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1	Single-cell chromatin profiling reveals demethylation-dependent
2	metabolic vulnerabilities of breast cancer epigenome
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17 Abstract

Metabolic reprogramming in cancer cells not only sustains bioenergetic and biosynthetic needs 18 but also influences transcriptional programs, yet how chromatin regulatory networks are rewired 19 by altered metabolism remains elusive. Here we investigate genome-scale chromatin remodeling 20 21 in response to 2-hydroxyglutarate (2HG) oncometabolite using single-cell assay for transposase accessible chromatin with sequencing (scATAC-seq). We find that 2HG enantiomers differentially disrupt exquisite control of epigenome integrity by limiting a-ketoglutarate (aKG)-dependent DNA and histone demethylation, while enhanced cell-to-cell variability in the chromatin regulatory 24 25 landscape is most evident upon exposure to L2HG enantiomer. Despite the highly heterogeneous 26 responses, 2HG largely recapitulates two prominent hallmarks of the breast cancer epigenome, i.e., global loss of 5-hydroxymethylcytosine (5hmC) and promoter hypermethylation, particularly 27 at tumor suppressor genes involved in DNA damage repair and checkpoint control. Single-cell 28 mass cytometry further demonstrates downregulation of BRCA1, MSH2 and MLH1 in 2HG-29 responsive subpopulations, along with acute reversal of chromatin remodeling upon withdrawal. 30 Collectively, this study provides a molecular basis for metabolism-epigenome coupling and 31 identifies metabolic vulnerabilities imposed on the breast cancer epigenome. 32

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33 Introduction

As a dynamic system, cancer cells continuously adapt to the fluctuating microenvironment by 34 rerouting metabolic fluxes and evolve from early initiation through progression and dissemination^{1,2}. Metabolic reprogramming in cancer cells facilitates energy production and 36 macromolecular synthesis to fuel cell proliferation^{3,4}. In addition to supporting bioenergetic and 37 biosynthetic needs, altered metabolism involves promiscuous production of non-canonical metabolic intermediates, which have been described as metabolic waste products or metabolite 39 damage^{5,6}. Recent studies suggest that these previously uncharacterized metabolites including 40 41 oncometabolites are linked to 'non-metabolic' signaling mechanisms in cell-type-specific fate decisions⁷. 42

The oncometabolite 2-hydroxyglutarate (2HG) occurs as two enantiomers and 43 accumulates up to millimolar concentrations in a broad range of hematological and solid 44 malignancies^{8,9}. Somatic mutations in isocitrate dehvdrogenase genes, *IDH1* and *IDH2*, found in 45 glioma and acute myeloid leukemia (AML) result in stereospecific production of the D-enantiomer 46 (D2HG)^{10,11}, while breast tumors frequently exhibit elevated levels of 2HG despite the lack of *IDH* 47 mutations^{12,13}. Recent studies indicate that the L-enantiomer (L2HG) can accumulate under 48 acidic^{14,15} and hypoxic conditions^{16,17} that often coexist in the tumor microenvironment, yet the 49 potential sources and functions of L2HG are less well established. Both enantiomers structurally resemble α -ketoglutarate (α KG), a key intermediate in the Krebs cycle, and potentially antagonize 51 αKG-dependent dioxygenases including ten-eleven translocation (TET) DNA hydroxylases and 52 Jumonji domain-containing histone demethylase (JHDM) enzymes¹⁸⁻²⁰, which catalyze oxidative 53 demethylation of DNA and histone proteins, respectively. 54

55 Promoter hypermethylation and global loss of 5-hydroxymethylcytosine (5hmC) are two 56 prominent hallmarks of the breast cancer epigenome²¹⁻²³. Genome-wide depletion of 5hmC is 57 frequently observed in a multitude of tumor types including breast cancer and is associated with 58 poor patient survival^{24,25}; however, its cause and pathological consequences are largely opaque.

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Similarly, promoter hypermethylation of tumor suppressor genes has also been considered a common and driving event in breast malignancies. Loss-of-function mutations in DNA hydroxylases (*TET1*, *TET2* and *TET3*) or overexpression of DNA methyltransferases (*DNMT1*, *DNMT3A* and *DNMT3B*)^{26,27}, and recently tumor hypoxia²⁸ have been reported to be associated with aberrant DNA methylation, yet the molecular origin of promoter hypermethylation in breast cancer remains obscure^{27,29}.

Here we show that the oncometabolite 2HG disturbs the fine-tuned spatial regulation of 65 the mammary epithelial epigenome, and initiates global loss of 5hmC and tumor-associated promoter hypermethylation by impairing α KG-dependent demethylation. The findings provide a 67 68 mechanistic framework in which altered metabolism mediates two pathological hallmarks of the breast cancer epigenome, thereby priming early epigenetic events to be exploited during the development of breast cancer, in particular basal-like subtype with high 2HG accumulation. By 70 leveraging two single-cell approaches, our study further highlights a role for 2HG oncometabolites 71 in the dynamics of cell-to-cell variability in the epigenome of this tumor type, whereby chromatin 72 regulatory modules are highly vulnerable to metabolic derangements. 73

74 Results

2HG enantiomers progressively modulate the mammary epigenome by limiting DNA and histone demethylation

To identify the regulatory mechanism involving cellular metabolism that mediates breast cancer
development, we first analyzed the intracellular levels of D2HG and L2HG using enantiomerselective liquid chromatography-mass spectrometry (LC-MS) following chiral derivatization of the
analyte (Fig. 1a,b). Relatively higher levels of D2HG were observed in both ERα-positive and negative breast cancer cell lines compared to benign and primary mammary epithelial cells,
whereas elevated L2HG levels were predominant in ERα-negative breast cancer cells (Fig. 1c,d).
In line with this, ERα-negative cells had higher levels of total 2HG (Supplementary Fig. 1a), which

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is supported by prior studies showing preferential accumulation of 2HG in ERg-negative or basal-84 like tumors^{12,13,30}. We next leveraged the recently developed comprehensive Cancer Cell Line 85 Encyclopedia (CCLE) metabolomics database^{31,32} and found that 2HG levels were remarkably elevated in basal-like tumor cells in comparison to other tricarboxylic acid (TCA) cycle metabolites 87 88 that are structurally similar to one another and are potentially involved in aKG-dependent dioxygenase reactions (Fig. 1e). Of note, our investigation of somatic mutations using two independent datasets from the Sanger Catalogue of Somatic Mutations in Cancer (COSMIC) and 90 CCLE consortia showed no evidence for gain-of-function mutations in *IDH1* or *IDH2* among 62 91 breast cancer cell lines, further corroborating the findings of infrequent IDH mutations and yet high accumulation of 2HG in breast tumors (Supplementary Fig. 1b)^{12,13,30,33}. It should be noted, however, that recurrent IDH2 mutations are found in a rare breast cancer subtype with elevated 94 intratumor 2HG levels^{34,35}. 95

To determine the global impact of oncometabolites on the chromatin landscape, primary 96 human mammary epithelial cells (HMECs), which exhibited low levels of endogenous 2HG 97 (Supplementary Fig. 1a), were exposed for 72 hr to the cell-permeable derivatives of D2HG and L2HG. Exposure to either of the two enantiomers led to a decrease in 5-hydroxymethylcytosine 99 100 (5hmC) and reciprocal increase in 5-methylcytosine (5mC) across the LINE-1 repetitive sequence elements in the genome (Supplementary Fig. 1c), indicating competitive inhibition of TET-101 mediated oxidation of 5mC to 5hmC during the process of active DNA demethylation³⁶ (Fig. 1f). 102 Similarly, immunofluorescence staining using a 5hmC-specific antibody showed a dose-103 dependent global loss of 5hmC in response to D2HG (Fig. 1g). In contrast, global levels of 104 H3K27me3 histone methylation were elevated in proportion to the increasing concentrations of 105 D2HG, via inhibition of JHDM-mediated histone demethylation (Fig. 1g,h and Supplementary Fig. 106 1d). Our observations thus indicated that short-term exposure at a relatively low range was 107 sufficient to induce a substantial change in the mammary epithelial epigenome. 108

