1	Lifestyle and Genetic Factors Modify Parent-of-Origin Effects on the
2	Human Methylome
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4	Yanni Zeng ^{1,2,3} *, Carmen Amador ⁴ , Chenhao Gao ¹ , Rosie M. Walker ^{5,6} , Stewart W. Morris ⁵ ,
5	Archie Campbell ⁵ , Azra Frkatović ⁷ , Rebecca A Madden ⁸ , Mark J. Adams ⁸ , Shuai He ⁹ ,
6	Andrew D Bretherick ⁴ Caroline Hayward ⁴ David I Porteous ⁵ James F Wilson ^{4,10} Kathryr
7	I Evans ⁵ Andrew M McIntosh ⁸ Pau Navarro 4† and Chris S Halev ^{4,11†}
8	L. Evans, Andrew W. Wennosh, I ad Wavarrov, and Chiris S. Harey
9	1. Faculty of Forensic Medicine, Zhongshan School of Medicine, Sun Yat-Sen University, Guangzhou
10	510080, China.
11	2. Guangdong Province Translational Forensic Medicine Engineering Technology Research Center,
12	Zhongshan School of Medicine, Sun Yat-Sen University, Guangzhou 510080, China.
13	3. Guangdong Province Key Laboratory of Brain Function and Disease, Zhongshan School of Medicine,
14	Sun Yat-Sen University, Guangzhou 510080, China.
15	4. MRC Human Genetics Unit, Institute of Genetics and Cancer, University of Edinburgh, Edinburgh, UK
16	5. Centre for Genomic and Experimental Medicine, Institute of Genetics and Cancer, University of
17	Edinburgh, Edinburgh, UK
18	6. Centre for Clinical Brain Sciences, Chancellor's Building, 49 Little France Crescent, Edinburgh
19	BioQuarter, Edinburgh, UK
20	7. Genos Glycoscience Research Laboratory, Borongajska cesta 83h, 10000 Zagreb, Croatia
21	8. Division of Psychiatry, University of Edinburgh, Edinburgh, United Kingdom
22	9. Sun Yat-sen University Cancer Center, State Key Laboratory of Oncology in South China,
23	Collaborative Innovation Center for Cancer Medicine, Guangdong Key Laboratory of Nasopharyngeal
24	Carcinoma Diagnosis and Therapy, Guangzhou, 510060, China
25	10. Centre for Global Health Research, Usher Institute, University of Edinburgh, Edinburgh, UK
26	11.Roslin Institute and Royal (Dick) School of Veterinary Studies, University of Edinburgh, Edinburgh,
27	UK
28	
29	* Corresponding author
30	zengyn5@mail.sysu.edu.cn
31	[†] equally contributed senior authors
32	chris.haley@ed.ac.uk, pau.navarro@ed.ac.uk
33	
34	Word counts: 2979 (exclude methods), 4470 (include methods)
35	

36 Abstract

37	Background: parent-of-origin effects (POE) play important roles in development and
38	complex disease and thus understanding their regulation and associated molecular and
39	phenotypic variation are warranted. Previous studies have mainly focused on the detection of
40	genomic regions or phenotypes regulated by POE. Understanding whether POE may be
41	modified by environmental or genetic exposures is important for understanding of the source
42	of POE-associated variation, but only a few case studies addressing these modifiable POE
43	exist.
44	Methods: in order to understand this high order of POE regulation, we screened 101 genetic
45	and environmental factors such as "predicted mRNA expression levels" of DNA
46	methylation/imprinting machinery genes and early/late lifestyle/environmental exposures.
47	POE-mQTL-modifier interaction models were proposed to test the potential of these factors
48	to modify POE at DNA methylation using data from Generation Scotland: The Scottish
49	Family Health Study(N=2315).
50	Results: a set of vulnerable/modifiable POE-CpGs were identified (modifiable-POE-
51	regulated CpGs, N=3). Four factors, "lifetime smoking status" and "predicted mRNA
52	expression levels" of TET2, SIRT1 and KDM1A, were found to significantly modify the POE
53	on the three CpGs in both discovery and replication datasets. Importantly, the POE on one of
54	the CpGs were modified by both genetic and environmental factors. We further identified
55	plasma protein and health-related phenotypes associated with the methylation level of one of
56	the identified CpGs.
57	Conclusions: the modifiable POE identified here revealed an important yet indirect path
58	through which genetic background and environmental exposures introduce their effect on
59	DNA methylation, motivating future comprehensive evaluation of the role of these modifiers
60	in complex diseases.

61 Keywords

62	parent-of-origin effect, imprinting, DNA methylation, interaction(modification) effect,
63	mQTL, DNA methylation machinery genes, smoking, lifestyle, environmental effect
64	
65	Key Messages
66	• Previous population studies showed that parent-origin-effects(POE) on human
67	methylome can be widespread and affect health-related traits and diseases.
68	• Whether the POE remained stable throughout the life or can be modified by genetic or
69	environmental factors were largely unknown.
70	• By systematically screening 101 genetic and environmental factors in a large
71	cohort(GS:SFHS) we provided the first population-level replicated evidence that
72	those measuring lifestyle (smoking) and predicted expression of DNA methylation- or
73	imprinting- machinery genes are amongst the factors that can modulate the POE of
74	mQTLs for a set of CpG sites.
75	• We found those modifiable-POE-regulated CpGs are also phenotypically relevant –
76	one is associated with the plasma levels of CLEC4C and health-related phenotypes
77	such as HDL levels.
78	• The modifiable POE identified here revealed an important yet indirect path through
79	which genetic background and environmental exposures introduce their effect on
80	DNA methylation and their potential phenotypic consequences. This also provided a
81	paradigm for further studies to explore how environmental and genetic effects can be
82	integrated at methylation level.
83	

