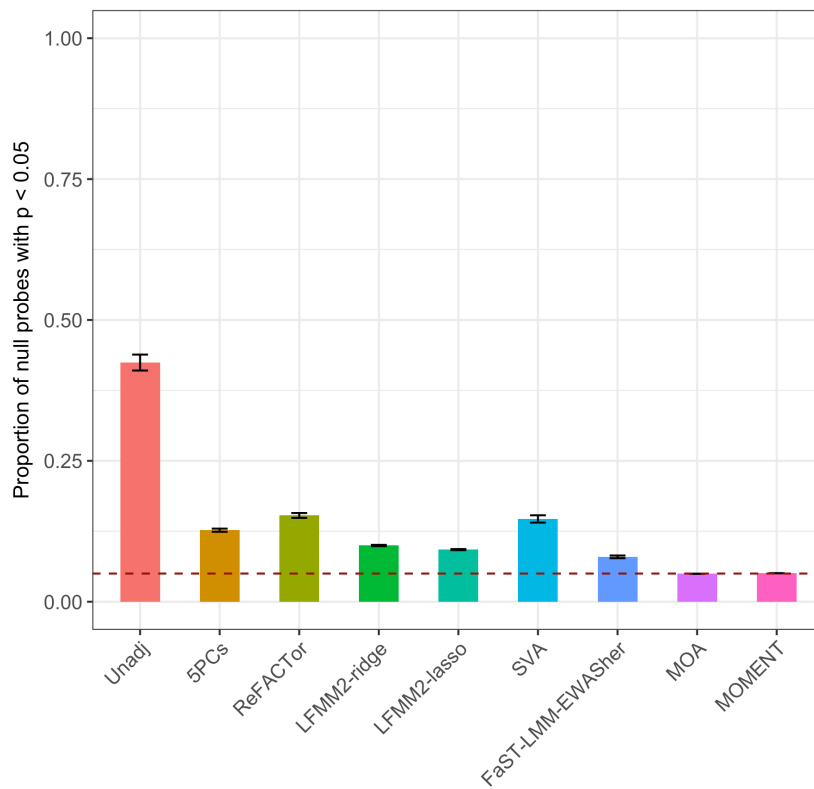




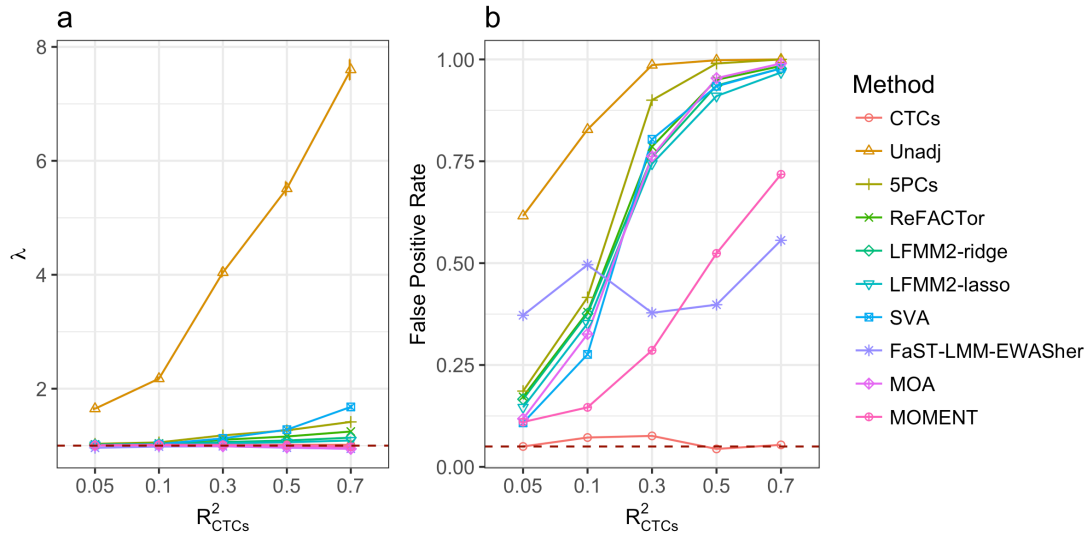
**Supplementary Figure 18** Manhattan plots of association p-values from 9 MWAS methods for a binary phenotype of smoking status (coded as 0 and 1 for non-smoker and former smoker or current smoker) in LBC.