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Unlike DNA methylation, lysine residues on histone tails can be mono-, di- and tri-109 methylated (Supplementary Fig. 1d) and we therefore employed a multiplexed LC-MS assay to 110 quantify changes in histone methylation. Exposure to 2HG enantiomers led to elevated 111 methylation levels in both repressive (H3K27me3, H3K9me3 and H4K20me3) and permissive 112 113 (H3K4me3, H3K36me3 and H3K79me3) histone marks as indicated by increases in mono-, di- or tri-methylation along with a reciprocal decrease in the levels of unmethylated lysine residues (Fig. 114 1i, Supplementary Fig. 1e and Supplementary Table 1). Consistently, repressive methylation 115 modifications on H3K27 residues were accumulated in relation to the increasing levels of 116 intracellular 2HG in the CCLE breast cancer cell lines (Supplementary Fig. 1f). Of note, there was 117 118 no detectable alteration in cell-cycle phase distribution upon 2HG supplementation (Supplementary Fig. 1g). Together, our findings support a model that the intratumor accumulation 119 of 2HG oncometabolites progressively modulates the mammary epigenome independent of cell 120 cycle progression, potentially leading to extensive chromatin remodeling. 121

122 Single-cell profiling of chromatin accessibility reveals epigenetic heterogeneity in 123 response to 2HG enantiomers

To delineate the genome-scale dynamics of epigenetic regulatory modules in response to 124 oncometabolite exposure, we applied single-cell assay for transposase-accessible chromatin with 125 high-throughput sequencing (scATAC-seq)³⁷. First, individual single cells were isolated from 126 HMECs cultured in media supplemented with either D2HG or L2HG using integrated fluidic 127 circuits (Fig. 2a). Following cell lysis and tagmentation of open, accessible chromatin regions by 128 Tn5 transposase, a total of 248 single-cell libraries were independently indexed with unique 129 barcodes and sequenced as a single pool. scATAC-seq reads exhibited the expected periodicity 130 of ~200-bp insert size fragments corresponding to nucleosome bands^{37,38} (Fig. 2b). Additionally, 131 aggregate scATAC-seq profiles of 248 single cells showed high concordance with the ensemble 132

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measurement of the accessibility landscape profiled by DNase-seq (Fig. 2c and Supplementary Fig. 2a; r = 0.76).

We next sought to globally visualize single-cell DNA accessibility profiles using principal 135 component analysis (PCA), which indicated distinct cell subpopulations that were discernible not 136 137 only between but also within the treatment groups (Fig. 2d and Supplementary Fig. 2b). Cell-tocell variability in the chromatin landscape was likewise detected among cells receiving the same 138 treatment by using cell similarity matrix analysis based on highly accessible genomic regions 139 (Supplementary Fig. 2c). In contrast, replicate samples were similarly distributed despite being 140 processed in different experiments (Supplementary Fig. 2d), further supporting the technical 141 142 robustness and reproducibility of the method. Interestingly, the first principal component (PC1) broadly separated L2HG-exposed cells from control and D2HG-exposed cells that were 143 distinguishable, albeit to a lesser extent, alongside the PC2 direction (Fig. 2d), indicating that the 144 two enantiomers could differentially modulate the chromatin organization. Furthermore, L2HG-145 exposed cells were clearly separated into different subpopulations oriented in the opposite 146 direction on the PC2 axis and showed a more variable distribution compared to unexposed control 147 cells, suggesting a substantial increase in cell-to-cell variability following L2HG exposure. 148

149 Consistent with the observation that epigenetic heterogeneity was most evident among L2HG-exposed cells, model-based clustering following PCA identified three major cell subsets in 150 L2HG-exposed cells, referred to as L1, L2 and L3, along with a total of five distinct clusters among 151 the 248 single cells (Fig. 2e and Supplementary Fig. 2e). When scATAC-seg data were 152 aggregated, notable differences in chromatin accessibility were observed throughout the genome 153 between L2HG subgroups (Supplementary Fig. 2f). Moreover, inspection of genome-wide 154 distribution of scATAC-seq signals over CpG islands (n = 28,690) and H3K4me3 peaks (n = 33,116) revealed a marked difference between L1 versus L2 and L3 subsets (Fig. 2f). In 156 agreement, Cluster 1 comprised cells from all three experimental groups that were clustered in 157 close proximity with similar multidimensional phenotypes (Fig. 2d,e), implying L1 subset being a 158

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cell subpopulation that is potentially less sensitive to oncometabolite perturbation. This was contrasted with no pronounced differences in scATAC-seq accessibility profiles either across CpG islands or H3K4me3 sites detected between the three experimental groups (Supplementary Fig. 2g). Together, single-cell DNA accessibility profiling revealed that the two enantiomers could distinctly modulate the mammary epigenome and drive cell-to-cell epigenetic diversity in the chromatin regulatory landscape.

165 **2HG** depletes promoter accessibility at highly methylated genes in breast cancer

To identify disease-relevant epigenetic signatures imposed upon 2HG exposure, we further 166 interrogated our scATAC-seg data using publicly available large-scale datasets including Encyclopedia of DNA Elements (ENCODE)³⁹, Roadmap Epigenomics⁴⁰, Cancer methylome⁴¹ and 168 The Cancer Genome Atlas (TCGA)⁴² (Fig. 3a). We first determined the global occupancy of open. 169 accessible chromatin regions by utilizing the 12-state chromatin segmentation defined in 170 HMECs⁴³. As expected, ATAC-seg signals in unexposed control cells were remarkably enriched 171 in active/weak gene promoters and strong enhancers but were significantly underrepresented in 172 inactive genomic regions such as heterochromatin and repetitive regions, both of which were 173 associated with nuclear lamina⁴⁰ (Supplementary Fig. 3a). Following 2HG exposure, chromatin 174 accessibility was reduced in genomic regions enriched with permissive chromatin marks 175 (H3K4me3, H3K27ac and H3K9ac)⁴⁰, such as active/weak promoters and strong/weak enhancers 176 (Fig. 3b). In contrast, genomic regions that are largely devoid of permissive chromatin marks 177 displayed a substantial increase in chromatin accessibility, suggesting that oncometabolites can 178 have two opposing impacts on the mammary epigenome, i.e., selective loss of accessibility in 179 active or poised chromatin and gain of accessibility in repressive or guiescent chromatin states. 180 The overall alterations in the chromatin landscape dynamics were particularly prominent in 181 response to L2HG, suggesting L2HG to be more potent in modulating the mammary epigenome. 182

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This is in line with earlier biochemical studies indicating that L2HG can competitively antagonize α KG-dependent dioxygenases to a greater extent¹⁸⁻²⁰.

To address the sparse nature of scATAC-seq data^{37,38}, we investigated regulatory variation in single-cell measurements by aggregating scATAC-seq signals over transcription start 186 187 sites (TSS) in the genome. As shown in Fig. 3c with each color representing DNA accessibility around TSS regions (n = 20.242) in a single cell, the chromatin occupancy pattern in untreated control cells was highly concordant whereas the peaks were found to be diffused and 189 heterogeneous in exposed cells, suggesting enhanced epigenetic variability in regulatory 190 modules imposed by 2HG. However, the differences between exposed and unexposed cells were 191 192 not quantitatively remarkable when chromatin accessibility was assessed over all TSS regions across the entire genome. In contrast, a marked reduction in accessibility was detected when a 193 set of highly methylated genes (n = 150) in breast tumors⁴⁴ was investigated (Fig. 3d and 194 195 Supplementary Fig. 3b). Similar results were obtained using genes that were independently found to be hypermethylated in promoter regions²⁸ (n = 150), indicating that 2HG led to reduced 196 chromatin accessibilities in gene promoters displaying DNA hypermethylation in breast cancer. In 197 contrast, no significant accessibility changes were observed in sets of genes that were highly methylated in HMECs (data not shown) or other tumor types including endometrial cancer. Next, 199 we investigated epigenetic variability among the three L2HG subpopulations and found that L2 and L3 subsets exhibited a significant decrease in accessibility in comparison to L1 subset, which 201 is consistent with earlier observations that L1 may represent a cell subpopulation that is potentially less responsive to oncometabolite perturbation (Fig. 3e). Collectively, single-cell chromatin profiling suggests that 2HG disrupts the fine-tuned spatial control of the mammary epigenome 204 and reshapes the chromatin accessibility atlas of regulatory modules, potentially leading to DNA methylator phenotype. 206

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207 2HG-mediated chromatin remodeling is linked to transcriptional repression and adverse 208 prognosis associated with tumor hypermethylation

To assess the clinical relevance of tumor-associated hypermethylated genes that exhibited concomitant chromatin compaction in response to 2HG, we first analyzed RNA-seq whole-210 211 transcriptome profiles of 521 breast tumors and 112 adjacent uninvolved tissues from the TCGA cohort (Fig. 4a). Upon unsupervised hierarchical clustering, the majority of highly methylated 212 genes appeared to be downregulated in all five PAM50 molecular subtypes, although no statistical significance was observed in luminal A tumors (Fig. 4a and Supplementary Fig. 4a). Strikingly, 214 215 transcriptional repression was most evident in basal-like breast cancer, 84% of which displayed 216 a triple-negative phenotype (i.e., negative for expression of estrogen, progesterone and HER2/neu receptors). These findings are in agreement with earlier results showing that 2HG 217 levels were elevated predominantly in ERa-negative or basal-like breast cancer. In addition, none 218 of the breast cancer patients investigated had 2HG-producing mutations in either the IDH1 or 219 IDH2 gene (Fig. 4a).

