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2 Copy number variation profile-based genomic subtyping of premenstrual

3 dysphoric disorder in Chinese

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23 Abstract

24 Premenstrual dysphoric disorder (PMDD) affects nearly 5% women of reproductive age. The 25 symptomatic heterogeneity, along with largely unknown genetics, of PMDD have greatly 26 hindered its effective treatment. In the present study, 127 Chinese PMDD patients of the 'invasion' and 'depression' subtypes clinically differentiated by us earlier were analyzed 27 28 together with 108 non-PMDD controls for genome-wide copy number variations (CNVs). Germline genomic DNA samples from white blood cells were subjected to AluScan 29 30 sequencing-based CNV profiling, which enabled clustering of patient samples readily into the V and D groups, dominated by the "invasion" and "depression" clinical subtypes, 31 32 respectively; the CNVs obtained with 100-kb windows yielded two clusters that were correlated with these subtypes with a consistency of up to 89.8%. Diagnostic correlation- and 33 34 frequency-based CNV features of either CNV-gain (CNVG) or CNV-loss (CNVL) that could differentiate between V and D subtypes were selected and analyzed. CNVG features located 35 preferentially in S2-phase replicating regions and enriched with steroid hormone biosynthesis 36 37 pathway of genes were found protective against PMDD. Moreover, machine learning 38 employing the correlation-based CNV features could predict with >80% accuracy whether a genomic sample was D-type, V-type or control. In terms of their CNV profiles, the D- and V-39 40 types differed more from one another than from the controls, thereby providing a genomic basis for the clinical D-V subtyping of PMDD. Genome-wide profiling of CNVs, as a new 41 approach to complex disease genetics, has revealed recurrent CNVs and genomic features 42 beyond individual genes and mutations underlying PMDD clinical diversity. 43

44

45 Introduction

Premenstrual dysphoric disorder (PMDD) is a syndrome that afflicts 5-10% of women in
their reproductive years (1). The severity of the syndrome is typically highest just before the

48 menstruation period, suggesting that the symptoms were linked to hormonal changes. This 49 has been confirmed by the findings of premenstrual neurosteroid fluctuations, and alterations 50 in the sensitivity of GABA_A receptors to neurosteroids giving rise to mood instability (2, 3). 51 Cortical gamma-aminobutyric acid (GABA) levels also declined during the menstrual cycle 52 in healthy women but increased in women with PMDD from the follicular phase to the mid-53 luteal and late luteal stages (4). Furthermore, PMDD has been associated with the estrogen 54 receptor alpha gene ESR1 (5), and the ESC/E(Z) genes affecting the interactions of sex 55 hormones with other genes (6). Five major contributors to the etiology of PMDD include: (1) 56 genetic susceptibility; (2) progesterone and its metabolite ALLO; (3) estrogen, serotonin and 57 brain-derived neurotrophic factor (BDNF); (4) brain structure and function; and (5) the 58 hypothalamic-pituitary-adrenal axis and hypothalamic-pituitary-gonadal axis (7). The 59 schizophrenia-associated SNPs in GABRB2, located in introns 8 and 9 near an AluYi6 60 insertion, have been associated with both schizophrenia and bipolar disorder (8, 9), heroin 61 addiction (10), altruism (11), autism and mental retardation (12). Deletion of gabrb2 genes 62 from knockout mice also brought about schizophrenic symptoms that were alleviated by the antipsychotic Risperidone (13). Recently, analysis of germline copy-number-variations 63 64 (CNVs) at the nsv1177513 site in Exon 11, and the esv2730987 site in Intron 6, of GABRB2 65 in PMDD and schizophrenia patients showed that CNV alterations at both esv2730987 and 66 nsv1177513 were significantly associated with schizophrenia in Chinese and Germans as 67 well as PMDD in Chinese (14). Moreover, subjects with different levels of susceptibility to cancer could be distinguished by means of diagnostic CNV marker features selected from the 68 69 germline genomes with the application of machine learning (15).