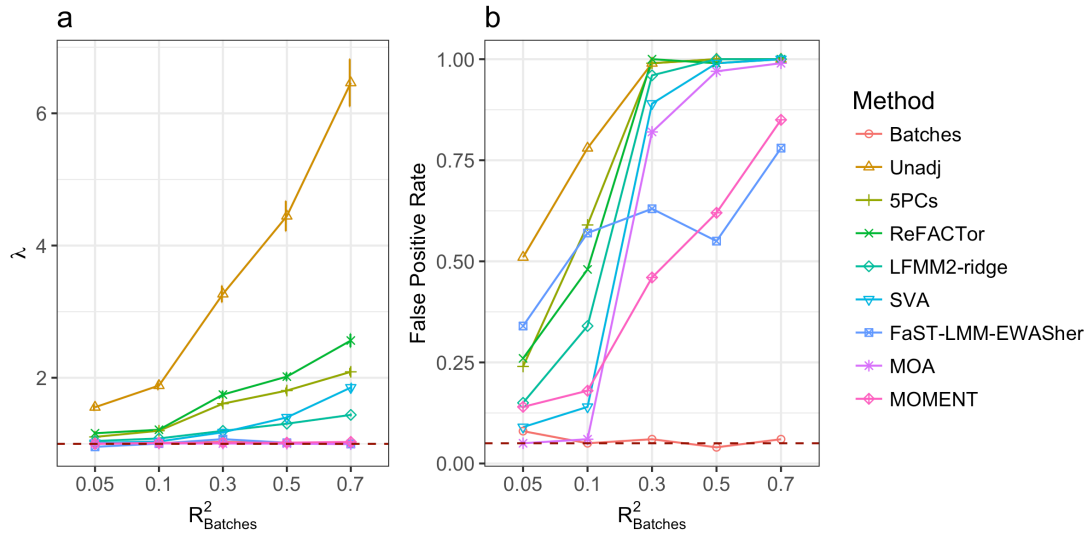
**Supplementary Figure 19** Correlation of the off-diagonal elements between GRM and ORM computed from genetic and DNAm data in LBC.



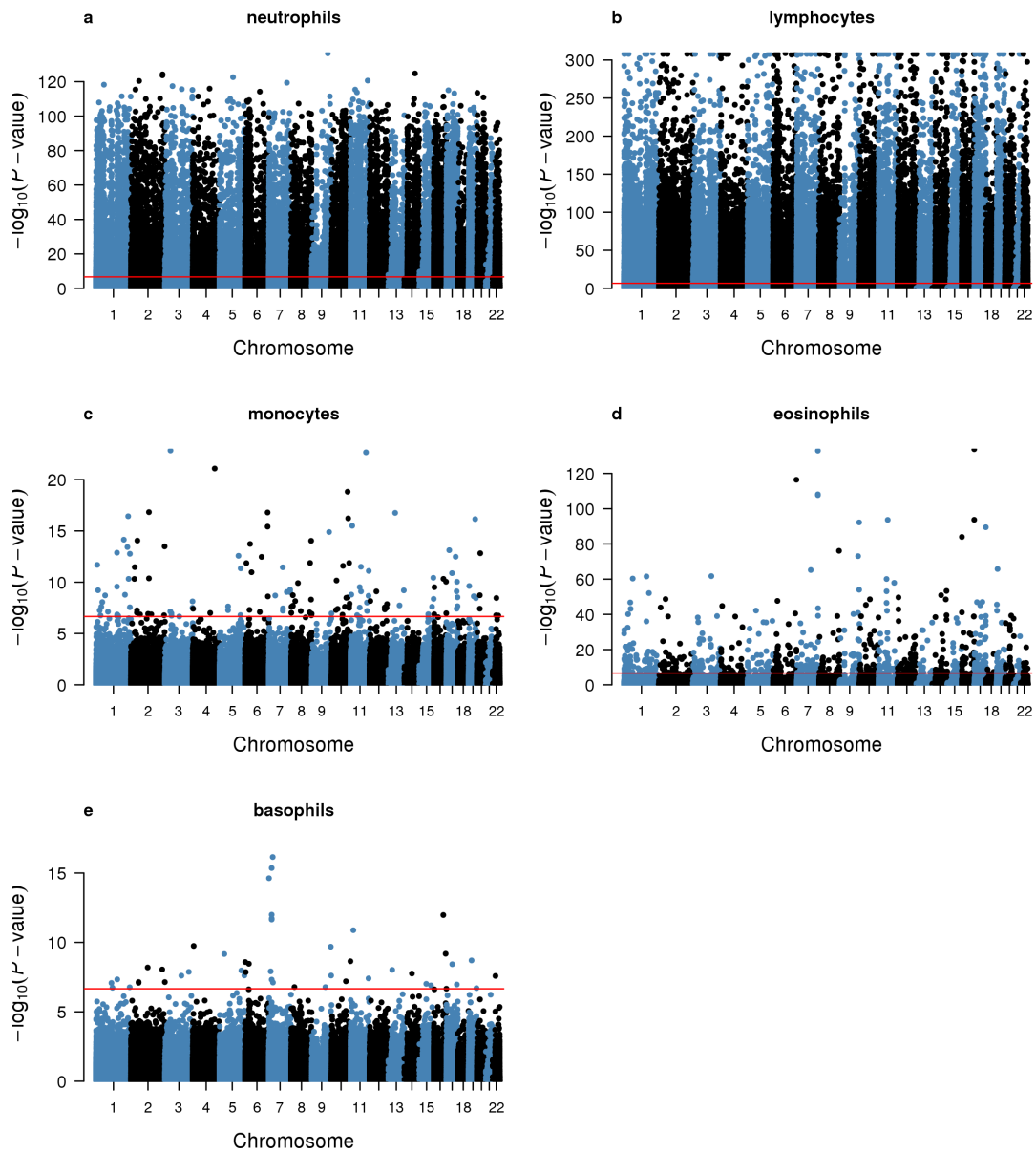
**Supplementary Figure 20** Proportion of null probes with  $P_{\text{MWAS}} < 0.05$  in simulation scenario 1. Each column represents the mean of proportion of null probes from a method across 100 simulation replicates with an error bar representing +/- SE of the mean.