We next adopted functional pathway enrichment analyses to examine the physiological 221 role of tumor-associated DNA hypermethylation. Ingenuity pathway analysis (IPA)⁴⁵ revealed enrichment of genes involved in hereditary breast cancer signaling, reproductive system disease and gene expression (Fig. 4b and Supplementary Fig. 4b). In line with IPA analysis, 39% of the 224 highly methylated genes were linked to DNA-templated transcription in Gene Ontology (GO) 225 226 biological processes (Fig. 4c). In addition to DNA damage response (DDR), the most enriched 227 GO pathways included lipid metabolic process, oxidation-reduction, fat cell differentiation and fatty acid beta-oxidation, all of which were relevant to intracellular metabolic signaling (Supplementary 228 Fig. 4c and Supplementary Table 2), and therefore suggest an intimate entwinning of metabolic derangements with DNA hypermethylation in breast cancer.

To investigate whether altered expression of hypermethylated genes can impact the clinical outcome in breast cancer patients, we performed survival analysis of the TCGA breast

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cancer cohort. Approximately 10% of the genes exhibited a significant association between low 233 expression and shorter disease-free survival (DFS) (Supplementary Fig. 4d). Strikingly, their 234 combination displayed a steeper drop in survival (HR = 2.24; 95% CI, 1.54 to 3.24; P = 0.00003). compared to when the genes were analyzed as single variables (Fig. 4d). This suggests that 236 237 concurrent downregulation of hypermethylated genes may have an additive adverse effect on patient prognosis. We further assessed the outcome of tumor hypermethylation on patient survival and found that the patients with a concurrent hypermethylation signature suffered decreased DFS 239 (Fig. 4e). Together, the results suggest that 2HG-mediated loss of promoter accessibility, DNA methylator phenotype and concurrent transcriptional repression may present a high competing 241 242 risk of mortality in breast cancer patients.

243 **2HG** enantiomers initiate tumor-associated promoter hypermethylation

To investigate whether transcriptional repression of hypermethylated genes is correlated with 244 chromatin accessibility landscape, we leveraged the recently reported ATAC-seg data of 70 245 primary breast cancers from the TCGA cohort⁴⁶. We found that the hypermethylated genes with 247 transcriptional repression (boxed in Fig. 4a) showed a decrease in chromatin accessibility in basal-like or HER2-enriched breast cancers in comparison to luminal A, luminal B and normal-248 like tumors (Fig. 5a,b). We next sought to investigate if tumor-associated chromatin landscape 249 could be attributable to 2HG-mediated epigenetic remodeling. To this end, we analyzed open 251 chromatin signals corresponding to ChromHMM-annotated active promoter regions. The scATAC-seq peaks in unexposed control cells were comparable with DNase-seq and H2AFZ/H2A.Z signals that are localized at gene promoters facilitating RNA polymerase II occupancy⁴⁷, while accessibility peaks were significantly reduced in D2HG- or L2HG-exposed 254 cells (Fig. 5c). This finding suggests that oncometabolites could induce a decrease in chromatin accessibility at promoter regions of highly methylated genes that are downregulated in breast cancer. Additionally, whole-genome bisulfite sequencing (WGBS) data indicated that accessible 257

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promoter regions were essentially devoid of DNA methylation in control HMECs. These observations prompted us to investigate whether 2HG can initiate tumor-associated promoter hypermethylation accompanied by restricted chromatin accessibility evident in breast tumors.

To evaluate DNA methylation at gene promoters, we utilized oxidative bisulfite (oxBS) 261 conversion followed by pyrosequencing. DNA methylation levels across promoter CpG sites of tumor suppressor genes including but not limited to DNA damage response (DDR) genes were elevated in 2HG-exposed cells (Fig. 5d). Specifically, a marked methylation gain was observed in 264 the majority of genes examined including BRCA1, MSH2 and MLH1. Promoter hypermethylation in response to 2HG was confirmed by methylated DNA immunoprecipitation followed by gPCR (MeDIP-qPCR) (Supplementary Fig. 5a). A similar, albeit less pronounced, accumulation of de 267 novo DNA methylation was also seen in immortalized, non-transformed mammary epithelial cells (hTERT-HME1) (Supplementary Fig. 5b). To further address the disease relevance of 2HGmediated promoter hypermethylation, we evaluated our breast cancer cohort consisted of 77 270 primary tumors and 10 uninvolved tissue specimens⁴⁸. Methyl-CpG binding domain proteins 271 followed by sequencing (MBDCap-seq) indicated accumulation of DNA methylation at target 272 promoter regions in tumor samples in comparison with their normal counterparts (Supplementary 273 274 Fig. 5c). Collectively, these data suggest that 2HG induces loss of promoter accessibility accompanied by DNA hypermethylation of tumor suppressor genes, which is a prominent 275 hallmark of the breast cancer epigenome. 276

277 Single-cell mass cytometry reveals epigenetic plasticity and phenotypic heterogeneity

To disentangle epigenetically heterogeneous responses to 2HG at single-cell resolution, we next performed high-dimensional mass cytometry^{49,50} on viably cryopreserved cell suspensions from 2HG-exposed or unexposed control HMECs as well as cells exposed to 2HG followed by 5-day withdrawal (Supplementary Fig. 6a,b). The panel of metal-conjugated antibodies was designed to detect both chromatin modifications and intracellular proteins including BRCA1, MSH2 and

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MLH1 that are involved in DDR and checkpoint signaling (Supplementary Fig. 6a). Consistent with mass spectrometry measurements (Fig. 1i and Supplementary Fig. 1e), mass cytometry analysis showed that 2HG exposure led to a substantial increase in all histone markers investigated (Supplementary Fig. 6c). The biaxial gating of live single cells indicated a concurrent increase in multiple distinct classes of histone methylation and the presence of cell populations that were potentially less responsive to 2HG oncometabolites (Supplementary Fig. 6c,d).

To further characterize cell-to-cell variability in the chromatin landscape, we next applied nonlinear dimensionality reduction using *t*-distributed stochastic neighbor embedding (*t*-SNE) analysis. The *t*-SNE visualization revealed that control and withdrawal groups had similar multidimensional phenotypes and cell density distributions, which were readily distinct from those of 2HG-perturbed cells (Fig. 6a). Accordingly, altered chromatin modifications were effectively reverted by 2HG withdrawal (Supplementary Fig. 6c,d), suggesting that chromatin remodeling imposed by 2HG is essentially reversible. Self-organizing maps generated by FlowSOM further identified six discrete clusters as shown in Fig. 6b-d. Strikingly, a large population of HMECs (Cluster 1) displayed a concomitant increase in histone markers following 2HG exposure and reciprocal decrease upon withdrawal (Fig. 6e).

We next asked if 2HG-induced chromatin remodeling correlated with altered expression of DDR genes displaying promoter hypermethylation in response to 2HG (Fig. 5d). As expected, 2HG-responsive Cluster 1 cell subsets exhibited diminished expression of BRCA1, MSH2 and MLH1, which was restored upon withdrawal (Fig. 6f). In addition, BRCA1 downregulation was inversely correlated with H4K20 methylation (Supplementary Fig. 6e) and, to our surprise, we observed a remarkable association between the expression of the *BRCA1* and *MSH2* genes in Cluster 1 (Fig. 6g). Interestingly, this positive association was also evident in the CCLE cancer cell lines as well as in the TCGA breast cancer cohort (Fig. 6h,i). Although the precise mechanism is currently unknown, the findings may suggest that the two DDR genes are controlled by a shared set of transcriptional regulators, possibly via epigenetic modulators. Taken together, the

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309 multidimensional investigation of chromatin regulators directly implicates that the epigenome 310 reprogramming imposed by 2HG and subsequent downregulation of DDR genes associated with 311 tumor hypermethylation could contribute to the pathogenesis of breast malignancies with high 312 2HG accumulation.