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It is recognized that the symptoms of PMDD are consistent with multiple clinical subtypes. A
Delphi survey led to the proposal of three symptoms-based types of PMDD, *viz.* a

73 predominantly physical type, a predominantly emotional type, and a mixed type (16); and 74 DSM-V proposed that PMDD is defined by one or more of the symptoms of marked affective 75 lability, marked irritability or anger, marked depressed mood and hopelessness, and marked 76 anxiety and tension, plus at least one of seven other symptoms. At the School of Basic 77 Medicine, Shandong University of Traditional Chinese Medicine, the medical records also 78 pointed to at least two major types of PMDD, viz. an irritability-marked 'invasion' type (58.9%) and a depressive mood-marked 'depression' type (27.5%) (17). In view of the 79 80 spectrum of PMDD symptoms, the objective of the present study was to enquire whether the two major clinical subtypes of PMDD could be corelated with genomic profiles. Through 81 82 genome-wide CNV profiling by AluScan next-generation sequencing (18, 19), the results revealed two large clusters of CNV profiles that were highly correlated with the clinical 83 84 "depression" and "invasion" subtypes. Furthermore, CNV-gain (CNVG) and CNV-loss 85 (CNVL) features diagnostic of PMDD or each of the two clinical subtypes were uncovered 86 among CNVs called from sequence windows of different sizes, which were variously 87 distributed in genomic regions of different replication timing and overlapped with genes in 88 various genetic pathways of potential clinical relevance. These results provided genomic 89 verification for the invasion- and depression-subtypes employed by us previously (17), which 90 corresponded to part of the complex symptoms stipulated by DSM-V (20) as diagnostic 91 criteria for PMDD.

92

93 Methods

94 Clinical assessments

95 Clinical diagnosis of PMDD patients (P-type subjects) from asymptomatic controls (C-type
96 subjects) was performed in accordance to the protocol in Diagnostic and Statistical Manual of
97 Mental Disorders (DSM-IV) by two psychiatrists independently. The identifications of

98 'depression-type' and 'invasion-type' subjects were carried out as previously described (17).

99

100 Genomic DNA samples

Peripheral white blood cell DNA samples were collected from PMDD patients and non-PMDD control subjects with approval by the institutional ethic committee of Shandong University of Chinese Medicine. The patients and healthy volunteers who participated in this study all signed the informed consent form. The samples consist of a control cohort of 108 subjects and a PMDD cohort of 127 cases. The latter cohort was further divided into the depression-subtype (71 cases) and invasion-subtype (56 cases). The subtypings of the 127 PMDD cases were given in Table S1.

108

109 AluScan sequencing and CNV calling

110 Samples of ~0.1µg DNA were subjected to inter-Alu PCR amplification using the four Alu-111 consensual primers AluY278T18, AluY66H21, R12A/267 and L12A/8 (18). The 200 bp to 112 ~ 6 kb amplicons in each sample were employed to build a library for sequencing on the Illumina platform with 100 bp paired-end reads. According to the standard framework, all the 113 114 reads were mapped to reference human genome hg19 downloaded from UCSC by BWA, 115 followed by base recalibration and local realignment by GATK (21). CNVs were called from 116 the AluScan sequences with the method of AluScanCNV2 (19, 22) based on sequence 117 windows of 50-500 kb in 50-kb increments on the 22 autosomes and the X chromosome. The 118 CNV profiles of all 108 control and 127 PMDD subjects were available in Table S2.

119

120 Clustering and grouping of patient samples based on CNV profiles

121 The profiles of CNVG and CNVL called from the 127 P-group samples using different CNV-

122 calling window sizes were separately subjected to correlation analysis and hierarchical

clustering with 1,000 bootstraps using the 'pvclust' R package (23). The derived correlation
heatmaps as well as the CNVG-based and CNVL-based dendrograms obtained for each
window size were employed to determine the two subgroups of CNV profiles using two
different grouping methods for cross validation.