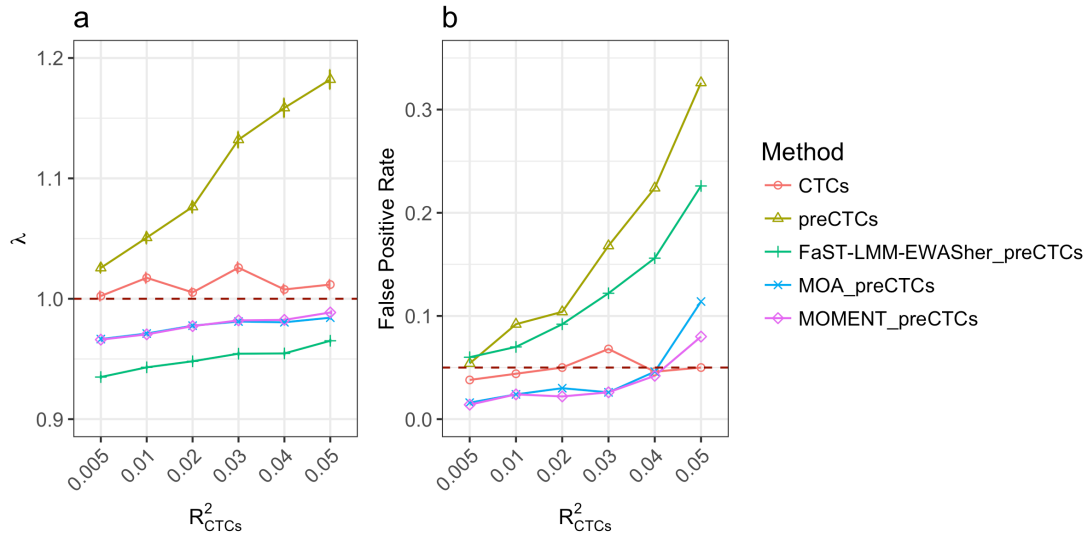
**Supplementary Figure 21** Genomic inflation factor and false positive rate for the MWAS methods in simulation scenario 2 with large  $R^2_{CTCs}$  (from 0.05 to 0.7). Shown on the horizontal axis are the  $R^2_{CTCs}$  values used to simulate the phenotype. (a) Each dot represents the mean  $\lambda$  value from 1000 simulation replicates given a specific  $R^2_{CTCs}$  value for a method with an error bar representing +/- the SE of the mean. (b) Each dot represents the false positive rate, calculated as the proportion of simulation replicates with one or more null probes detected at a genome-wide significance level.