313 Discussion

Breast cancer cells accumulate high levels of 2HG with preferential concentration of L2HG in 314 basal-like subtypes. Here we show that either of the 2HG enantiomers is sufficient to broadly confer two hallmarks of the breast cancer epigenome, i.e., global loss of 5hmC and promoter 316 hypermethylation. Following 2HG exposure, promoter regions of the tumor suppressor genes 317 involved in DDR signaling displayed reduced chromatin accessibility accompanied by methylation 318 319 gain. The associated downregulation of BRCA1, MSH2 and MLH1 in 2HG-responsive cell subpopulations was validated by mass cytometry. Dysfunctional DDR pathway is one of the inherent characteristics of 'BRCAness', which is commonly seen in basal-like breast tumors and 321 is manifested by an enhanced mutation rate and genomic instability⁵¹. Besides 2HG-mediated inhibition of active DNA demethylation, recent studies show that 2HG can directly inhibit aKGdependent DDR signaling^{19,52,53} or indirectly alter expression of DNA repair genes^{54,55}, suggesting 324 that intratumor accumulation of 2HG potentially induces DDR deficiency via multiple signaling 325 pathways. It is of interest to note in this context that 2HG exposure has been reported to establish the BRCAness phenotype in clinically pertinent models including patient-derived glioma cell lines 327 and primary AML bone marrow cultures⁵⁵. These findings may be relevant for designing treatment 328 strategies for breast cancer patients with high intratumor 2HG, since effector pathways such as 329 defective DDR signaling could represent an alternate targetable vulnerability in specific tumor subtypes with a stem cell-like transcriptional signature³⁰, other than counteracting 2HG 331 overproduction per se, for instance by using IDH small molecule inhibitors.

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333	Aside from promoter hypermethylation, we show that 2HG inhibits a multitude of histone
334	demethylases resulting in accumulation of both repressive and permissive chromatin marks.
335	Further, genome-scale profiling of chromatin accessibility revealed selective loss of accessibility
336	in active or poised chromatin and gain of accessibility in repressive or quiescent chromatin states
337	in response to 2HG. These results indicate previously uncharacterized, two opposing effects of
338	the oncometabolites imposed on the cellular epigenome, suggesting multifaceted entwinning of
339	cancer metabolism with epigenetic regulation. Moreover, alterations in open chromatin occupancy
340	were detected at enhancer and insulator regions. Of note, intratumor D2HG has been shown to
341	dysregulate insulator or chromatin boundary function and promote aberrant gene-enhancer
342	interaction, leading to constitutive activation of the glioma oncogene PDGFRA ⁵⁶ . The findings
343	therefore suggest that metabolic perturbations in breast cancer may modulate key aspects of
344	chromatin functions including the three-dimensional (3D) genome topology.

Tumor heterogeneity is implicated in a wide range of neoplastic events involved in tumor evolution, dissemination, relapse or drug resistance². Characterization of the molecular origin of 346 intratumor diversity is thus integral to understanding and harnessing tumor heterogeneity and may 347 provide new opportunities to define tumor subtypes or to design effective treatment. While genetic 349 alterations have provided early insights into tumor heterogeneity, less attention has been paid to epigenetic diversity in breast cancer. In this study, scATAC-seq was applied to address cell-tocell variability in the chromatin regulatory landscape and we found that the two enantiomers 351 induced distinct chromatin accessibilities in the mammary epigenome. It is noted in this context that L2HG-exposed cells exhibited greater variability in comparison to D2HG-exposed cells, which is supported by the observations that hypoxic induction of L2HG could contribute to the 354 development of epigenetic heterogeneity in glioblastoma¹⁷. Furthermore, single-cell profiling of epigenetic modifications by mass cytometry identified multiple cell subpopulations differentially 357 responding to 2HG enantiomers. These observations suggest that metabolic dysfunction may

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- enhance epigenetic cell-to-cell variability in chromatin regulatory modules, which can functionally
 and dynamically contribute to intratumor heterogeneity.
- Of note, our findings and previous studies have suggested that high 2HG breast tumors without *IDH* mutations are associated with poor survival³⁰, whereas a rare breast cancer subtype 361 carrying *IDH* mutations has been reported to show better prognosis^{34,35}. Consistently, prolonged survival has been observed in glioblastoma and anaplastic astrocytoma patients with IDH mutations^{57,58}. These observations imply that the pathological mechanisms of high 2HG tumors 364 may vary in the presence or absence of *IDH* mutations, which can be partly ascribed to the different potencies of the two enantiomers, i.e., L2HG is relatively more potent than D2HG that is produced by mutated IDH enzymes¹⁸⁻²⁰. Alternatively, L2HG induction has been shown to be more 367 sensitive to metabolic disturbances and generated via promiscuous enzymatic activity under hypoxic^{16,17} or acidic conditions^{14,15}, which may yield cumulative adverse impacts on patient prognosis. Additionally, L2HG has been shown to promote the development of epigenetic cell-tocell variability¹⁷. Intriguingly, more recent studies indicate that JHDM histone demethylases can 371 directly sense cellular oxygen levels to regulate cell fate decisions^{59,60}. In analogy, it might be plausible that aKG-dependent dioxygenases including TET DNA hydroxylases and JHDM histone 374 demethylases could serve as metabolic sensors by detecting intratumor 2HG levels, which may reflect profound metabolic disturbances accompanied by underlying acidosis and hypoxia implicated in the tumor microenvironment. 376

Collectively, the present study substantiates that 2HG imposes metabolic footprints on the mammary epithelial epigenome by impairing DNA and histone demethylation, and provides a molecular basis in which altered metabolism leads to loss of 5hmC and associated promoter hypermethylation, thereby priming early epigenetic events to be exploited during breast cancer development (Fig. 6j). This in turn suggests that defective metabolic fluxes can disrupt epigenetic homeostasis resulting in loss of chromatin integrity. Nonetheless, 2HG-induced epigenetic liabilities are found to be dynamic and essentially reverted upon withdrawal, highlighting the

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inherent plasticity of the cellular epigenome. Finally, our findings suggest that chromatin and its
 regulatory modules are highly vulnerable to intracellular metabolic cues and future investigation
 on metabolism-epigenome coupling may lead to the identification of key molecular signatures that
 determine breast cancer susceptibility.

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388 Methods

389 Cell lines, growth conditions and reagents

Human breast cancer cell lines BT20, BT474, MCF7, MDA-MB-157, MDA-MB-231 and MDA-MB-361, and non-malignant immortalized epithelial cells hTERT-HME1, 184B5 and MCF12A were 391 acquired from the American Type Culture Collection (ATCC). Unless otherwise stated, cancer cell lines were maintained in DMEM (Gibco) supplemented with 10% fetal bovine serum (Sigma-Aldrich) and 100 U/ml penicillin plus 100 µg/ml streptomycin (Gibco) as previously reported^{61,62}. 394 Primary HMECs were obtained from Invitrogen and maintained at low passage number (below 5). HMECs, hTERT-HME1, 184B5 and MCF12A cells were cultured in mammary epithelial growth 396 medium according to the manufacturer's instructions. Authentication of cell line genomic DNA 397 was performed at ATCC using DNA fingerprint analysis of polymorphic, short tandem repeat sequences. Exposure to cell-permeable 2HG analogues was carried out by supplementing octyl esters of R-2-hydroxyglutarate or S-2-hydroxyglutarate (Cayman Chemical) to the culture medium 400 at a final concentration 72 hr before harvesting. Dimethyloxalylglycine (DMOG) was obtained from 401 Sigma-Aldrich. Culture medium was replaced daily with fresh complete medium with or without 402 oncometabolite supplementation. 403

404 Metabolite extraction and quantification by LC-MS

Following dissociation, cells were washed twice with ice-cold phosphate-buffered saline (PBS) 405 and cell pellets were flash-frozen on dry ice. For aKG analysis, metabolites were extracted with 406 80:20 methanol:water (-80°C) containing stable isotope-labeled internal standard [1,2,3,4-13C4]α-407 ketoglutaric acid (Cambridge Isotope Laboratories) and incubated at -80°C for 1 hr as described 408 previously^{63,64}. Extracts were then centrifuged at 13,800g for 10 min and supernatants were 409 transferred to glass autosampler vials for high-performance liquid chromatography-electrospray 410 ionization-mass spectrometry (HPLC-ESI-MS) measurements. For 2HG analysis, cells were 411 processed as mentioned above except that [1,2,3,4-13C4]L-malic acid (Cambridge Isotope 412