127

128 In the first method, viz. the straightforward 'cutree' method, the sub-clustering was carried out using the 'cutree' function from the 'dendextend' R package (24) to cut each dendrogram 129 130 into 2-8 sub-clusters (Figure S1). The DNA samples located in the sub-cluster populated with 131 the highest number of clinical depression-type samples among all the sub-clusters was 132 referred as D-type genomic samples; and the DNA samples located in the remaining sub-133 clusters were combined and referred as V-type genomic samples. In the second, or 'semi-134 supervised' method, some branches on the dendrograms were first rotated around their 135 respective nodes to bring the closely co-localized samples into tightly knit sub-clusters 136 enclosed by black square boxes on the diagonal of each heatmap. Thereupon, all the samples 137 within the same block box were all designated as D-type or V-type genomic samples depending on whether the majority clinical subtype of the samples were depression-type or 138 invasion-type. The designated D- and V-type genomic samples derived using the two 139 140 grouping methods for ten different window sizes are shown in Table S3 and exemplified by 141 the blue and red branches in Figure 1 and Figure S2 respectively for the 100-kb CNV profiles. 142

For either the '*cutree*' method or the '*semi-supervised*' method, let the number of CNV-based D-type samples that also belonged to the clinical depression-subtype be represented by $True_D$, and the number of CNV-based V-type samples that also belonged to the clinical invasionsubtypes be represented by $True_V$. Accordingly, the consistency (*Y*) between CNV-based classification and the clinical classification of PMDD patient samples could be estimated by:

$Y = (True_D + True_V)/127$

148 On this basis, the levels of consistency between CNV-based and clinical subtypings for the 149 different CNVs called using different window sizes for both the 'cutree' and 'semi-supervised' 150 methods are shown in Table S4. 151 Selection of diagnostic CNV features 152 153 The selection of diagnostic CNV features was performed using either (a) correlation-based 154 method or (b) frequency-based method as described (15). CfsSubsetEval from the Weka 155 package was employed together with BestFirst search method to select the correlation-based 156 diagnostic CNV features. Fisher's exact tests were employed to select the frequency-based 157 CNV features that showed significantly different occurrence frequencies between a pair of 158 sample groups (e.g. P-vs-C or D-vs-V) with a false discovery rate (FDR) less than 0.01.

159

160 Predictive subtyping of genomic samples by machine learning

161 Earlier, diagnostic germline CN-gains and CN-losses from leucocyte DNA samples of 162 subjects with or without past episodes of cancers in tissues other than leucocytes were found 163 to provide a useful basis to predict the propensity of the subject to cancer (15). Since the 127 164 P-group and 108 C-group DNA samples from PMDD and control subjects consisted of a 165 mixture of D-type, V-type and C-type DNAs, the question arose whether it was possible to 166 predict the typing of DNA samples between the D-vs-V, D-vs-C and V-vs-C choices 167 employing the diagnostic CNVG and CNVL features obtained with the correlation-based 168 method.

169

For example, in a choice between the P-vs-C types, a mixture of P- and C-type samples wererandomly separated into a labeled Learning Band and an unlabeled Test Band, with equal or

172 near equal number of samples in the two bands. Diagnostic CNVG and CNVL features were 173 selected from the labeled Combined Learning Band with machine learning using the 174 correlation-based method and employed to estimate the risk factor R for each DNA sample in 175 the Test Band according to Eqn. 1.

176
$$R = \log\left(\frac{Pr(PMDD | Features)}{Pr(Control | Features)}\right)$$
Eqn. 1

 $\Pr(PMDD|Features) = \Pr(Features|PMDD) \times \Pr(PMDD)/\Pr(Features)$

 $Pr(Control|Features) = Pr(Features|Control) \times Pr(Control)/Pr(Features)$

177 where Pr(PMDD|Features) was the posterior probability of membership in the PMDD group 178 given the CNV data of a particular Test Band sample; Pr(Control|Features) was its posterior 179 probability of membership in the Control group given the same test CNV data; 180 Pr(Features|PMDD) was the likelihood function of the test CNV data given membership in 181 the PMDD group; Pr(Features|Control) was the likelihood function of the test CNV data given membership in the Control group; Pr(PMDD) and Pr(Control) were the prior 182 183 distributions of PMDD and Control samples respectively within the Learning Band; and Pr(Features) was the prior distribution of CNV-features among all the CNVs within the 184 185 Learning Band.