84 Introduction

85 Illustrating the sources of variation in DNA methylation lays the foundation for 86 understanding epigenetic-based biomarkers for disease risk and progress prediction [1, 2]. 87 DNA methylation is known to be influenced by additive and non-additive genetic and 88 environmental factors [3-5]. As a special form of non-additive genetic effects, parent-of-89 origin effects (POE) on the human methylome manifest as differences in methylation levels 90 between the reciprocal heterozygotes of the mQTL depending on the allelic parent-of-origin 91 (Figure 1)[6]. Through selectively silencing the maternal or paternal allele, genomic 92 imprinting has been considered as the major driving force creating the POE phenomenon [6]. 93 We and others have shown that POE-influenced methylation sites are not rare, many are 94 regulated by mOTLs, and that they follow one of the three classical imprinting patterns: 95 parental, bipolar dominance and polar dominance (Figure 1) [4, 7, 8]. Although they only 96 comprise a small proportion of the genome, POE (imprinting)-regulated CpGs and genes 97 have been found to be important for developmental, metabolic and behavioral traits [4, 9]. 98 99 Despite their functional importance, the POE patterns in those POE (imprinting)-influenced

100 regions can fluctuate as a consequence of genetic and environmental variation. Previous 101 studies have reported that a large fraction of imprinted regions deviated from mono-allelic 102 expression and that birth phenotypes were associated with the extent of this deviation [10]. A 103 case study on an imprinting influenced long non-coding RNA, lncRNA nc886, found that the 104 imprinting status of this locus is tunable by both genetic variants and environmental factors 105 such as maternal nutrition and maternal age[11]. Importantly, the altered POE has phenotypic 106 consequences: loss of imprinting of nc886 in infants at birth resulted in increased body mass 107 index (BMI) in childhood [11]. For the majority of other POE-influenced regions, however, 108 whether POE are modifiable under certain conditions remains unknown. Here we aim to

- 109 explore modifiable POE, manifesting as the altered methylation difference between
- 110 reciprocal heterozygotes of the mQTL due to effects from certain genetic or environmental
- 111 modifiers (Figure 1), which potentially represents an important layer of POE-related
- 112 regulation requiring systematic examination.
- 113



114

115 Figure 1 Patterns of classical and modifiable parent-of-origin effect (POE) regulation on DNA methylation. X

116 axis: mQTL genotypes, left purple: paternal allele, right pink: maternal allele. Y axis: methylation level of the

regulated CpG. Upper panel: classical POE patterns including parental and complex (dominance) POE patterns.

- 118 Parental patterns show two levels of methylation depending on the expressed allele and the allelic effect.
- 119 Complex POE manifests as the two homozygous group having the same methylation level whereas the
- 120 heterozygous groups are different. Dashed box: difference between methylation level of heterozygous groups of
- 121 the mQTL is the hallmark of POE. Bottom: scenarios when the POE is modified by genetic or environmental
- 122 factors, leading to the alteration of POE for different levels of the modifier.

123

124	To search for modifiable POE on CpGs, a key question is which modifiers may have the
125	potential to regulate the POE. Genomic imprinting, which likely underlies the POE, involves
126	complex and multi-stage DNA methylation reprogramming processes, from the slow erasure
127	of methylation at primordial germ cell stage, to the establishment of imprinted methylation
128	signatures at germ cell stage, followed by pre-implantation maintenance of the imprinted
129	methylation pattern during the global demethylation event, which is subsequently maintained
130	post-implantation [12]. A number of gametic and zygotic genetic factors were found to be
131	involved in these processes, such as those functioning in folate metabolism, the DNA
132	methylation machinery (writers, erasers) and the proteins with which they interact [12].
133	Additionally, imprinting-related processes have also been found to be sensitive to
134	environmental insults, such as the stress induced by assisted reproductive technologies,
135	nutritional deficiency and adverse exposures [12-14]. Given that previous studies of
136	modifiers of genomic imprinting were mostly case studies of individual factors, a systematic
137	and population-wide scanning for genetic and environmental modifiers of POE is essential to
138	fully characterize POE regulation.
139	

140 In this study, we used Generation Scotland: The Scottish Family Health Study (GS:SFHS), a 141 large family-based population cohort with extensive environmental and phenotypic records 142 [15, 16], genome-wide genotypes and DNA methylation data [17, 18], to identify genetic and 143 environmental factors that modify the POE on the human methylome (Figure 1). Figure 2 144 illustrates the study design. Based on the 2372 previously identified independent mQTL-145 CpGs pairs containing mQTLs with parent-of-origin effect (1895 independent mQTLs; 381211 SNPs in total) and their regulated CpGs (399 independent CpGs; 586 CpGs in 146 147 total)[4], we proposed an interaction model which tests for significant interaction effects

- 148 (Figure 1) between each of the 101 candidate environmental/genetic modifiers available in
- 149 GS:SFHS and the parent-of-origin effect of each mQTL on the corresponding targeted CpG.
- 150 Significant results from discovery samples (GS:SFHS set1, N=1663) were tested in
- 151 replication samples (GS:SFHS set2, N=652). Plasma protein levels and health-related
- 152 phenotypes associated with the modifiable-POE-regulated CpGs were also identified,
- 153 suggesting phenotypic relevance for this special class of CpGs.
- 154



156	Figure 2 Design	of the study. Cov:	covariates fitted in the model.	Zeng et al.(2019): the	study which reported
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157 CpGs regulated by POE and the mQTLs that induce the POE for 586 CpGs (reference 4).

158

159 Methods

160 **Population sample**

- 161 Generation Scotland: the Scottish Family Health Study (GS:SFHS) is a deeply phenotyped
- 162 population cohort [15, 16] with genome-wide genotypes available for 19994 participants,
- among which 9526 also have DNA methylation data available[15, 17, 18]. We used
- 164 GS:SFHS to identify CpGs regulated by modifiable POE, and to explore phenotypes
- 165 associated with those CpGs.

166

- 167 ORCADES is a family-based cross-sectional study which recruited 2078 participants
- 168 between 2005 and 2011 from the Orkney Isles in northern Scotland [19]. Proteomic and DNA
- 169 methylation data were available for a subset of 940 participants and were used here for
- 170 association test between methylation sites and plasma protein levels (see below).
- 171

172 GS:SFHS cohort: genotypes and inferences of parent-of-origin transmission of alleles in
173 offspring

174 Genome-wide genotypes were generated using the Illumina Human OmniExpressExome -8-

175 v1.0 array [20]. Phasing, imputation and quality control were described previously [4, 21]. In

total, 7108491 high-quality imputed common SNPs (MAF \geq .01, info score \geq 0.8) for 19994

- 177 participants were available for subsequent analyses. Among those individuals, there were
- 178 7139 offspring with at least one of their parents genotyped in GS:SFHS, which allowed us to
- 179 successfully infer parent-of-origin allelic inheritance of all imputed common SNPs in 7106
- 180 offspring with high accuracy [4].