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Laboratories) was added as an internal standard and dried extracts were derivatized with diacetyl-413 L-tartaric anhydride (DATAN, Sigma-Aldrich). HPLC-ESI-MS detection was conducted on a 414 ThermoFisher Q Exactive mass spectrometer with on-line separation by a ThermoFisher Dionex 415 Ultimate 3000 HPLC. HPLC conditions for αKG analysis were: column, Synergi Polar-RP, 4 μm, 416 417 2x150 mm (Phenomenex); mobile phase A, 0.1% formic acid in water; mobile phase B, 0.1% formic acid in acetonitrile; flow rate, 250 µl/min; gradient, 1% B to 5% B over 5 minutes, 5% B to 418 95% B over 1 min and held at 95% B for 2 min. HPLC conditions for 2HG analysis were: column, 419 Luna NH2, 3 µm, 2x150 mm (Phenomenex); mobile phase A, 5% acetonitrile in water containing 420 20 mM ammonium acetate and 20 mM ammonium hydroxide, pH 9.45; mobile phase B, 421 422 acetonitrile; flow rate, 300 µl/min; gradient, 85% B to 1% B over 10 min and held at 1% B for 10 min. The conditions used to selectively quantify D2HG and L2HG were: column, Kinetex C18, 2.6 423 µm, 2.1x100 mm (Phenomenex); mobile phase, 1% acetonitrile with 125 mg/l ammonium formate, 424 pH 3.6; flow rate, 400 µl/min. Full scan mass spectra were acquired in the orbitrap using negative 425 ion detection over a range of m/z 100-800 at 70,000 resolution (m/z 300). Metabolite identification 426 was based on accurate mass match to the library ±5 ppm and agreement with the HPLC retention 427 time of authentic standards. Quantification of metabolites was carried out by integration of 428 429 extracted ion chromatograms with the corresponding standard curves.

430 Immunofluorescence staining

Cells were plated in 8-well chamber slides (Falcon) at a density of 1-2x10⁴ cells/well at least 24
hr prior to 2HG exposure. Cell were then fixed with 4% paraformaldehyde (PFA) in PBS for 10
min at room temperature (RT) and permeabilized with 0.2% Triton X-100 in PBS for 10 min at RT.
For 5hmC staining, permeabilized cells were treated with 2N HCl for 30 min at RT and neutralized
with 100 mM Tris-HCl (pH 8.5). Nonspecific binding was blocked with 10% goat serum in 0.2%
Triton X-100 and PBS for 1 hr at RT and stained with primary antibodies in PBS with 5% goat
serum and 0.2% Triton X-100 overnight at 4°C. After incubation with Alexa Fluor-conjugated

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438 secondary antibodies (Molecular Probes) for 1 hr at RT, nuclei were stained for 5 min with DAPI
439 (Sigma-Aldrich). Single optical sections were acquired using a Zeiss LSM710 confocal
440 microscope and image quantification was performed with NIH ImageJ software (version 1.52n).
441 Primary antibodies included rabbit polyclonal anti-5hmC (1:500; 39769, Active Motif) and rabbit
442 monoclonal anti-H3K27me3 (1:800; 9733, Cell Signaling Technologies).

443 Tet-assisted bisulfite (TAB) pyrosequencing

TAB pyrosequencing was used to differentiate 5hmC from 5mC⁶⁵. High molecular weight genomic 444 DNA was extracted using Gentra Puregene reagents (Qiagen), followed by an additional ethanol 445 precipitation and resuspension in low-EDTA TE buffer (10 mM Tris-HCI, 0.1 mM EDTA, pH 8.0). 446 RNase A and proteinase K digestion were included in the isolation procedure. UV absorbance 447 448 was measured on a NanoDrop 2000 (ThermoFisher) and each DNA sample was routinely examined by agarose gel electrophoresis with GelRed staining to ensure the absence of 449 contaminating RNA and degradation of genomic DNA. Isolated genomic DNA was then subjected 450 to Tet-assisted bisulfite (TAB) treatment as we previously described⁶⁶. After bisulfite conversion 451 452 using EpiTect Fast Bisulfite Conversion kit (Qiagen), pyrosequencing was conducted on a PyroMark Q96 MD instrument using CpG LINE-1 assay (973043, Qiagen). To monitor bisulfite 453 conversion efficiency, a C outside a CpG site was added within dispensation order for the 454 sequence to be analyzed as a built-in control. The quantitative levels of 5mC and 5hmC for each 455 CpG dinucleotide were determined using PyroMark CpG software (version 1.0, Qiagen). 456

457 Multiplexed chromatin profiling by mass spectrometry

Nuclei were isolated from 2x10⁶ cells using Nuclear Isolation Buffer (NIB) composed of 15 mM
Tris-HCI (pH 7.5), 60 mM KCI, 15 mM NaCl, 5 mM MgCl₂, 1 mM CaCl₂, 250 mM sucrose, 0.3%
NP-40, 1 mM DTT plus 10 mM sodium butyrate added immediately prior to use, for 30 min on ice.
Nuclei were pelleted at 600*g* for 5 min at 4°C and detergent was removed by washing twice with

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NIB without NP-40. Histones from isolated nuclei were acid extracted with 5 volumes of 0.2 M H₂SO₄ for 1 hr at RT. Cellular debris was removed by centrifugation at 4,000*g* for 5 min. Trichloroacetic acid was added to the supernatant at a final concentration of 20% (v/v) and incubated for 1 hr to precipitate histone proteins. Histones were pelleted at 10,000*g* for 5 min, washed once with 0.1% HCl in acetone, twice with 100% acetone followed by centrifugation at 15,000*g* for 5 min, and then briefly air-dried. Histones were derivatized, digested and analyzed by targeted LC-MS/MS as described previously⁶⁷⁻⁶⁹.

469 Flow cytometry

Cell cycle phase distribution was analyzed by flow cytometry. Cells were fixed with ice-cold 70% methanol for 1 hr on ice. Following centrifugation, cells were washed with PBS and stained with 10 µg/ml propidium iodide (Sigma-Aldrich) solution in PBS containing 1 µg/ml DNase-free RNase A (ThermoFisher) and incubated in the dark on ice for 1 hr. Samples were then processed on a BD FACSCalibur flow cytometer equipped with CellQuest Pro software (version 5.2.1, Becton Dickinson) and data were analyzed using FlowJo software (version 7.6.5, Tree Star).

476 Single-cell ATAC-seq library preparation

Single-cell ATAC-seq libraries were prepared on a Fluidigm C1 workstation using 'ATAC Seq-477 Cell Load and Stain Rev C' script as previously described³⁷ with modifications. Briefly, cells were 478 passed through a 20 µm cell strainer (CellTrics, Sysmex Partac) to remove debris and remaining 479 cell aggregates and mixed at a ratio of 7:3 with C1 suspension reagent. The resulting single-cell 480 suspension was loaded on C1 Single-Cell Open App IFC chip (1862x, 10-17 µm, Fluidigm) at a 481 concentration of 350 cells/µl. Captured cells were stained with 2 µM green-fluorescent calcein-482 AM and 4 µM red-fluorescent ethidium homodimer-1 (Molecular Probes) and visualized under an 483 484 EVOS FL cell imaging station (Life Technologies) to ensure successful capture and to determine cell viability. The single-cell capture rates were typically >80% and >90% of captured single cells 485

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486	were alive. After cell lysis and Tn5 transposition, 8 cycles of pre-amplification were run on IFC
487	chip. Pre-amplified PCR products were transferred to 96-well plates and further amplified for an
488	additional 13 cycles using custom Nextera dual-index primers and NEBNext High-Fidelity 2X PCR
489	master mix (New England Biolabs). Individually barcoded libraries were pooled and purified on a
490	single MinElute column (Qiagen). The quality and size distribution of pooled libraries were
491	evaluated on an Agilent 2100 Bioanalyzer using High Sensitivity DNA reagents (Agilent).