For every sample in the Test Band, its value of R estimated using Eqn. 1 would predict whether the sample belonged to the Control group or PMDD group: it would predictively belong to Control group (*viz.* 'non-PMDD') if R < 0; belong to PMDD group if R > 0; or no prediction could be made if R = 0. For every PMDD sample in the Test Band, R > 0represented a 'true' prediction whereas R < 0 represented a 'not true' prediction. On the other hand, for any Control sample in the Test Band, R > 0 represented a 'not true' prediction whereas R < 0 represented a 'true' prediction. Accuracy of prediction was therefore given by:

194
$$Accuracy = \frac{[True \ predictions \ of \ Control] + [True \ predictions \ of \ PMDD]}{[Total \ predictions \ of \ Control] + [Total \ predictions \ of \ PMDD]} \times 100\% \quad Eqn. 2$$

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195

- 196 Repetition of this procedure 1,000 times would yield 1,000 Accuracy estimates, and in turn197 the Average Accuracy regarding the P-vs-C typing.
- 198

199 Functional annotation of genes overlapping with diagnostic CNV features

200 By comparing the genomic coordinates of all the frequency-based diagnostic CNV features to 201 of retrieved those the known genes from the R package 202 'TxDb.Hsapiens.UCSC.hg19.knownGene' version 3.2.2 (25), and considering any gene to be 203 'overlapping' with a CNV feature if any proportion of its sequence (from > 0% to 100% in 10% 204 increments) coincided with part or all of the CNV feature, the list of CNV-overlapping genes 205 obtained was uploaded to DAVID Bioinformatics Resources as a test-list employing the 206 'RDAVIDWebService' R package (26). All the known genes on chromosomes 1-22 and X 207 were also uploaded as the background-list. Comparison of the two lists using the 208 'getFunctionalAnnotationChart' of the 'RDAVIDWebService' R package revealed gene 209 pathways or categories, as defined in the GO, KEGG and INTERPRO databases, that were 210 enriched with the *test-list* of genes among the *background-list* of genes. The pathways or 211 categories yielding <0.05 Benjamini-corrected *p*-values were regarded to be significantly 212 enriched in the genes on the *test-list* (Table S5).

213

214 Genomic-feature content of diagnostic CNV features in different replication phases

DNA sequences on 22 autosomes and chromosome X were subject to replication-time segmentation according to Long & Xue (27). Briefly speaking, experiment-assessed replication timing of all 1-kb sequence windows in the genomes of fifteen human cell lines were retrieved from the 'UW Repli-seq track' in the UCSC Table Browser (28), and the representative replication phase of each sequence window was identified as one of the six

types of sequencing segments (viz. G1b, S1, S2, S3, S4 and G2) based on their experiment-

- assessed replication timing in all fifteen human cell lines.
- 222

The density or intensity of genomic features were quantified as described in Ng et al (29) in the diagnostic CNV features and the non-diagnostic-CNV regions in each type of replication phase. The genomic feature content of diagnostic CNV features is indicated by the fold change of the density or intensity of the genomic feature in diagnostic CNV features relative to the non-diagnostic-CNV regions.

228

229 Statistical analysis

230 All comparisons of CNV frequencies were conducted using Fisher's exact tests, and the p-231 values were adjusted by false discovery rate for multiple comparisons. In functional 232 annotation of genes, *p*-values from DAVID web service were subject to Benjamini-correction 233 for multiple comparisons. When annotating the genes that overlapped with any diagnostic 234 CNV feature, empirical *p*-values were estimated using Monte Carlo methods with 1,000 235 simulations to validate the significant gene pathways/categories based on the 50-, 100- or 236 450-kb size groups of CNV features. In each round of simulation, sequence windows of the 237 same size as the targeted group of CNV features were randomly selected from chromosomes 238 1-22 and X, with the number of selected windows being equal to the average number of CNV 239 features in the different type-comparisons to be analysed (see Table S6). For each simulation, 240 the genes that overlapped with any of the selected sequence windows were functionally 241 annotated. The empirical p-value of a targeted pathway was given by (r+1)/(n+1), where $n = n + \frac{1}{2}$ 242 1,000 and r = number of simulations that displayed significant enrichment (<0.05 Benjamini-243 corrected *p*-values) in the targeted pathway.