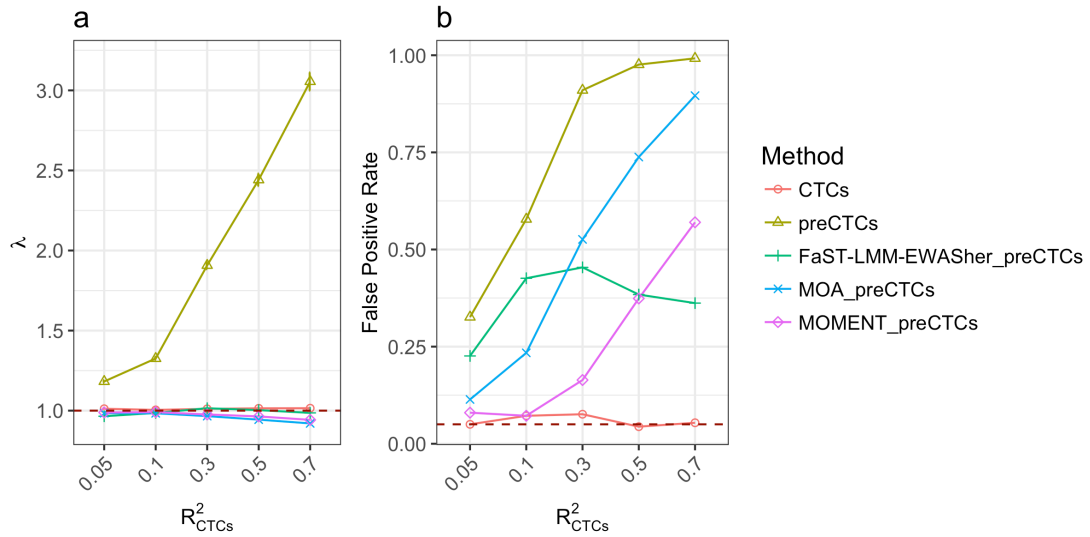
**Supplementary Figure 22** Genomic inflation factor and false positive rate for the MWAS methods in simulation scenario 2 with large  $R^2_{\text{batch}}$  (from 0.05 to 0.7). Shown on the horizontal axis are the  $R^2_{\text{batch}}$  values used to simulate the phenotype. (a) Each dot represents the mean  $\lambda$  value from 100 simulation replicates given a specific  $R^2_{\text{batch}}$  value for a method with an error bar representing +/- the SE of the mean. (b) Each dot represents the false positive rate.



**Supplementary Figure 23** Manhattan plots of association p-values from linear regression for 5 CTCs. DNAm probe measures were adjusted for age, sex, experimental batches, and smoking status.

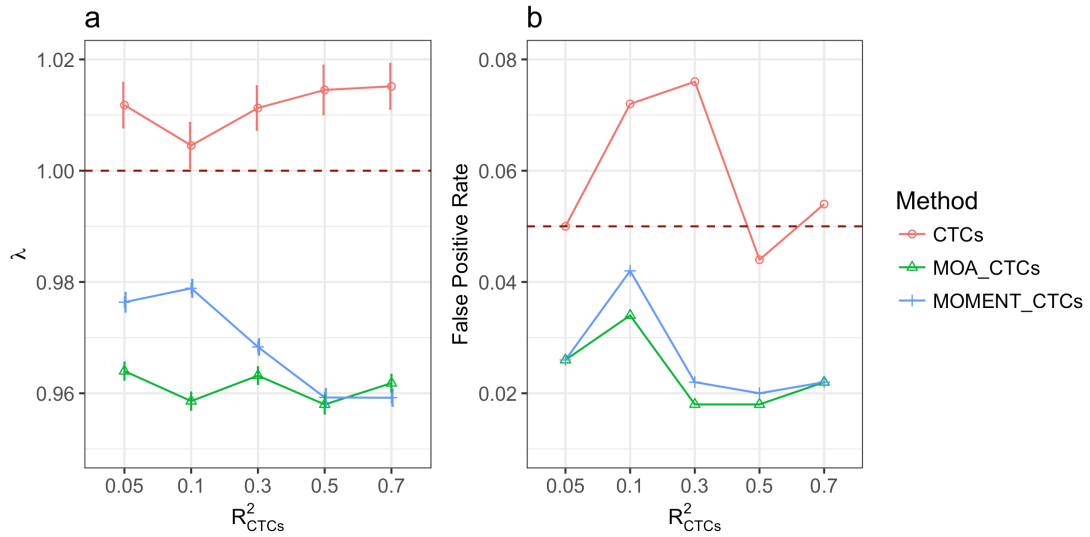


**Supplementary Figure 24** Genomic inflation factor and false positive rate for the MWAS methods with the measured and predicted CTCs fitted as covariates in simulation scenario 2. (a) Mean  $\lambda$  value from 1000 simulation replicates given a specific  $R^2_{CTCs}$  value for a method with an error bar representing +/- the SE of the mean. (b) False positive rate. CTCs: linear regression with the measured CTCs fitted as covariates. “preCTCs” or “\_preCTCs”: analysis with the predicted CTCs fitted as covariates.