492 Single-cell ATAC-seq data analysis

scATAC-seq libraries were sequenced on a NextSeq 500 platform with High Output reagents 493 (Illumina) using paired-end 75-bp reads. All scATAC-seg data were preprocessed as essentially 494 described³⁷. In short, adapter and primer sequences were trimmed and initial guality control 495 496 checks were performed using FastQC tools (https://www.bioinformatics.babraham.ac.uk/ projects/fastgc/). Sequencing reads were aligned to the GRCh37/hg19 assembly of the human 497 genome using Bowtie2 (ref. ⁷⁰) with the parameter '-X2000' to ensure paired reads were within 2 498 kb of one another. PCR duplicates were eliminated using Picard tools (version 2.9.2, 499 http://broadinstitute.github.io/picard/) and alignments with mapping quality less than 30 were subsequently removed by samtools. Reads mapped to the mitochondria and unmapped contigs 501 were filtered out and excluded from further analysis. PCA projections of scATAC-seq profiles were performed using SCRAT⁷¹, and gene feature was applied to aggregate sequencing reads from each cell, in which 3,000 bp upstream to 1,000 bp downstream of TSS is regarded as the region 504 of interest for each gene. After aggregation, the signals for each feature were normalized to adjust for library size and model-based clustering (mclust) module was utilized to identify cell 506 subpopulations. Peak calling was performed using MACS2 with the following settings: --nomodel 507 --nolambda --keep-dup all --call-summits. Artifact signals were excluded using ENCODE 508 blacklist⁷². Circular visualization of ATAC-seq signals was carried out by employing Circos tools (version 0.69-6, http://circos.ca). 510

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511 Breast cancer cohorts, resources and data analysis

Level 3 TCGA Breast Invasive Carcinoma (BRCA) data of tumor and normal samples were 512 accessed from the Broad GDAC Firehose (http://gdac.broadinstitute.org) and RSEM-normalized RNA-seq values were log2 transformed before analysis. Unsupervised hierarchical clustering was 514 515 utilized to distinguish mRNA expression profiles among different genes and heat maps were generated using heatmap.2 function implemented in gplots package of R statistical program. Clinical data including PAM50 intrinsic subtypes, ER/PR/HER2 expression and IDH mutation 517 status were retrieved using the Cancer Genomics cBioPortal⁷³ and were integrated into RNA-seq 518 heat map. TCGA DNA methylation data generated using Infinium Human Methylation 450K 519 (HM450K) BeadChip array were retrieved from the cBioPortal database. Normalized methylation 520 scores at each CpG dinucleotide are expressed as β values, representing a continuous 521 measurement from 0 (completely unmethylated) to 1 (completely methylated). In the event of 522 multiple CpG probes per gene, the most negatively correlated with mRNA expression was selected. Chromatin accessibility data of TCGA primary tumor tissue samples were extracted from 524 the UCSC Xena browser (https://xenabrowser.net/). After z-scale normalization of ATAC-seq 525 signals, open chromatin occupancies at promoter regions were correlated with PAM50 gene 527 signature to evaluate DNA accessibility profiles across breast cancer subtypes. Our breast cancer methylome data generated using MBDCap-seg are available at The Cancer Methylome System (http://cbbiweb.uthscsa.edu/KMethylomes/). Global chromatin profiling and metabolomics 530 datasets were retrieved from the Broad Institute CCLE (https://portals.broadinstitute.org/ccle).

531 Oxidative bisulfite (oxBS) pyrosequencing

To selectively detect 5mC modification, genomic DNA was subjected to oxBS conversion⁷⁴ using TrueMethyl oxBS module (NuGEN Technologies) as per the manufacturer's recommendations. In short, genomic DNA was affinity-purified using 80% acetonitrile (Fisher Scientific) and TrueMethyl magnetic beads to eliminate potential contaminating compounds. After the

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denaturation step, genomic DNA was oxidized to convert 5-hydroxymethylcytosine to 5formylcytosine. Bisulfite treatment was then carried out to convert 5-formylcytosine to uracil, 537 leaving 5-methylcytosine intact. Following desulfonation and purification, converted DNA was quantified using Qubit ssDNA assay (Invitrogen). PCR amplification of oxBS converted DNA was 540 carried out with biotin-labeled primers. Primer design was carried out using PyroMark Assay Design software (version 2.0, Qiagen). Pyrosequencing of biotinylated PCR products was 541 performed using PyroMark Q48 Advanced CpG reagents (Qiagen) on a Pyromark Q48 Autoprep 542 apparatus (Qiagen) following the manufacturer's protocol. 5mC levels at CpG sites were determined using PyroMark Q48 Autoprep software (version 2.4.2, Qiagen) in CpG Assay mode. 544 545 All samples were prepared, amplified and sequenced in triplicates. PCR and pyrosequencing primers are listed in Supplementary Tables 3 and 4.

547 Methylated DNA precipitation PCR (MeDIP-qPCR)

Prior to the 5mC immune-capture procedure, genomic DNA was fragmented to an average length 548 of 200-600 bp using a Covaris 220 system. MeDIP was performed using MeDIP reagents (Active Motif) as per the manufacturer's instructions. In brief, fragmented DNA was heat-denatured and immunoprecipitated with anti-5mC antibody (39649, Active Motif). An additional quantity of 551 fragmented DNA equivalent to 10% of DNA being used in the immunoprecipitation reaction was also denatured and saved as input DNA. Immunoprecipitated DNA and input DNA were then purified with phenol/chloroform extraction and amplified using GenoMatrix Whole Genome 554 Amplification kit (Active Motif). Quantitative PCR was performed using PowerUP SYBR Green master mix on an ABI StepOnePlus real-time PCR instrument (Applied Biosystems). All PCR 556 reactions were run in triplicates. The relative enrichment of target sequences after MeDIP was evaluated by calculating the ratios of the signals in immunoprecipitated DNA versus input DNA. Locus-specific primers were designed with NCBI Primer-BLAST and synthesized by Integrated DNA Technologies. Primer sequences are provided in Supplementary Table 5.

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561 Panel design and heavy-metal labeling of antibodies

Prior to antibody conjugation, the antibody panel was designed by allocating targets to specific 562 heavy-metal isotopes depending on the sensitivity of the mass cytometer, e.g., assigning low abundance targets to high sensitivity channels in order to minimize potential spectral overlap⁷⁵. 564 Subsequently, in-house conjugation of antibodies was performed using Maxpar X8 antibody labeling reagents (Fluidigm) as previously described⁷⁶ with some modifications. Briefly, up to 100 µg of carrier-free IgG antibody was subjected to buffer exchange by washing with R-buffer using 567 a 50 kDa Amicon filter (Millipore) that was pre-soaked with R-buffer. Antibodies were then partially reduced with 4mM TCEP (ThermoFisher) for 30 min at RT followed by washing with C-buffer. In 570 parallel, metal chelation was carried out by adding lanthanide metal solutions (Fluidigm) to chelating polymers (Fluidigm) in L-buffer. Metal-loaded polymers were then washed with L-buffer 571 and concentrated on a 3 kDa Amicon filter (Millipore). Partially reduced antibodies were incubated 572 with metal-loaded polymers for 90 min at RT followed by washing with W-buffer. Following conjugation, antibody concentration was determined by spectrometry with a NanoDrop 2000 574 (ThermoFisher). Metal-conjugated antibodies were stored in antibody stabilization solution 575 (Candor Bioscience) supplemented with 0.05% sodium azide at 4°C. The panel of metal-577 conjugated antibodies is provided in Supplementary Table 6.