182 GS:SFHS cohort: DNA methylation

183	In GS:SFHS, genome-wide DNA methylation data were produced through a related
184	Stratifying Resilience and Depression Longitudinally (STRADL) project [18]. In 2016, the
185	first wave of methylation data was generated on 5081 participants. These were used as
186	discovery subset. 1663 of these participants also had imputed genotype information with
187	parent-of-origin alleles successfully inferred and were used for the scanning for modifiable
188	POE here. In 2019, another wave of methylation data was generated on an independent
189	subset of 4445 participants. These data were used as replication subset. 652 out of these 4445
190	participants had imputed genotype information with parent-of-origin alleles successfully
191	inferred. Based on a pipeline proposed previously [4], the two datasets were generated,
192	processed and quality controlled in consistent way [22], which was briefly described in text
193	s1.
194	
194 195	GS:SFHS cohort: Environmental/genetic modification variables
194 195 196	GS:SFHS cohort: Environmental/genetic modification variables <u>Environmental modifier variables</u>
194 195 196 197	GS:SFHS cohort: Environmental/genetic modification variables Environmental modifier variables The core GS:SFHS cohort has rich collections of environmental variables[15]. Moreover,
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- 205 1) Predicted mRNA expression levels of 17 DNA methylation or imprinting-specific
- 206 machinery genes imputed by PrediXcan [23].

- 207 2)Nine genetic risk scores for folate metabolism.
- 208 Details of those genetic modifiers were described in Text s2 and table s1,2.
- 209

210 **POE-mQTL-modifier interaction models**

- 211 We applied a POE-mQTL-interaction model to test whether environmental or genetic factors
- could modify the POE induced by mQTL on CpGs. The model built on a linear regression
- 213 model that we used to identify POE-specific mQTL-CpG pairs (mQTL with a parent-of-
- 214 origin effect and the CpG it regulated) in our previous study [4, 24]:
- 215
- 216 *model 1 non-interaction model:*
- 217 <u> $Methyl_{cpg} = Add_{mOTL} + Dom_{mOTL} + POE_{mOTL} + covariates + error</u>$ </u>
- 218
- 219 Where for the additive genetic variable (Add_{mQTL}), the dominance genetic variable
- 220 (Dom_{mQTL}) and the parent-of-origin effect (POE_{mQTL}), genotypes were coded as below:

	AA	Aa	aA	aa
Additive	0	1	1	2
Dominance	0	1	1	0
Parent-of-origin	0	-1	1	0

- In this study, we applied an interaction model that additionally includes a modifier variable,
- 223 *Mod*, and its interaction with the additive genetic effect and the POE:
- 224
- 225 <u>model2 interaction model:</u>
- 226 $\underline{Methyl_{cpg}} = \underline{Add_{mOTL}} + \underline{Dom_{mOTL}} + \underline{POE_{mOTL}} + \underline{Mod} + \underline{Add_{mOTL}} \times \underline{Mod} + \underline{POE_{mOTL}} \times \underline{POE_{$
- 227 <u>covariates + error</u>

229	Where the modifier variable (Mod) was one of the environmental/genetic variables
230	collected/derived as described in the section "GS:SFHS cohort: Environmental/genetic
231	modification variables". Covariates included age, sex, cell proportions, smoking variables
232	("pack years" and "lifetime smoking status", which were not included as covariates when
233	they were the tested modifier factor) and principal components (PCs) derived from an
234	OMIC-relationship-matrix (ORM) created in OSCA [25] using all measured DNA
235	methylation sites. To avoid removing genetic signals of interest by fitting ORM-PCs, we only
236	included ORM-PCs among the top 20 ORM-PCs that were not significantly associated with
237	any common SNP(determined through performing GWAS for ORM-PCs). We applied this
238	model and tested the significance of the interaction effect between each mQTL's POE and
239	the modifier variable ($POE_{mQTL} x Mod$) on the corresponding CpG. The mQTL-CpG pairs
240	tested were the 2372 independent POE-specific mQTL-CpG pairs which we reported
241	previously [4]. The interaction between the additive effect and the modifier (Add x Mod) was
242	jointly fitted in the model. For simplicity we did not fit an interaction between the dominance
243	effect and the modifier (Dom x Mod) in the global scan, but we did this in sensitivity tests for
244	the significant trios we identified. The results indicated only a minor contribution of the
245	$Dom_{mQTL} x Mod$ effect (Table s3). Multiple testing correction was performed by a
246	combination of a global permutation test and mQTL-modifier-CpG trio-specific permutation
247	tests for $POE_{mQTL} \times Modifier$ interaction effect at discovery stage(FDR ≤ 0.05 , details see Text
248	s3, Table s4). A successful replication required to both reach statistical significance
249	(FDR≤0.05) and patten consistency (details in Text s3, Table s4-6). Visualization of the
250	results was performed using the R package coMET and ggplot2 [26, 27].
251	

252 Identification of proteins and mRNAs associated with CpGs regulated by modifiable

- 253 **POE**
- 254 Association between DNA methylation and protein levels
- 255 ORCADES cohort- DNA methylation and proteomic data:
- 256 DNA methylation was measured from whole blood samples using Illumina MethylationEPIC
- Array for 794627 CpG sites in 1052 samples (quality control and pre-correction in Text s4).
- 258 Abundance of plasma proteins was measured from the fasted EDTA plasma samples for a
- subset of 1051 participants using Olink Proseek Multiplex cardiometabolic, cell regulation,
- 260 cardiovascular 2 and 3, developmental, immune response, inflammation 1, metabolism, neuro
- 261 exploratory, neurology, oncology and organ damage panels. The raw NPX values were used
- in analysis.
- 263
- 264 Association test between DNA methylation and plasma protein levels:
- 265 A linear mixed model was used to compute methylation residuals after accounting for genetic
- structure in ORCADES by fitting a random effect represented in the genomic relationship
- 267 matrix. To assess whether the CpGs (N_{cpg}=3) significantly regulated by interaction effects
- 268 ($POE_{mQTL} \times Mod$) were associated with the abundance of any plasma protein (N_{protein}=1092),
- the association between adjusted methylation of CpGs of interest with each measured protein
- was tested using a linear regression model in 940 participants where DNA methylation andproteomic data were simultaneously available:
- 272
- 273 Methyl = protein + cell proportion + age + sex + season of sampling + smoking status +
 274 error
- 275
- 276 The Bonferroni method was applied to correct for multiple testing (N_{correction}=3x1092=3276).