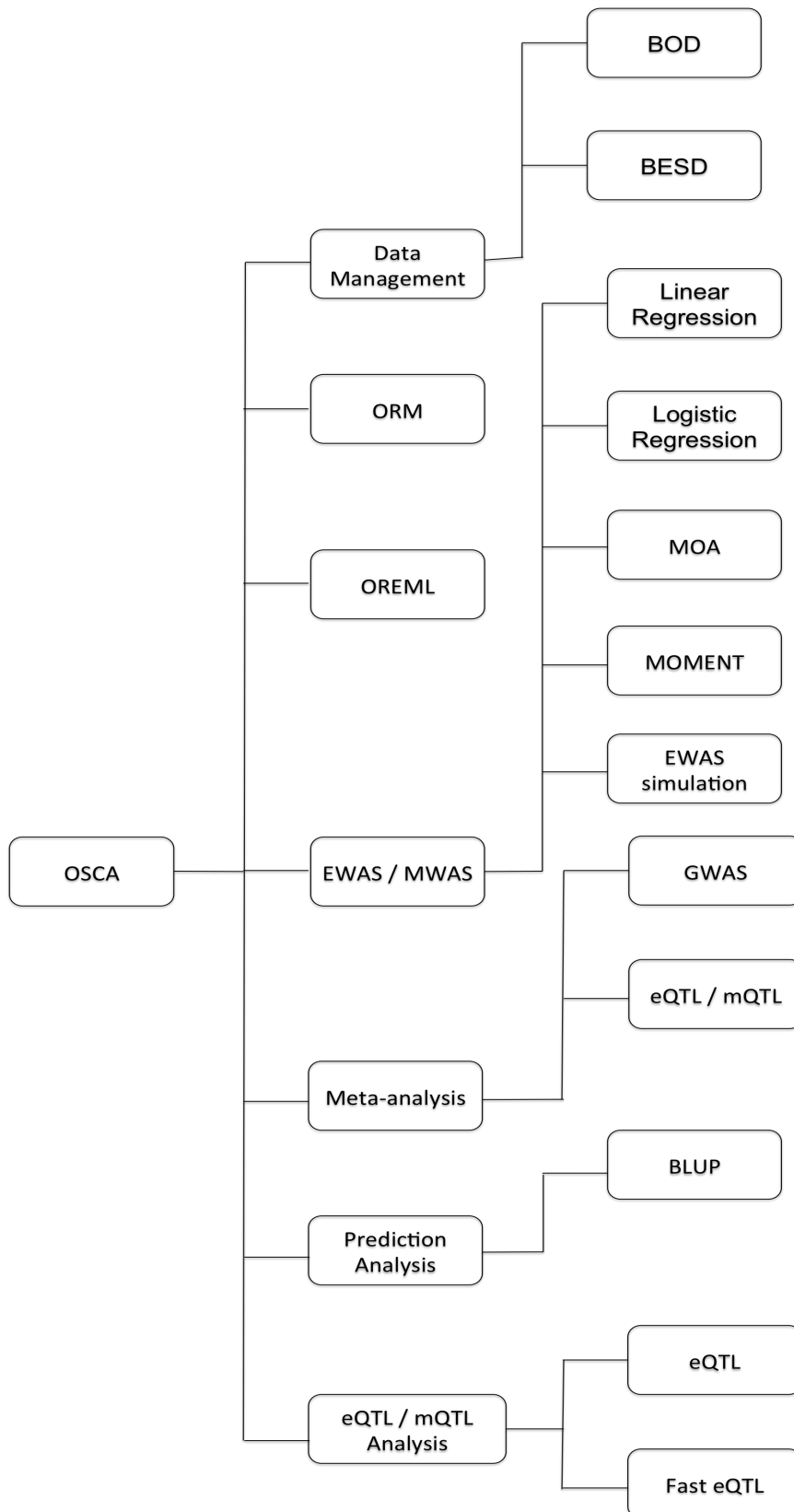


**Supplementary Figure 25** Genomic inflation factor and false positive rate for the MWAS methods with the predicted CTCs fitted as covariates in simulation scenario 2 with large  $R^2_{CTCs}$  (ranging from 0.05 to 0.7). (a) Mean  $\lambda$  value from 1000 simulation replicates with an error bar representing +/- the SE of the mean. (b) False positive rate. CTCs: linear regression with the measured CTCs fitted as covariates. “preCTCs” or “\_preCTCs”: analysis with the predicted CTCs fitted as covariates.





**Supplementary Figure 26** Genomic inflation factor and false positive rate for MOA and MOMENT with the measured CTCs fitted as covariates in simulation scenario 2 ( $R^2_{CTCs}$  ranging from 0.05 to 0.7). (a) Mean  $\lambda$  value from 1000 simulation replicates with an error bar representing  $\pm$  SE of the mean. (b) False positive rate. CTCs: linear regression with the measured CTCs fitted as covariates. MOA\_CTCs (or MOMENT\_CTCs): MOA (or MOMENT) analysis with the measured CTCs fitted as covariates.