578 Multidimensional chromatin profiling by mass cytometry

Cell suspensions were prepared at a concentration of 1x10⁷ cells/ml in serum-free, protein-free medium and stained with 1 μM cisplatin (195Pt) for 5 min at RT to determine cell viability. After quenching with CyTOF buffer composed of PBS with 1% BSA (Invitrogen), 2mM EDTA (Ambion) and 0.05% sodium azide (Teknova), staining with lanthanide-conjugated antibodies was performed as previously described⁵⁰, but with the following modifications. In brief, following extracellular marker staining, cells were fixed with 1.6% PFA (Electron Microscopy Sciences) for 15 min at RT and permeabilized with ice-cold methanol (Fisher Scientific) for 30 min at 4°C. After

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adding Fc receptor blocker (BioLegend), cells were labeled overnight at 4°C with a cocktail of antibodies recognizing chromatin modifications or intracellular components. On the next day, 587 excess of antibodies were washed off with CyTOF buffer and cells were stained with 250 nM 191/193Ir-containing DNA intercalator (Fluidigm) in PBS with 1.6% PFA for 30 min at RT. After 590 resuspending in double-deionized water, samples were kept on ice. Immediately prior to acquisition, cells were prepared at a concentration of 0.2-1.0x10⁶ cells/ml in 0.1X EQ bead 591 solution containing four element calibration beads (Fluidigm) and filtered through a 20 µm cell strainer (CellTrics, Sysmex Partac) to remove any potential aggregates. Cells were then acquired at a rate of 300-500 events/s using a Helios mass cytometer (Fluidigm) and CyTOF software 594 (version 6.7) with noise reduction, a lower convolution threshold of 400, event length limits of 10-150 pushes, a sigma value of 3 and a flow rate of 0.030 ml/min. 596

597 Mass cytometry data analysis

Data analysis was conducted using the cloud-based platform Cytobank⁷⁷ and the statistical 598 programming environment R. Following data acquisition, mass cytometry data were normalized using EQ calibration beads as previously described⁷⁸. Bead-normalized data were then uploaded onto Cytobank platform to carry out initial gating and population identification using the indicated 601 gating schemes (Supplementary Fig. 6b). For downstream analysis, live single cells were identified based on 140Ce bead, event length, DNA content (191Ir) and live/dead (195Pt) channels. Histograms and two-dimensional contour plots were generated to assess the global 604 levels of chromatin modifications across the samples. Using an equal number of randomly selected live singlets from each sample, dimensionality reduction was implemented by t-SNE 606 analysis with the following settings: perplexity = 60, theta = 0.5, iteration = 1.000. FlowSOM 607 clustering was carried out on the same data using the standard parameters to quantify changes 608 in cell subsets in an unbiased manner. The 2D coordinates of the t-SNE map were fed to FlowSOM analysis for population identification based on hierarchical consensus clustering. 610

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Comparisons of chromatin modifications among the samples in each cluster were performed by
 generating heat maps in R using gplots package and median signal intensities extracted from
 Cytobank.

614 Statistical analysis

Pairwise comparisons were carried out with a two-tailed unpaired Student's *t*-test and multiple comparisons were assessed using a one-way ANOVA followed by Dunnett's multiple comparison post-hoc test unless otherwise indicated in the figure legends. For Kaplan-Meier survival analysis, expression or methylation values were classified as high or low by using the median as a cutoff value and disease-free survival data was used to measure prognosis. Log-rank (Mantel-Cox) test was used to evaluate statistical differences and hazard ratio was reported with 95% confidence interval. Statistical analyses were performed using GraphPad Prism program (version 8.1). For all statistical analyses, differences of P < 0.05 were considered statistically significant. All quantitative data are presented as mean \pm s.e.m. unless specified otherwise.

624 Data availability

The raw and processed single-cell ATAC-seq data have been deposited in the National Center for Biotechnology Information (NCBI) Gene Expression Omnibus (GEO) and are available under accession GSE135412. The R code used in the study is available upon request from the authors. All other data described, analyzed and represented in the figures that support the findings of this study are available from the corresponding authors upon request.

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Author contributions

T.H.M.H., K.M. and M.K. jointly conceived the project, designed the experiments, interpreted the results and prepared the manuscript with contributions from all co-authors. M.K. carried out the majority of experiments and data analysis. J.R., M.Z. and C.L.L assisted with scATAC-seq data analysis, computational modeling and statistical methods. K.M. and M.K. established the methods for chromatin mass cytometry. C.M.W, N.D.L and N.K assisted with validation of metal-tagged antibodies. All authors read and approved the manuscript.

647 Competing interests

- T.H.M.H holds stock options and is on the medical advisory board of LiSen Imprinting Diagnostics
- 649 Wuxi Co., Ltd. All other authors have no competing interests.
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818 Figure legends

Fig. 1 | 2HG imposes a global loss in 5hmC and progressive gain in histone methylation 819 on the mammary epithelial epigenome. a, Schematic of reductive conversion of αKG to the enantiomers of 2HG. 2HG is stereospecifically produced from aKG by mutant IDH proteins 821 (mIDH1/2) or by promiscuous enzymatic reactions. b, Extracted-ion chromatogram showing chiral derivatives of 2HG detected in breast cancer cells. c.d. Chiral LC-MS analysis of the two enantiomers D2HG (c) and L2HG (d) in breast cancer cell lines, benign and normal mammary 824 epithelial cells (n = 3 independent replicates). e, Intratumor levels of αKG , 2HG, succinate and fumarate in the CCLE breast cancer cell lines. αKG, 2HG, succinate and fumarate are structurally 827 similar to one another and are potentially involved in DNA and histone demethylation processes. *P < 0.05 versus basal-like tumor cells by one-way ANOVA with Dunnett's multiple comparison test. f, Schematic of 2HG-mediated inhibition of aKG-dependent DNA demethylation by the TET family of DNA hydroxylases. TET enzymes catalyze oxidation of 5mC to 5hmC with oxygen and Fe^{2+} as cofactors. **g**, Global levels of 5hmC and H3K27me3 following 72-hr exposure to D2HG. 831 Line plot is shown for the mean intensity of 5hmC (blue) and H3K27me3 (red) assayed by immunofluorescence staining. ***P < 0.001 versus control cells by one-way ANOVA with 834 Dunnett's multiple comparison test (n = 8 images per condition). ns, not significant. At least 60 nuclei were examined and signal intensities were normalized to DAPI nuclear counterstain. h. Representative immunofluorescence images of HMECs after 72-hr exposure to D2HG at the 837 indicated concentrations. Scale bar, 10 µm. i, Fold change in different types of histone methylation upon 2HG exposure. Following 72-hr exposure to 100 µM of either D2HG or L2HG, global levels of methylated/unmethylated lysine residues were assayed by multiplexed mass spectrometry. 839 While two major histone H3 variants H3.1 and H3.3 are highly similar in their amino acid composition, H3.1 is predominantly localized at heterochromatin, which is in contrast to the 841 preferential H3.3 accumulation in intragenic regions of transcribed genes. *P < 0.05, **P < 0.01, ***P < 0.001 versus control unexposed HMECs by two-tailed unpaired Student's t-test with Holm-

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Sidak correction for multiple comparisons (n = 3 independent replicates). Error bars in column
charts or line plot represent s.e.m. αKG, α-ketoglutarate; 2HG, 2-hydroxyglutarate; IDH, isocitrate
dehydrogenase; ER, estrogen receptor; LC-MS, Liquid chromatography-mass spectrometry;
CCLE, Cancer Cell Line Encyclopedia; HER2, human epidermal growth factor receptor 2; 5hmC,
5-hydroxymethylcytosine; 5mC, 5-methylcytosine; TET, ten-eleven translocation; me0,
unmethylated; me1, monomethylated; me2, dimethylated; me3, trimethylated histone lysine
residues.

Fig. 2 | Single-cell ATAC-seg identifies epigenetically heterogeneous responses to 2HG 851 exposure. a, Schematic view of the scATAC-seq protocol. Culture medium was replaced daily by freshly prepared media with or without oncometabolite supplementation (arrowheads). b, Insert 854 size distribution of ATAC-seq fragments from a single cell displaying characteristic nucleosomeassociated periodicity. Diagnostic insert sizes for mononucleosome, dinucleosome and trinucleosome are labeled. c, Representative genome browser tracks showing open chromatin regions in HMECs detected by scATAC-seq, which are highly consistent with DNase 858 hypersensitive sites (DHS) detected by bulk DNasel-seg (GSE29692). Single cell profiles are shown below the aggregated profiles. d, Principal component analysis (PCA) of 248 single cells to identify cell subpopulations based on the chromatin accessibility landscape. Ctrl (n = 83), D2HG- (n = 90) and L2HG-exposed (n = 75) cells are colored by sample type. Each data point 861 represents a single cell. e, Proportions of cell subpopulations identified by model-based clustering. Cell clusters are color-coded as indicated. f, Whole-genome heat maps showing enrichment of scATAC-seq signals in L2HG cell subsets over a 20-kb region centered on CpG 864 islands and H3K4me3 peak summits. Each row represents one individual genomic locus and is sorted by decreasing scATAC-seg signal. The color represents the intensity of chromatin accessibility. Intervals flanking indicated feature are shown in kilobases. ATAC, assay for 867 transposase accessible chromatin; HMECs, human mammary epithelial cells.