245 Software for data processing and visualization

Data processing tasks were carried out using custom R codes, except that tasks requiring
machine learning were processed using Weka package. All figures were drawn under R
environment using the 'ggplot2' (30), 'pheatmap' (31) and 'quantsmooth' (32) packages,
except for Figure 3 which was drawn using http://bioinformatics.psb.ugent.be/webtools/Venn/,
and Figure 5 using Integrative Genomics Viewer 2.3.69 (33).

251

252 **Results**

253 Correlations between clinical diagnosis and CNV profiles

254 In order to examine whether there might be significant correlation between the clinical 255 symptoms of PMDD patients and their germline CNV profiles, the CNVGs and CNVLs 256 called from different sizes of sequence windows on the 127 P-type DNA samples, were 257 subjected to hierarchical clustering in each instance. The CNVGs and CNVLs called from 258 100-kb sequence windows of the 71 depression-subtype and 56 invasion-subtype patient 259 samples were segregated using the cutree and semi-supervised methods into distinct D-type 260 and V-type clusters in the dendrograms as shown in Figure S2 and Figure 1 respectively. The 261 clusters obtained from the CNVG dendrograms were designated as D_G and V_G clusters, and 262 the clusters obtained from the CNVL dendrograms were designated as D_L and V_L clusters. 263 Notably, the cutree method yielded 72 V_G -type and 55 D_G -type CNVG profiles with 81.10% 264 consistency between the invasion-vs-depression clinical classification and the V-vs-D 265 CNVG-based classification (Figure S2A); whereas the semi-supervised method yielded 61 266 V_{G} -type and 66 D_{G} -type CNVG profiles with 89.76% consistency between the invasion-vs-267 depression clinical classification and the V-vs-D CNVG-based classification (Figure 1A). 268 Therefore, using either the cutree method or the semi-supervised method, the CNVG-based classification was highly correlated with the clinical symptom-based classification of the 269

270 PMDD genomes; this was likewise the case with the D_L -type and V_L -type CNVLs. 271 Altogether, for the CNVGs and CNVLs in, the 50-500 kb window sizes, the cutree method 272 yielded consistencies of 68-91%, and the semi-supervised method yielded consistencies of 273 88-98%, between the CNV-based and symptom-based classifications. The semi-supervised 274 classifications of P-type samples based on CNVs called from 50-500 kb window sizes were 275 available in Figure S3. These results demonstrated that both the CNVGs and CNVLs 276 contributed to the etiology of the depression-type and the invasion-type symptoms. Moreover, 277 the comparable results obtained using the cutree and semi-supervised methods confirmed the 278 robustness of the CNV-symptom correlations. When the CNVGs or CNVLs called from 100-279 kb sequence windows of the 108 C-type control samples were subject to hierarchical 280 clustering along with the P-type samples, ~40% of the C-type CNV profiles formed a tight 281 sub-cluster and ~60% were dispersely distributed in the dendrogram, forming sub-clusters 282 with the depression-subtype or invasion-subtype PMDD samples (Figure S4).