**Supplementary Figure 27** Schematic diagram of OSCA

**Supplementary Table 1** Summary of the results from all the MWAS methods in simulation scenario 1

	100 Causal Probes				Odd chromosomes				Even chromosomes (null)				$\bar{D}$	s.e.m.	FPR	Power
	$\overline{\chi^2}$	s.e.m.	$\overline{\chi_{adj}^2}$	s.e.m.	$\overline{\chi^2}$	s.e.m.	$\bar{\lambda}$	s.e.m.	$\overline{\chi^2}$	s.e.m.	$\bar{\lambda}$	s.e.m.				
Unadjusted	15.60	0.769	2.41	0.076	8.78	0.672	7.92	0.56	8.58	0.66	7.67	0.532	0.405	0.013	1.00	0.17
5PCs	7.71	0.087	4.76	0.045	1.70	0.030	1.65	0.024	1.67	0.028	1.63	0.023	0.118	0.003	0.97	0.89
ReFACTor	8.00	0.091	4.34	0.062	1.93	0.044	1.90	0.045	1.91	0.044	1.90	0.045	0.149	0.005	0.99	0.81
LFMM2-ridge	7.42	0.065	5.28	0.04	1.43	0.010	1.41	0.010	1.42	0.010	1.41	0.009	0.083	0.002	0.92	0.93
LFMM2-lasso	7.07	0.061	5.25	0.041	1.37	0.008	1.35	0.008	1.36	0.008	1.35	0.008	0.073	0.001	0.82	0.93
SVA	8.52	0.153	4.92	0.087	2.00	0.085	1.83	0.064	1.97	0.081	1.81	0.061	0.134	0.007	0.96	0.80
FaST-LMM- EWASher	6.43	0.132	5.15	0.054	1.26	0.020	1.25	0.020	1.25	0.020	1.24	0.019	0.054	0.003	0.63	0.94
MOA	6.06	0.05	6.08	0.051	1.00	0.001	1.00	0.001	1.00	0.001	1.00	0.001	0.002	4e-4	0.10	0.98
MOMENT	5.46	0.05	5.42	0.051	1.01	0.001	1.01	0.001	1.01	0.001	1.01	0.001	0.004	5e-4	0.03	0.95

$\overline{\chi^2}$ : mean chi-squared value.

s.e.m.: standard error of the mean.

$\overline{\chi_{adj}^2}$ : mean chi-squared value adjusted by the genome inflation factor of the null SNPs on the even chromosomes.

$\bar{\lambda}$ : mean genome inflation factor.

$\bar{D}$ : Kolmogorov-Smirnov statistic to measure deviation of the p-value distribution from the expected distribution under the null.

**Supplementary Table 2** Summary of the results from all the MWAS methods in simulation scenario 3

	100 Causal Probes				The target odd chromosomes				The even chromosomes				$\bar{D}$	s.e.m.	FPR	Power
	$\overline{\chi^2}$	s.e.m.	$\overline{\chi_{adj}^2}$	s.e.m.	$\overline{\chi^2}$	s.e.m.	$\bar{\lambda}$	s.e.m.	$\overline{\chi^2}$	s.e.m.	$\bar{\lambda}$	s.e.m.				
Unadjusted	15.42	0.746	2.43	0.077	8.99	0.683	7.77	0.566	8.80	0.664	7.57	0.547	0.400	0.013	1.00	0.14
5PCs	7.63	0.086	4.76	0.042	1.67	0.021	1.63	0.018	1.64	0.020	1.61	0.017	0.116	0.003	0.96	0.88
ReFACTor	7.96	0.087	4.27	0.064	1.94	0.041	1.93	0.043	1.93	0.041	1.92	0.044	0.152	0.005	0.99	0.72
LFMM2-ridge	7.41	0.070	5.28	0.039	1.43	0.011	1.41	0.010	1.42	0.010	1.40	0.009	0.083	0.002	0.94	0.97
LFMM2-lasso	7.05	0.065	5.26	0.039	1.37	0.009	1.35	0.008	1.35	0.009	1.34	0.008	0.072	0.001	0.80	0.98
SVA	8.57	0.142	4.93	0.079	2.07	0.096	1.85	0.068	2.03	0.092	1.83	0.066	0.136	0.007	0.96	0.85
FaST-LMM- EWASher	6.18	0.127	5.08	0.055	1.23	0.021	1.22	0.020	1.22	0.020	1.25	0.020	0.048	0.004	0.53	0.93
MOA	6.07	0.049	6.09	0.050	1.01	0.001	1.00	0.001	1.00	0.001	1.00	0.001	0.002	4e-4	0.11	0.98
MOMENT	5.48	0.054	5.45	0.053	1.01	0.001	1.01	0.001	1.01	0.001	1.001	0.001	0.004	5e-4	0.08	0.95

$\overline{\chi^2}$ : mean chi-squared value.

s.e.m.: standard error of the mean.