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Fig. 3 | 2HG decreases chromatin accessibility at genes that are highly methylated in breast cancer patients. a, Workflow of the integration of scATAC-seq data with high-throughput omics 870 datasets to characterize clinically relevant epigenetic signatures imposed upon 2HG exposure. b. 871 Distribution of ATAC-seq signals across ENCODE-ChromHMM functionally annotated regions in 872 873 response to 2HG perturbation. c, Metagene analysis of chromatin accessibility assayed by scATAC-seq. Epigenomic accessibility landscape is centered on TSS across the genome (n =874 20,242 genes). Colors represent individual cells. Solid lines indicate mean values and semi-875 transparent shade around the mean curve shows s.e.m. across the region. While a sharp and abrupt peak is evident over TSS in unexposed control cells, accessibility peaks are distorted in 877 878 2HG-exposed cells (arrowheads). d, Chromatin accessibility profiles for highly methylated genes in the TCGA cancer cohorts. scATAC-seg profiles in 2HG-exposed and unexposed cells are centered on TSS of highly methylated genes (n = 150 genes) in breast cancer (two independent datasets) and endometrial cancer patients. Colors represent single cells (left) and average 881 accessibility profiles in each experimental condition (right). e, Chromatin accessibility profiles in L2HG subpopulations across TSS of highly methylated genes (n = 150 genes) in the TCGA cancer cohorts. **P* < 0.05, ***P* < 0.01, ****P* < 0.001 versus unexposed control cells by one-way 884 ANOVA followed by Dunnett's multiple comparison test. ENCODE, Encyclopedia of DNA Elements: ChromHMM, chromatin Hidden Markov Modeling: TSS, transcriptional start site: TCGA, The Cancer Genome Atlas; Txn transition, transcriptional transition; Txn elongation, 887 888 transcriptional elongation; Weak Txn, weak transcribed; CNV, copy number variation.

Fig. 4 | Tumor-associated DNA hypermethylation is linked to transcriptional repression and poor patient prognosis in basal-like breast cancer. a, Heat map depicting mRNA expression of highly methylated genes whose promoter regions showed diminished chromatin accessibility following 2HG exposure. The column dendrogram indicates unsupervised hierarchical clustering of 150 genes that are highly methylated in the TCGA breast cancer cohort.

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Rectangle outlined in white represent genes downregulated in basal-like tumors. Vertical sidebars 894 indicate the category of each patient with regard to IDH1/2 mutations (mIDH1/2), ER, PR, HER2 and PAM50 status. b. Overrepresented canonical signaling and metabolic pathways from IPA 896 profiling of highly methylated genes in the TCGA breast cancer cohort. Colored bars (top x axis) 897 898 represent $-\log_{10} P$ values obtained by Fisher's exact test whereas the black line (bottom x axis) indicates the ratio between the number of genes compared to the total number of genes in a given pathway. c, Pie chart indicating GO biological processes enriched in genes associated with tumor 900 hypermethylation. See also Supplementary Table 2. d.e. Prognostic significance of concurrent 901 transcriptional repression (d) and hypermethylation (e) of genes shown in Supplementary Figure 902 903 4d. Disease-free survival (DFS) was investigated using Kaplan-Meier analysis, and log-rank (Mantel-Cox) P values and hazard ratios (HR) are shown (see Methods for further details). TCGA, 904 The Cancer Genome Atlas; ER, estrogen receptor; PR, progesterone receptor; HER2, human 905 epidermal growth factor receptor 2; PAM50, prediction analysis of microarray 50; IPA, Ingenuity Pathways Analysis; GO, Gene Ontology. 907

Fig. 5 | 2HG induces DNA hypermethylation of tumor suppressor genes accompanied by loss of promoter accessibility. a, Heat map showing a decrease in chromatin accessibility of 909 hypermethylated genes (n = 150) in basal-like and HER2-enriched breast cancer subtypes. Rectangle outlined in white represents genes downregulated in basal-like tumors as indicated in 911 Fig. 4a. Vertical sidebar indicates five different molecular subtypes. b, Quantitative comparison 912 of chromatin accessibility of hypermethylated genes across the TCGA breast cancer subtypes. The upper and lower whiskers indicate the minimum and maximum values of the data, center 914 lines indicate the median, and the first and third guartiles are indicated by the bottom and top 915 edges of the boxes respectively. ***P < 0.001 versus basal-like tumors by one-way ANOVA with Dunnett's multiple comparison test: basal-like (n = 15), HER2-enriched (n = 11), luminal A (n = 15) 917 18), luminal B (n = 25) and normal-like (n = 1) subtypes. c, IGV genome browser tracks showing 918

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diminished chromatin accessibility at gene promoters following 2HG exposure. ChromHMMdefined chromatin states (GSE38163), DNasel-seq (GSE29692), H2AFZ/H2A.Z ChIP-seq (GSE29611), WGBS profiles (GSE86732) from HMECs are shown. Arrows indicate TSS and 921 direction of transcription initiation, and y-axes show read coverage. Histone variant H2A.Z is enriched around TSS. **d**, Promoter methylation measured by oxBS pyrosequencing. *P < 0.05, **P<0.01, ***P<0.001 versus control by one-way ANOVA with Dunnett's multiple comparison 924 test (n \ge 3 individual replicates). Error bars denote s.e.m. Validation by MeDIP-qPCR was also done in the same samples and promoter hypermethylation following 2HG exposure was confirmed using hTERT-HME1 cells (see Supplementary Figure 5a,b). IGV, Integrative Genomics 927 928 Viewer; ChromHMM, chromatin Hidden Markov Modeling; WGBS, whole-genome bisulfite sequencing; TSS, transcriptional start site; oxBS, oxidative bisulfite; MeDIP, methylated DNA immunoprecipitation.

Fig 6 | Single-cell mass cytometry demonstrates downregulation of hypermethylated 931 genes in 2HG-responsive cell subpopulations. a, Representative t-SNE plots showing levels of histone modification markers in response to 2HG exposure. C, unexposed control cells; D, cells exposed to D2HG for 72 hr; L, cells exposed to L2HG for 72 hr; LW, cells exposed to L2HG for 934 72 hr followed by 5-day withdrawal of L2HG. Each data point on the t-SNE maps represents an individual cell and its color corresponds to cellular levels of each marker assessed. Density plots at the bottom show cell population distribution in each experimental group (~10,000 cells per 937 condition). b, t-SNE plot of HMECs from all experimental groups merged. Each data point is 938 colored by condition. c, t-SNE projections of epigenetically distinct cell subsets defined by 939 FlowSOM. Cells are colored according to the cluster they were assigned to using consensus hierarchical clustering in FlowSOM analysis. d, Bar chart showing changes in cell frequency 941 distribution across different treatment groups. e, Heat maps depicting epigenetically 942 heterogeneous responses upon 2HG exposure. Normalized median values of signal intensities 943

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944	are shown for each cluster. Pie charts indicate the proportion of cells from different experimental
945	groups in each cluster. f, Violin plots showing expression levels of the BRCA1, MSH2 and MLH1
946	genes in Cluster 1. **P<0.01, ***P<0.001 versus control by one-way ANOVA followed by
947	Dunnett's multiple comparison test. g,h,i, Scatter plots showing the correlation between the
948	expression of BRCA1 and MSH2 in the mass cytometry Cluster 1 (g), CCLE breast cancer cell
949	lines (h) and TCGA breast cancer cohort (i). Data in g are transformed to arcsinh scales with the
950	cofactor of 5 and four experimental groups (C, D, L and LW) are indicated by different colors. In
951	the CCLE and TCGA datasets, red and brown dots indicate cancer cell lines or tumors with
952	mutations in the BRCA1 and MSH2 genes respectively. Spearman's correlation coefficient (r with
953	P value) is indicated at the bottom of the panel. j, A model for metabolic rewiring of the breast
954	cancer epigenome. TCA cycle metabolite αKG enhances TET and JHDM enzyme activities
955	facilitating active DNA and histone demethylation such that promoter regions of tumor suppressor
956	genes (TSG) remain accessible. Cancer metabolism accompanied with intratumor accumulation
957	of 2HG oncometabolites, which antagonize DNA hydroxylases or histone demethylases, may
958	drive global loss of 5hmC and promoter hypermethylation leading to DNA methylator phenotype.
959	L2HG exposure could also confer enhanced cell-to-cell variability in the chromatin regulatory
960	landscape by reversibly remodeling the breast cancer epigenome, potentially contributing to
961	extensive intratumor heterogeneity. t-SNE, t-distributed stochastic neighbor embedding;
962	FlowSOM, flow cytometry data analysis using self-organizing maps.

Figure 1



Figure 2





Figure 4



Figure 5