283

284 Use of diagnostic CNV-features for predictive subtyping

285 The correlation between germline CNV profiles and clinical subtypes of PMDD suggests that 286 it would be practicable to predict from the germline CNVs of women their propensity to 287 develop PMDD, as well as the likely subtype of the PMDD clinical condition. Toward this 288 objective, the method developed earlier by us through the use of diagnostic CNV-features 289 selected with machine learning to assess a subject's propensity for cancer (15) could be 290 employed as described in 'Selection of diagnostic CNV features' under Method. Figure 2 291 shows the diagnostic CNV features selected by either the correlation method or the frequency 292 method for prediction the propensity of a test subject's germline CNVs for which of the P, C, 293 V_G , D_G , V_L and D_L genomic groups: the P-type and C-type outcomes would be assessed 294 based on PMDD symptoms; V_G and D_G would be based on the distinction between the V and

D clusters in the CNVG dendrogram in Figure 1A; and V_L and D_L would be based on the distinction between the V and D clusters in the CNVL dendrogram in Figure 1B. The diagnostic CNVG and CNVL features selected using the correlation and frequency methods are given in Table S7.

299

300 Figure 2A shows the sets of diagnostic CNV features selected using the correlation-based 301 (red triangles) or frequency-based (black circles) method to enable a choice between a pair of 302 genomic groups. For example, the D_G-vs-C panel of Figure 2A contained a mixture of 66 D_G-303 type samples and 108 C-type samples. The diagnostic CNV features selected from the total of 304 144 samples by means of either the correlation method (red triangles) or the frequency 305 method (grey circles) were distributed in a crescent near the y-axis and another crescent near 306 the x-axis. Accordingly, any DNA sample in the mixture that was enriched with near-y 307 diagnostic CNV features would be predicted to be endowed with a greater propensity for C-308 type over D_G-type, whereas any DNA sample that was enriched with near-x diagnostic CNV 309 features would be predicted to be endowed with a propensity for D_{G} -type over C-type. In the 310 D_G-vs-C panel of Figure 2B, diagnostic CNV features selected using the correlated method 311 was employed to predict the D_G-vs-C nature in the 174-sample mixture as described under 312 the 'Predictive subtyping of genomic samples by machine learning' section in Methods. After 1,000 trial runs, each with a random partition of the samples into an 87-sample Learning 313 314 Band and an 87-sample Test Band, the average prediction accuracy obtained was 83.0%. 315 Altogether, the seven panels in Figure 2B yielded average prediction accuracies ranging from 316 81.0% to 88.4%. Interestingly, the list of correlation-based CNV features useful for 317 differentiating between the propensities toward the D and V subtypes (Table S8) showed that 318 the CNV features biased in favor of V-type samples were mostly CNVL features (27/42 for

319 V_G and 14/17 for V_L). The accuracies of sample-classification predictions derived from the 320 cutree method are available in Figure S5.

321

322 Favorable diagnostic CNV-features were often shared by more than one PMDD types, as 323 indicated by the overlaps between the colored circles for the P-vs-C (blue), D-vs-C (red) and 324 V-vs-C (green) comparisons in the Venn diagrams (Figure 3A and B). A range of CNV 325 features were shared by all three kinds of circles, suggesting that they represented key CNV 326 features differentiating between the control and PMDD patient samples (Table S9). Notably 327 also, in all the panels in Figure 3, there was no CNV feature was shared only by the red 328 circles for D-vs-C and the green circles for V-vs-C, which suggests that the CNV-features 329 favoring the D-type genomes differed diametrically from the CNV-features favoring the V-330 type genomes. As well, there were more D-favoring CNVG features than CNVL features, but 331 more V-favoring CNVL features than CNVG features.

332

333 Genome-wide distribution of diagnostic CNV features

334 In order to have a global view of CNV profiles, the locations and replication timing of all 335 frequency-based diagnostic CNV features, whether overlapping with any known genes or not, 336 were plotted on Figure S6. The results showed that the CNV features were widely spread on 337 all the somatic chromosomes and chromosome X. Chromosomes 4, 13, 18 21 and X were 338 particularly abundant in CNV features that replicated in the G2 phase. Given the correlation 339 between the clinical symptom-based typing of PMDD cases and the clustering of germline 340 diagnostic CNV features, these CNV features could be useful guides in a search for some of 341 genomic sites underlying PMDD.