$\overline{\chi_{adj}^2}$ : mean chi-square value adjusted by the genome inflation factor of the null SNPs on the even chromosomes.

$\bar{\lambda}$ : mean genome inflation factor.

$\bar{D}$ : Kolmogorov-Smirnov statistic to measure deviation of the p-value distribution from the expected distribution under the null.

**Supplementary Table 3** Genome-wide significant DNAm probes identified by MOA for three traits in LBC

<b>Trait</b>	<b>CHR</b>	<b>Probe</b>	<b>bp</b>	<b>Gene</b>	<b><math>\beta</math></b>	<b>SE</b>	<b><i>P</i></b>	<b>#Methods</b>
BMI	17	cg11202345	76976057	LGALS3BP	4.50	0.74	1.07E-09	9
BMI	22	cg20496314	39759864	SYNGR1	3.78	0.69	5.29E-08	5
Lung Function	5	cg05575921	373378	AHRR	2.76	0.28	1.69E-22	8
Lung Function	2	cg05951221	233284402	ALPPL2	4.19	0.44	2.83E-21	8
Lung Function	19	cg03636183	17000585	F2RL3	4.00	0.44	1.50E-19	7
Lung Function	2	cg01940273	233284934	ALPPL2	4.19	0.51	2.57E-16	7
Lung Function	6	cg06126421	30720080	IER3	2.67	0.35	4.27E-14	7
Lung Function	15	cg00310412	74724918	SEMA7A	4.86	0.75	1.16E-10	6
Lung Function	6	cg15342087	30720209	IER3	5.51	0.88	3.08E-10	6
Lung Function	1	cg09935388	92947588	GFI1	2.18	0.35	3.34E-10	6
Lung Function	6	cg24859433	30720203	IER3	4.74	0.77	6.46E-10	6
Lung Function	17	cg19572487	38476024	RARA	2.74	0.47	5.05E-09	6
Lung Function	14	cg13525276	81426012	TSHR	-2.40	0.43	2.22E-08	6
Lung Function	11	cg11660018	86510915	PRSS23	3.24	0.61	1.04E-07	4
Lung Function	11	cg20886049	76493545	TSKU	2.93	0.56	1.46E-07	4
Lung Function	17	cg18181703	76354621	SOCS3	3.15	0.60	1.91E-07	6
Walk Speed	20	cg05232694	48809539	CEBPB-AS1	-1.66	0.30	3.58E-08	5

#Methods: number of methods (out of a total of 9) by which the probe was identified at a genome-wide significance level.

**Supplementary Table 4** Number of genome-wide significant DNAm probes identified by different MWAS methods with smoking status fitted as a covariate for lung function

	Lung Function	
	Lambda	Number of significant associations
Unadj	0.891	1
5PCs	1.064	1
ReFACTor	1.049	3
FaST-LMM-EWASher	0.996	1
MOA	0.893	1
CTCs	0.945	0

Unadj: linear regression with smoking status fitted as a covariate. 5PCs: linear regression with the top 5 PCs and smoking status fitted as covariates. ReFACTor: linear regression with 5 sparse PCs from ReFACTor and smoking status fitted as covariates. FaST-LMM-EWASher: FaST-LMM-EWASher with smoking status fitted as a covariate. MOA: MOA with smoking status fitted as a covariate. CTCs: linear regression with smoking status and 5 cell types fitted as covariates.

**Supplementary Table 5** The accuracy of predicting smoking status by DNAm probes in the LBC cohorts.

	3 probes identified by MOMENT	89 probes identified by MOA	149 probes identified by linear regression
AUC	0.895	0.843	0.801

Note: 1) The LBC1936 cohort ( $n = 906$ ) was used as the training set and the LBC1921 cohort ( $n = 436$ ) as used as the test set. 2) The numbers of probes detected by the three methods in the training set were smaller than those in the whole set because of the smaller sample size of the training set than the whole set. 3) The area under the ROC curve (AUC) for the categorical phenotype (coded as 0, 1 or 2) was computed using the R package pROC [5].

**Supplementary Table 6** Estimated proportion of variance in a phenotype captured by all DNAm probes by OSCA-OREML from 500 simulations based on the LBC data

	NULL		uni (0.1)		multi50 (0.2)		multi500 (0.5)	
	Mean $\hat{\rho}^2$	s.e.m.	Mean $\hat{\rho}^2$	s.e.m.	Mean $\hat{\rho}^2$	s.e.m.	Mean $\hat{\rho}^2$	s.e.m.
Probes standardised	0.0051	0.0008	0.098	0.0023	0.198	0.0022	0.501	0.0024
Probes centralised	0.0048	0.0009	0.106	0.0024	0.210	0.0023	0.511	0.0024

Probes standardised: each probe is standardised across all individuals to compute the ORM.