277

278 <u>Correlations between DNA methylation vs mRNA levels:</u>

279 Transcriptomic and DNA methylation data from human peripheral monocytes and T cells in 280 the Multi-Ethnic Study of Atherosclerosis (MESA) study were downloaded from the NCBI 281 GEO database (Series GSE56047 and GSE56580) [28]. mRNA was measured using the 282 Illumina HumanHT-12 v4 Expression BeadChip, DNA methylation levels were measured 283 using the Illumina HumanMethylation450 BeadChip [28]. Quantile-normalized signal for 284 mRNA (log2 transformed) and DNA methylation data (M-values) were simultaneously 285 available for peripheral monocytes (CD14+) in 1202 participants and for peripheral T cells 286 (CD4+) in 214 participants and were used to calculate the Spearman correlation between 287 DNA methylation and mRNA.

288

289 <u>Correlations between mRNAs levels:</u>

290 At the population-level, correlations between mRNA levels of target genes were calculated

using the Spearman method on GTEx whole-blood data using the GEPIA portal [29]. At

single cell level, a normalized single-cell matrix for 63628 peripheral blood mononuclear cell

293 (PBMC) cells from a healthy donor were obtained from the website http://tisch.comp-

294 genomics.org/gallery/. Feature counts for each cell were normalized by "LogNormalize", a

295 global-scaling method that normalizes the cellular feature expression by dividing the total

counts for that cell, multiplied that by a scale factor (10000 by default), followed by a

297 natural-log transformation. Spearman's correlation between mRNA levels of target genes was

298 calculated using cells where normalized expression levels of both genes were larger than

299 zero.

300

301 Phenome-wide association test for DNA methylation sites regulated by modifiable POE

302 We collected 79 phenotypes measured in GS:SFHS (recorded dataset and linked data) to identify phenotypes correlated with DNA methylation levels at CpG sites targeted by 303 304 modifiable POE. The full list of phenotypes tested can be found in Table s7. The correlation 305 was tested by regressing the adjusted M-values of methylation sites on each phenotype 306 variable, covariates included age, age², cell proportion, sex, top 20 ORM-PCs and smoking 307 variables ("pack years" and "lifetime smoking status". These were not included as covariates 308 when they were the tested phenotype). The test was performed in the discovery and 309 replication samples separately and meta-analyzed using a random effect model using the R 310 package metafor [30]. The sample size varied depending on the number of missing samples 311 for each specific phenotype (Table s8). The Bonferroni method was used for multiple testing 312 correction ($N_{correction} = 79*3=237$).

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314 **Results**

315 DNA methylation sites targeted by modifiable POE

316 In GS:SFHS, we utilized information on 75 environmental and 26 genetic variables to test if 317 any of them significantly modified the parent-of-origin effects of the mQTLs on methylation 318 level of the targeted CpGs, altering the methylation difference between reciprocal 319 heterozygotes of the mQTLs (Figure 1). The environmental modifiers reflected the 320 environments/events the participants have been exposed to or have experienced, including 321 those measuring baseline non-genetic effects (sex, age), medication, lifestyle, socioeconomic 322 status, birth-related phenotypes (measured before or after participants' birth) and 323 menarche/menopause-related events; the genetic modifiers were genetic factors known to be 324 involved in DNA methylation and imprinting processes, including "predicted whole blood 325 mRNA expression levels" of DNA methylation- or imprinting-specific machinery genes, and 326 polygenic risk scores (PRSs) for folate-related metabolism (details in methods and Table s1).

328	In the discovery stage, a global permutation test was combined with mQTL-modifier-CpG
329	trio-specific permutation tests to determine mQTL-modifier-CpG trios for significant
330	$POE_{mQTL} x Modifier$ interaction effect on DNA methylation(methods). In the replication
331	stage, a successful replication required both statistical significance and pattern
332	consistency(direction-of-effect) for both the main POE and the $POE_{mQTL} x$ Modifier
333	interaction effect in tested trios. In total, four mQTL-modifier-CpG trios reached significance
334	in the discovery sample ($P_{global_permutation(FDR_adjusted)} < 0.05$, $P_{trio_permutation(Bonferroni_adjusted)} < 0.05$
335	0.05) and were successfully validated in the replication sample (Table 1, text s2, tables s4-6).
336	These four trios involved one environmental modifier: "lifetime smoking status"; and three
337	genetic modifiers: "predicted mRNA expression levels" of SIRT1 (a gene that protects
338	methylation at imprinted loci by directly regulating acetylation of DNMT3L), TET2 (a DNA
339	demethylation gene) and KDM1A (a gene involved in removal of methylation and histone
340	H3K4 in imprinted genes). Three CpGs, cg18035618, cg21252175, and cg22592140 were the
341	methylation sites affected by these modification effects (Table 1), with the $POE_{mQTL}x$
342	Modifier interaction effect explaining between 1.0% to 2.2% of their methylation variation
343	(Figure 3a, Table s3). These CpGs displayed intermediate methylation levels, when
344	compared with the less-peaked distribution of methylation levels of POE-regulated CpGs not
345	influenced by modifiable effects, or the bi-directionally distributed methylation level of
346	genomic CpGs not influenced by POE (Figure 3b). One of the three CpGs, cg18035618, was
347	simultaneously targeted by both environmental and genetic modification effects (Table 1).
348	

349	Table 1	Genetic/e	environmenta	l modifiers	displaying	g a significat	nt interactior	n with the l	POE(mQ	TL) a	and the C	pGs the	interaction	effects a	ffect
						7 (7									