342

343 In Figure 4, the distributions of the CNV features among DNA regions replicating at different 344 cell cycle phases exhibited a number of characteristics: (a) In terms of the number of CNV features that differed between a pair of CNV-types, the P-vs-C panel (viz. P>C or P<C) gave 345 346 rise to the smallest difference, whereas the D-vs-V pair ($D_G > V_G$ or $D_G < V_G$) gave rise to the 347 largest difference; (b) the ratio of CNVL features relative to CNVG features (viz. L/G on 348 chart) that favored the C-type over P-type were 1.32 for 50-kb CNV features, 2.13 for 100-kb 349 ones and 2.05 for 450-kb ones, all greater than unity (Figure 4A); (c) the P-vs-C comparisons 350 were suggestive of protective effects of smaller size CNVLs in the early replication phases 351 and larger CNVLs in the later phases (Figure 4A); (d) the CNVLs captured by 50-kb 352 windows included significantly more V-favoring than either C-favoring or D-favoring ones 353 (L/G = 2.41 in Figure 4C and 1.80 in Figure 4D); (e) the CNVGs were significantly enriched 354 in D-favoring features compared to C-favoring or V-favoring ones, whereas CNVLs were 355 significantly enriched in V-favoring features compared to C-favoring or D-favoring ones; (f) 356 D-vs-V comparisons suggest that V-type PMDD was correlated with smaller CNVG features 357 belonging to the early replication phases and large CNVGs belonging to the later phases; (g) 358 Large CNVG features were enriched in the G2-phase replicating sequences, especially 359 among the features selected for the D-vs-C and D-vs-V comparisons (see G2-phase columns 360 marked with red asterisks in Figure 4B and D); (h) More than half of the large G2-phase 361 CNVG features in the C>D_G group are identical to those of the V_G >D_G group, suggesting the 362 shared genetic variations in G2 phase underlying V and C types; (i) Large CNVL feature were enriched in S3-phase replicating sequences in the C>V_G and D_G>V_G groups but not in 363 364 the $V_G > C$ or $V_G > D_G$ groups. The replication-phase distributions of CNV features obtained 365 based on the D_{L-} or V_{L-} type samples derived from the CNVL dendrogram in Figure 1B were 366 available in Figure S7.

368 Pathways and genes enriched in diagnostic CNV features

369 A wide range of genes showed sequence overlaps with the frequency-based diagnostic 370 CNVG and CNVL features of a range of KEGG pathways in PMDD and its subtypes (Table 371 1) which pointed to their possible contributions to the PMDD disorder, and some major genes 372 were contained in more than one pathway (Table 2). It was striking that, as indicated in lines 373 1-5 of Table 2, the control C-type was favored by high frequencies of CNVG features relative 374 to the diseased P-, D- or V-type, suggesting that a major causal factor of the PMDD disorder 375 could be decreased levels of the CNVG features overlapping with the steroid hormone 376 biosynthesis pathway, with the involvement of CYP- and UGT-genes replicating in phases S2 377 and S1. As shown in lines 9-17 of Table 2, the C-type and V-type profiles were favored over 378 the D-type by high frequencies of CNVL features in the *GRI*-genes, which were involved in 379 pathways of nicotine addiction, circadian entrainment, serotonergic synapse, dopaminergic 380 synapse and cAMP signaling. The chromosomal sites of these genes and their overlaps with 381 the 100-kb CNV features are shown in Figure 5.

382

383 The 50-kb CNV features overlapped with the genes in the glutamatergic-synapse, alcoholism, 384 and systemic lupus erythematosus pathway genes, as well as steroid hormone biosynthesis 385 pathway genes replicating in S2 and S3 (Table S5). On the other hand, the 450-kb CNV features overlapped with chemokine signaling pathway genes (Table S5). Because high 386 387 regional density of genes could impact on gene annotations by yielding false-positive co-388 localizations when a CNV feature incidentally captured a gene cluster belonging to a pathway, 389 empirical *p*-values based on Monte Carlo simulations were also estimated for the 100-kb 390 CNV features (Table S10), which provided additional support for some of the pathway in 391 Table 2 through the elimination of such false positives (see 'Statistical analysis' in Methods).