Probes centralised: each probe is centralised across all individuals to compute the ORM.

NULL: the phenotype was simulated from a standard normal distribution with no probe effects.

uni (0.1): randomly sample 1 probe as the causal probe to simulate the phenotype with  $\rho^2 = 0.1$ .

multi50 (0.2): randomly sample 50 probes as the causal probes to simulate the phenotype with  $\rho^2 = 0.2$ .

multi500 (0.5): randomly sample 500 probes as the causal probes to simulate the phenotype with  $\rho^2 = 0.5$ .

s.e.m.: standard error of the mean.



**Supplementary Table 7** Proportion of phenotypic variance explained by all the DNA methylation probes estimated by OSCA-OREML for height and BMI in LBC.

	Height				BMI			
	$\hat{h}_{\text{SNP}}^2$	$\hat{\rho}_{me}^2$	Joint $\hat{h}_{\text{SNP}}^2$	Joint $\hat{\rho}_{me}^2$	$\hat{h}_{\text{SNP}}^2$	$\hat{\rho}_{me}^2$	Joint $\hat{h}_{\text{SNP}}^2$	Joint $\hat{\rho}_{me}^2$
Probes standardised	0.39 (0.25)	-0.0050 (0.0086)	0.39 (0.25)	-0.0056 (0.0083)	0.42 (0.25)	0.065 (0.038)	0.40 (0.24)	0.065 (0.038)
Probes centralised		0.0068 (0.02)	0.39 (0.25)	0.0063 (0.02)		0.075 (0.044)	0.39 (0.24)	0.074 (0.044)

$\hat{h}_{\text{SNP}}^2$ : estimate of the proportion of variance explained by all the SNPs (i.e. SNP-based heritability).

$\hat{\rho}_{me}^2$ : estimate of the proportion of variance captured by all the DNAm probes.

Joint  $\hat{h}_{\text{SNP}}^2$ : proportion of variance explained by all the SNPs estimated when the GRM and MRM are fitted jointly in OSCA-OREML.

Joint  $\hat{\rho}_{me}^2$ : proportion of variance captured by all the DNAm probes estimated when the GRM and MRM are fitted jointly in OSCA-OREML.

**Supplementary Table 8** Summary descriptive of phenotypes for the unrelated individuals in LBC

	<b>LBC1936</b>	<b>LBC1921</b>
Sample size	906	436
Age (years)	69.60 (0.58)	79.14 (0.83)
Percentage of Female	49.45%	60.32%
BMI (kg/m <sup>2</sup> )	27.75 (4.37)	26.18 (4.05)
Height (cm)	166.37 (8.96)	163.00 (9.25)
Lung Function (L)	2.36 (0.69)	1.87 (0.63)
Walk Speed (seconds)	3.86 (1.22)	4.75 (1.98)

**Supplementary Table 9** A summary of the sample sizes used in different analyses in LBC

	<b>LBC1936 (<i>n</i> = 920)</b>	<b>LBC1921 (<i>n</i> =446)</b>
Unrelated individuals	1,342	
Sample size for Height	1,338	
Sample size for BMI	1,337	
Sample size for lung function	1,336	
Sample size for walk speed	1,332	
Number of individuals with CTC data	1,319	

**Supplementary Table 10** Associations of the 5 cell types ( $x$ ) with the 4 traits ( $y$ ) in LBC

	BMI				Height				Lung Function				Walk Speed			
	$\beta$	SE	Adjusted $R^2$	$n$	$\beta$	SE	Adjusted $R^2$	$n$	$\beta$	SE	Adjusted $R^2$	$n$	$\beta$	SE	Adjusted $R^2$	$n$
Neutrophils	-0.032	0.02	0.016	1315	0.009	0.02	0.0011	1316	-0.059	0.02	0.047	1314	0.034	0.02	0.0139	1310
Lymphocytes	0.027	0.02			-0.030	0.02			-0.032	0.02						
Monocytes	0.403	0.16			-0.224	0.16			-0.657	0.16						
Eosinophils	0.276	0.19			-0.206	0.19			-0.489	0.19						
Basophils	2.31	0.72			0.38	0.72			-0.939	0.70						

**Supplementary Table 11** Descriptive summary of each wave of the LBC data

	Total sample size	Female sample size	Male sample size	Mean age	Median age
LBC21_WAVE1	436	263	173	79.1	79.2
LBC21_WAVE3	174	94	80	86.7	86.6
LBC21_WAVE4	82	44	38	90.1	90.1
LBC36_WAVE1	906	448	458	69.6	69.6
LBC36_WAVE2	801	381	420	72.5	72.6
LBC36_WAVE3	619	296	323	76.3	76.3

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