350

	mQTL-CpG-modifer trio information						Discovery				Replication					
CpG: id	CpG- chr	CpG- POS	mQTL: id	mQTL- chr	mQTL- POS	Modifier	Modifier type	P(dis)	Est(dis)	N(dis)	P (trio- specific -perm)	Adjusted P (trio-specific- perm)	P(rep)	Est(rep)	N(rep)	Adjusted P(rep)
cg2259214 0	7	13013241 9	rs14205321 7	7	13025892 6	mRNA expression of KDM1A	Genetic	1.35E- 06	6.35	1607	1.00E- 05	1.09E-02	6.09E-04	6.52	645	2.79E-02
cg2125217 5	15	64973903	rs11183438 7	15	64062211	mRNA expression of TET2	Genetic	1.54E- 06	3.77	1607	<1e-5	< 0.01	7.76E-11	13.80	647	2.43E-08
cg1803561	20	57415978	rs11702012 4	20	57347435	Lifetime smoking status	Env	9.94E- 07	-0.04	1607	<1e-5	< 0.01	1.42E-03	-0.05	647	4.85E-02
8			rs11782335 1	20	57369773	mRNA expression of SIRT1	Genetic	3.68E- 10	-0.24	1607	<1e-5	< 0.01	1.01E-03	-0.22	646	3.95E-02

351

352 CpG-POS/mQTL-POS: genomic position of the CpG and mQTL(hg19). Env: environmental modifier. dis: discovery sample, rep: replication sample. N: sample size.

353 P(dis)/P(rep) and Est(dis)/Est(rep): P values and coefficients for the POEmQTL x Modifier effect in the interaction model in discovery/replication samples. P(trio-specific-

354 perm): P value for the *POEmQTL x Modifier* effect from the trio-specific permutation test. Genomic position of the significant genetic modifiers: *KDM1A*: chr1: 23345941-

355 23410182; *TET2*: chr4: 106067,032-106200973; *SIRT1*: chr10: 69644427-69678147.

356





- 373 *POE_{mOTL} x Modifier* interaction between its mQTL, rs117020124, and "lifetime smoking"
- 374 status" ($P_{dis}=9.94 \times 10^{-7}$, $P_{rep}=1.42 \times 10^{-3}$, figure 4a, table 1), with current smokers displaying
- 375 larger contrast in methylation levels of cg18035618 between heterozygous groups of the

- 376 mQTL when compared with ex-smokers and never-smokers (Figure 5a). For this CpG a
- 377 significant $POE_{mQTL} \times Modifier$ interaction was also detected between another independent
- mQTL, rs117823351, and "predicted mRNA expression levels of SIRT1" (P_{dis} =3.68x10⁻¹⁰,
- 379 $P_{rep}=1.01 \times 10^{-3}$, figure 4b, table 1. SIRT1 is located in chromosome 10), with lower SIRT1
- 380 expression corresponding to an increased contrast of methylation levels between
- 381 heterozygous groups of the mQTL (Figure 5b).
- 382



- 384 Figure 4 Regional plot of the modifiable-POE affecting cg18035618 and nearby CpGs within a 20kb distance. a.
- 385 Interaction effect between the POE of cg18035618's mQTL rs117020124 and "lifetime smoking status"; b.
- 386 Interaction effect between the POE of cg18035618's mQTL rs117823351 and 'predicted mRNA expression
- 387 levels of SIRT1'. Upper panel: -log10 (P-value): minus log10 P-value of the POEmQTL x Modifier interaction
- 388 effect. Dots show nearby measured CpGs located within a 20kb distance from cg18035618, filling colour
- 389 represents the correlation of methylation levels with cg18035618: red: positive correlation ; blue:negative
- 390 correlation; white: no significant correlation. . Middle panel: genes located within the 40kb genomic region.
- 391 Bottom panel: correlation matrix between CpGs.





Figure 5. Both environmental and genetic factors significantly modified the POE of mQTLs on cg18036618.
a.top:cg18036618 was regulated by the POE of the mQTL rs117020124. bottom: the POE of rs117020124 was
modified by lifetime smoking status. The contrast in methylation levels of cg18035618 between heterozygotes
of the mQTL rs117020124 is largest in current smoker group. b.top:cg18036618 was regulated by the POE of
the mQTL rs117823351. bottom: the POE of rs117823351 was modified by "predicted mRNA expression level

of *SIRT1*". The contrast in methylation levels of cg18035618 between heterozygotes of the mQTL rs117823351
is larger in individuals with low SIRT1 expression.

400

401 To rule out the possibility that the sharing of the methylation target (cg18035618) by both 402 genetic and environmental modifiers was due to genetically influenced environmental effects 403 (i.e., *SIRT1* expression influences smoking status) [31], we calculated the correlation between 404 "lifetime smoking status" and "predicted mRNA expression levels of *SIRT1*" and found no 405 significant correlation (R=0, P=0.968).

406

407 cg21252175 (hg19: chromosome15: 64973903) is located in the 3' UTR region of gene

408 ZNF609 (Figure s1a). For this CpG, a significant $POE_{mQTL} \times Modifier$ interaction was

409 detected between the mQTL rs111834387 and "predicted mRNA expression levels of TET2"

410 $(P_{dis}=1.54 \times 10^{-6}, P_{rep}=7.76 \times 10^{-11}. TET2 \text{ is located in chromosome 4})$, with lower expression

411 of *TET2* reducing the contrast in methylation levels of cg21252175 between heterozygous

412 groups of the mQTL (Table 1, figure s2a). cg22592140, a CpG located in an intron of gene

413 *MEST* (Figure s1b), was significantly regulated by a $POE_{mQTL} x$ *Modifier* interaction between

414 its mQTL rs142053217 and "predicted mRNA expression levels of *KDM1A*" (P_{dis} =1.35x10⁻⁶,

415 $P_{rep}=6.09 \times 10^{-4}$. *KDM1A* is located in chromosome 1), with lower expression of *KDM1A*

416 increasing the contrast in methylation levels of cg22592140 between heterozygous groups of

417 the mQTL (Table 1, figure s2b).

418

419 Localization of regulatory SNPs contributing to the genetic modification effect.

420 Considering that the three identified genetic modifiers ("predicted mRNA expression levels"

421 of SIRT1, TET2, KDM1A) are essentially weighted combinations of allelic scores at multiple

422 regulatory SNPs, we next tested whether the genetically driven modification effects we

423 detected here can be recapitulated by the $POE_{mQTL} x SNP$ interactions between mQTLs and

$\tau 2\tau$ include of the standard conclusion mounters, since breaking matrix concession	424	the SNPs used to	o drive the significant	genetic modifiers. Since	"predicted mRNA ex	pression"
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- 425 of SIRT1, KDM1A and TET2 was derived from two, one and two SNPs respectively by the
- 426 MASHR method in PrediXcan(Methods)[32], we tested $POE_{mOTL} x SNP$ interactions for
- 427 those 5 SNPs (N_{test}=5). We identified four of the five SNPs significantly interacting with the
- 428 POE_{mQTL}, that is, regulating the CpGs where the interaction effect was initially detected
- 429 (Table 2, Figure 6). For example, for cg18035618 we detected a significant interaction effect
- 430 $(P_{dis}=3.69 \times 10^{-9}, P_{rep}=4.33 \times 10^{-3})$ between rs932658, a SNP used in the prediction model for
- 431 SIRTI expression, and rs117823351, the mQTL that significantly interacted with "predicted
- 432 mRNA expression levels of *SIRT1*". When accounting for these significant *POE_{mQTL} x SNP*
- 433 interaction effects as conditional items in the interaction model for the three genetic-
- 434 modifiers, the interaction effect at the genetic-modifier-level ($POE_{mQTL} x Modifier_{Genetic}$) were
- 435 reduced to a non-significant level, suggesting the leading role of $POE_{mQTL} x SNP$ underlying
- 436 the significant interaction effect from genetic modifiers we detected here (Table s10).

439

mQTL-CpG		SNP modifier		Discovery				Replication		
CpG: id	mQTL: id	SNP id	Relation to G modifier	P(dis)	Adjust_P(dis)	Est(dis)	N(dis)	P(rep)	Est(rep)	N(rep)
cg22592140	rs142053217	rs75667410_T	SNP used in predict <i>KDM1A</i> exp	1.35E-06	6.75E-06	0.18	1607	6.09E-04	0.18	645
cg21252175	rs111834387	rs11729069_G	SNP used in predicting TET2 exp	1.05E-08	5.25E-08	0.18	1607	Not enough data*		
		rs7661349_T		3.51E-02	1.76E-01	-0.06	1607	Not significant in Discovery sample		ample
cg18035618	rs117823351	rs932658_A	SNP used in predict SIRT1 exp	3.69E-09	1.85E-08	-0.07	1607	4.33E-03	-0.06	646
		rs3740053_G		1.55E-04	7.75E-04	-1.00E-01	1607	6.01E-03	-0.10	646

440

441 dis: discovery sample, rep: replication sample. N: sample size. P(dis)/P(rep) and Est(dis)/Est(rep): P values and coefficients for the POE_{mQTL} x SNP interaction in the

442 interaction model in discovery/replication samples. *, due to the relatively small minor allele frequency (MAF) of rs111834387(MAF=0.01) and the limited sample size of

443 replication sample, there was not enough data for this test in replication samples. Number of individuals within heterozygous groups available for testing *POE(rs111834387)*

444 *x SNP(rs11729069)* interaction effect on cg21252175 in replication samples were shown in Table s9.



Figure 6. The three modifiable-POE-targeted CpGs were also significantly regulated by $POE_{mQTL} x SNP$ interaction effects between the mQTLs and the SNPs used to drive the genetic modifiers. The contrast in methylation levels of the candidate CpGs in mQTL heterozygotes varied depending on the allelic dosage of the SNP used to derive the corresponding genetic modifier. *due to the limitation of sample size, minor homozygous/heterozygous genotype groups were missing in some tests.

451

445

452 Proteins associated with modifiable-POE-regulated methylation sites

- 453 Association tests were performed using DNA methylation and proteomic data from
- 454 ORCADES cohort (N_{sample}=940, N_{total_protein}=1092) to identify proteins associated with the

455 three CpGs regulated by the modifiable POE. Only one CpG-protein pair passed Bonferroni-

- 456 based multiple testing correction (N_{test} =3,276, full results in Table s11): cg21252175 was
- 457 significantly associated (in *trans*) with plasma protein level of CLEC4C, a protein from the
- 458 Olink immune-response panel (Beta=0.049, $P_{adj}=0.002$).
- 459
- 460 Since cg21252175 is located in the UTR3 of gene *ZNF609*, we further examined whether the
- 461 association between cg21252175 and CLEC4C protein levels implied a link between ZNF609
- 462 and *CLEC4C*. Using data from MESA study [28], a significant and positive correlation was
- 463 detected between methylation levels of cg2125217 and mRNA levels of *ZNF609* in both

464 CD4+ peripheral T cells (R=0.15, P=0.03) and CD14+ peripheral monocytes (R=0.15,

- 465 $P=1.52 \times 10^{-6}$, figure s3a). Using whole blood data from the GTEx consortium through the
- 466 GEPIA portal[29, 33], mRNA expression level of ZNF609 was significantly correlated with
- 467 mRNA expression levels of *CLEC4C* at population level (R=0.21, $P=1.1x10^{-4}$, figure s3b).
- 468 Using a single-cell RNA-seq data of PBMC in an adult donor, mRNA expression levels of
- 469 ZNF609 and CLEC4C were significantly correlated at the cellular level (R=0.36, P=0.0002,
- 470 figure s3c).

471

472 Phenotypes associated with modifiable-POE-regulated methylation sites

473 To explore the association between variation in CpGs targeted by modifiable POE and

474 heath/disease-related phenotypes, we collected 79 phenotypes in GS:SFHS (Table s7).

475 Phenome-wide association tests relating methylation levels to phenotypes were performed for

- 476 the three identified modifiable-POE-regulated CpGs using the whole GS:SFHS methylation
- 477 sample (meta-analyzed across discovery (N_{sample}=5081) and replication (N_{sample}=4445)
- 478 samples; N_{sample}=9526.). After Bonferroni-based multiple testing correction
- 479 (N_{test}=79x3=237), two CpG-phenotype associations reached phenome-wide significance:

480	cg21252175 was both associated with "lifetime smoking status" ($P_{adj} = 9.0 \times 10^{-5}$) and high-
481	density lipoprotein (HDL) levels (P_{adj} =0.006) (Figure 7, Table s8). Although limited by
482	sample size(Figure 7), cg21252175 was also associated with gestational age (measured as
483	weeks at birth) at an adjusted P \leq 0.06 level (P_{adj} =0.056). These associations displayed
484	consistent patterns across discovery and replication samples (Figure 7, Table s8).
485	

Phenotypes/samples		P values Effect sizes [95% CI]		
Lifetime smoking status				
GS:SFHS discovery (N=4,810)	_	3.81e-4	-0.010 [-0.015, -0.004]	
GS:SFHS replication(N=4,109)		2.87e-4	-0.010 [-0.016, -0.005]	
Meta (random effect, n=8,919)		3.78e-7	-0.010 [-0.014, -0.006]	
HDL				
GS:SFHS discovery (N=4,762)	⊢	6.51e-3	0.003 [0.001, 0.006]	
GS:SFHS replication (N=4,069)	■	1.11e-3	0.004 [0.002, 0.006]	
Meta (random effect, n=8,831)	•	2.31e-5	0.004 [0.002, 0.005]	
Gestational age				
GS:SFHS discovery (N=1,339)	—	2.64e-3	0.006 [0.002, 0.010]	
GS:SFHS replication (N=335)		2.19e-2	0.011 [0.002, 0.020]	
Meta (random effect, n=1,674)	•	2.34e-4	0.007 [0.003, 0.011]	
-0.025 -0.010	0.000 0.010 Effect size	0.020		

cg21252175 - associated phenotypes

486

487 Figure 7. Forest plot for phenotypes associated with cg21252175. HDL: high-density lipoprotein.

488 Meta: Meta-analysis performed using the random effect model.

489

490 Discussion

- 491 In this study, we reported significant and replicated modification effects from both genetic
- 492 and environmental variables on the parent-of-origin effect that affects DNA methylation
- 493 levels at three CpGs. Identified environmental modifiers included "lifetime smoking status";

494 identified genetic modifiers included "predicted mRNA expression levels" of several DNA 495 methylation/imprinting machinery genes (SIRT1, TET2, KDM1A). Importantly, we found that 496 both genetic and environmental modifiers were targeting the same CpG (cg18035618). These 497 provided evidence for a special type of CpGs in the human genome regulated by the parent-498 of-origin-effects that are modulated by genetic or environmental modifiers. We further found 499 that these CpGs are likely to be phenotypically relevant: at the molecular level, DNA 500 methylation level at one the CpG, cg21252175, was associated with protein levels of the 501 immune-response-related protein CLEC4C. At the phenotypic level, this CpG was associated 502 with "lifetime smoking status", HDL levels and gestational age(the latter at the suggestive 503 significance level). 504 505 Statistically, the model we proposed here for detecting modifiable POE is built on a previous 506 POE-mQTL model which we used to localize regulatory mQTLs for the POE-influenced CpGs (model 1 in Methods) [4, 24]. For those CpGs, one of the hallmarks of the POE-507 508 regulation was the methylation difference between the two heterozygous mQTL genotype 509 groups (Figure 1)[4, 6]. Here, our new interaction model tests whether that difference 510 remains stable or varies under certain conditions, that is, if the parent-of-origin effects are the 511 same or different across different environments or in different genetic backgrounds. 512 Biologically, this implies the existence of a new and different layer of regulation for DNA 513 methylation: genetic/environmental factors could influence the level of DNA methylation of 514 CpGs, not only through direct effects, but also through interacting with the POE (Figure 1). 515 516 Our results support this hypothesis. Smoking has been widely studied for its direct influence 517 on DNA methylation [34, 35] and its interactions with additive genetic effects on methylation 518 levels [36]. Here, for the first time, our study reported that smoking could also affect DNA

519 methylation variation indirectly through interaction with a non-additive genetic effect, POE. Similarly, variation in DNA methylation and imprinting machinery genes, either in the forms 520 521 of variable expression or mutation, have been known to directly affect DNA methylation. 522 SIRT1 regulates DNA methylation and protects methylation at imprinted loci by directly 523 regulating acetylation of DNMT3L [12, 37]. TET2 promotes DNA demethylation by 524 converting 5-methyl-cytosine to 5-hydroxymethyl-cytosine and is required for demethylation 525 at imprinted loci in the germline [12, 38]. KDM1A removes methylation of histone H3K4 in 526 imprinted genes, its deficiency is associated with alterations in DNA methylation and 527 expression at imprinted genes [12, 39]. Here, for the first time, we showed that besides 528 known direct effects, these genetic factors also introduce indirect regulatory effects on DNA 529 methylation levels through interactions with POE. 530

531 The detection of interactions between genetic modifiers and POE led us to further identify 532 significant and replicated $POE_{mOTL} x SNP$ interaction effects between mQTLs and SNPs used 533 in imputing genetic modifiers. One important feature of the genetic modifier variables we 534 derived here is that they represent the proportion of mRNA variation determined by germline 535 genetic variation, which is constant and stable throughout the life [40]. Our results 536 demonstrated that an individual's genetic background of DNA methylation and imprinting 537 machineries has the potential to modify POE. The localization of the genetic-based 538 modification effect at regulatory SNPs of these DNA methylation and imprinting machinery 539 genes strongly supports this, and importantly, indicated that genetic variation in machinery 540 genes is an important source of epistasis. One of the machinery genes, SIRT1, has been well 541 known for its role in mental disorders such as depression[41], but very few studies have 542 examined its role as a modifier for non additive genetic effect such as POE. Our result 543 revealed a new potential path of variation in this gene to introduce molecular differences.

544

545	The reason why POE can ever be modified is deeply rooted in the unique nature of genomic
546	imprinting: established at an early developmental stage, needing to be protected from global-
547	demethylation and maintained throughout the lifespan [12]. These complex and multi-stage
548	processes have been shown to be vulnerable to environmental fluctuations and involve
549	delicate regulation of multiple gametic and zygotic genetic factors, including TET2, SIRT1,
550	KDM1A as we identified here.[11, 12]. Indeed, the vulnerability of at least a subset of POE-
551	CpGs was revealed here, as the $POE_{mQTL} x$ Modifier interaction effect explained a non-
552	negligible proportion of methylation variance (1%-2.2%), and that at least one (cg18035618)
553	of the three CpGs identified was targeted by independent environmental and genetic
554	modifiers. Molecularly, we found one of the modifiable-POE influenced CpG (cg21252175)
555	was associated with CLEC4C, an immune-response transmembrane protein treated as a
556	marker gene for plasmacytoid dendritic cells [42]. Phenotypically, cg21252175 was
557	associated with "lifetime smoking status", HDL levels and gestational age (the latter at the
558	suggestive significance level) (Figure 7) in our analysis, and was previously found to be
559	associated with maternal body mass index/overweight/obesity [43]. These convergent lines
560	indicated that this newly uncovered class of vulnerable POE-CpGs may play an important
561	role in connecting early life stress, variations in genetic background and later life health
562	issues.

563

564 There are limitations in this study. First, mRNA expression levels used here were predicted 565 and only reflect genetically influenced expression variation (and not necessarily all of it). 566 Future studies examining measured mRNA expression will be necessary to account for the 567 modification effect from the environmentally determined fraction of mRNA expression. 568 Second, since the analyses performed here simultaneously require DNA methylation data and

569 SNP data with information of parent-of-origin of the alleles transmitted to the offspring, the 570 sample size was relatively limited in this study. This is a proof of principle study and larger 571 sample sizes will be needed to uncover more modifiable POE. Finally, the exact time window 572 or developmental stage in which each environmental modifier exerted their influences 573 remains unknown. Cohort data with higher resolution of environmental exposure records, in 574 particular those measuring early life exposures, will be crucial to understand the vulnerable 575 stage or stages for CpGs influenced by modifiable POE. 576

577 Conclusions

578 we provided the first population-level evidence for modification effects from multiple

579 genetic and environmental factors on parent-of-origin-effects at the DNA methylation level.

580 A subset of parent-of-origin-effect-influenced CpGs that are vulnerable to modification

581 effects were uncovered, which opens new questions for future profiling of the modification

582 patterns and phenotypic consequences of this class of CpGs.

583

584 Funding

585 YZ was supported by the General Program of National Natural Science Foundation of China

586 (81971270) and Sun Yat-sen University Young Teacher Key Cultivate Project. The work of

587 AF was supported by European Union's Horizon 2020 research and innovation programme

588 IMforFUTURE under H2020-MSCA-ITN grant agreement number 721815. ADB would like

589 to acknowledge funding from the Wellcome PhD training fellowship for clinicians

590 (204979/Z/16/Z), the Edinburgh Clinical Academic Track (ECAT) programme. The authors

- 591 want to acknowledge support from the MRC Human Genetics Unit programme grant,
- ⁵⁹² "Quantitative traits in health and disease" (U. MC_UU_00007/10), and grant
- 593 MC_PC_U127592696. Generation Scotland has received core funding from the Chief

594	Scientist Office of the Scottish Government Health Directorates CZD/16/6 and the Scottish
595	Funding Council HR03006. Genotyping of the GS samples was carried out by the Genetics
596	Core Laboratory at the Wellcome Trust Clinical Research Facility, Edinburgh, Scotland and
597	was funded by the UK MRC and the Wellcome Trust (Wellcome Trust Strategic Award
598	"Stratifying Resilience and Depression Longitudinally" (STRADL) Reference
599	104036/Z/14/Z). DNA methylation profiling of the GS:SFHS samples was funded by the
600	Wellcome Trust Strategic Award [10436/Z/14/Z]. The Orkney Complex Disease Study
601	(ORCADES) was supported by the Chief Scientist Office of the Scottish Government
602	(CZB/4/276, CZB/4/710), a Royal Society URF to J.F.W., the MRC Human Genetics Unit
603	quinquennial programme "QTL in Health and Disease", Arthritis Research UK and the
604	European Union framework program 6 EUROSPAN project (contract no. LSHG-CT-2006-
605	018947). MESA and the MESA SHARe projects are conducted and supported by the
606	National Heart, Lung, and Blood Institute (NHLBI) in collaboration with MESA
607	investigators. Support for MESA is provided by contracts 75N92020D00001,
608	HHSN268201500003I, N01-HC-95159, 75N92020D00005, N01-HC-95160,
609	75N92020D00002, N01-HC-95161, 75N92020D00003, N01-HC-95162, 75N92020D00006,
610	N01-HC-95163, 75N92020D00004, N01-HC-95164, 75N92020D00007, N01-HC-95165,
611	N01-HC-95166, N01-HC-95167, N01-HC-95168, N01-HC-95169, UL1-TR-000040, UL1-
612	TR-001079, UL1-TR-001420, UL1-TR-001881, and DK063491. The MESA Epigenomics &
613	Transcriptomics Studies were funded by NIH grants 1R01HL101250, 1RF1AG054474,
614	R01HL126477, R01DK101921, and R01HL135009.
615	

616 Ethics approval

- 617 This study was ethically approved by the Tayside Research Ethics Committee (reference
- 618 05/S1401/89). Participants all gave written consent after having an opportunity to discuss the
- 619 research and before any data or samples were collected.
- 620

621 Data Availability Statement

Generation Scotland data are available from the MRC IGC Institutional Data Access / Ethics
Committee for researchers who meet the criteria for access to confidential data. Generation
Scotland data are available to researchers on application to the Generation Scotland Access
Committee (access@generationscotland.org). The managed access process ensures that
approval is granted only to research which comes under the terms of participant consent
which does not allow making participant information publicly available.

628

629 Acknowledgements

630 We want to acknowledge support from Genetics Core Laboratory at the Wellcome Trust 631 Clinical Research Facility (Edinburgh, Scotland) for genotyping of the GS samples. We are 632 grateful to all the families who took part, the general practitioners, and the Scottish School of 633 Primary Care for their help in recruiting them, and the whole Generation Scotland team, 634 which includes interviewers, computer and laboratory technicians, clerical workers, research 635 scientists, volunteers, managers, receptionists, healthcare assistants and nurses. We would 636 like to acknowledge the invaluable contributions of the research nurses in Orkney, the 637 administrative team in Edinburgh and the people of Orkney. MESA and the MESA SHARe 638 projects want to acknowledge the supported from the National Heart, Lung, and Blood 639 Institute (NHLBI) in collaboration with MESA investigators. YZ wants to acknowledge 640 support from Dr. Lucija Klaric for pre-processing the ORCADES data.

641

Conflict of interest statement

643 The authors declare that they have no competing interests.

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