392

393 Genomic features enriched in diagnostic CNV features

394 Co-localization analysis revealed various associations between 100-kb frequency-based CNV 395 features and a wide spectrum of genomic features in different replication phases (Table 3 and 396 Table S11). D versus V differences in genomic feature contents can be identified from the 397 thermal scale plots of co-localization scores illustrated in Figure 6 and Figure S8. The 398 genomics features apparently differed between D and V types included: (1) In terms of 399 retrotransposons, D-favoring CNVG features enriched with more of the subfamily of 400 evolutionarily very young short transposons SVAef, while V-favoring CNVG and D-favoring CNVL features enriched with the very young long transposon subfamily, L1vy. (2) With 401 402 respect to genetic markers, P-favoring, especially D-favoring CNVL features were enriched 403 with recombination events as well as genetic variation hotspots and clusters (27). GWAS 404 reported markers were co-localized with D-favoring CNVGs in S1, V-favoring CNVLs in S4 405 and C-favoring CNVLs G1b. As well, ClinVar markers were enriched in V-favoring CNVG 406 of S2 phase and D-favoring CNVL of S1. (3) In respect to the group of CpG-related genomic 407 features, the main difference between the two types was that D-favoring CNVL features were 408 more enriched with CpG features such as MeBS in S4 replicating sequences. Compared with 409 D- and V-favoring, the C-favoring CNV features were more prominently enriched with CpG 410 features, especially for C-favoring CNVG in S3 and CNVL in G2 and S4 phases. (4) In 411 regard to non-coding RNA, LINC was enriched in V-favoring CNVL as well as C-favoring 412 CNV features, but not in D-favoring features. (5) To a lesser extent, the enrichment of histone 413 binding sites in D-favoring CNVG features of G2 and S2 phases. In contrast, histone sites 414 were enriched in V-favoring CNVL features of S4 phase. This trend was clearly visible from 415 Figure 6, where twelve kind histone binding sites were analyzed separately and displayed 416 side-by-side.

417

418 Some of the strongly enriched genomic features with great than one-fold enrichment was 419 listed in Table 3. For example, enrichment of DNase I hypersensitive sites (DNase) was 420 found in C>P CNVL and C>V_L CNVG features in G2-phase replicating sequences and P>C 421 (as well as D>C and V>C) CNVL features in S4-phase replicating sequences. Regulatory 422 elements isolated by formaldehyde (FAIRE) were found to enrich in C>V, D>C and D>V 423 CNVL features that located in the late-replicating S4 and G2 phases. Disease- or trait-424 associated SNPs identified by genome-wide association studies (GWAS) were enriched in 425 C>V CNVLs in G1b phase, and P>C CNVGs in S1 phase reaching a fold-change of 5.5 426 relative to non-diagnostic-CNV regions in S1 phase. The C-favoring (C>P and C>D_L) CNVG 427 features and C-favoring CNVL (C>P and C>V_G) features tend to co-localize with CpG 428 islands (CpGi) in median to late-replicating S3-G2 phases. A range of methylation-related 429 features (Me450, MeBS, and MeMRE) were found to enrich in C-favoring CNVG features 430 mainly in early to median G1b-S3 phases, and C-favoring CNVL features in late-replicating 431 S4-G2 phases. Long intergenic non-coding RNAs (LINC) were found to be enriched in C-432 favoring CNVGs mainly in S2 phase or CNVLs mainly in G2 phase, D-favoring CNVGs in 433 G1b phase, and V-favoring CNVLs in S3-G2 phases.

434

435 **Discussion**

Application of either the cutree method or the semi-supervised method to the hierarchically clustered CNVGs or CNVLs in the germline genomes of PMDD subjects enabled the distinction between the D-type and V-type CNV profiles. The high degree of consistency between the clinical depression-subtype and D-type CNV profiles, and between the clinical invasion-subtype and V-type CNV profiles, indicated that the two clinical PMDD subtypes were intrinsically correlated with the two dissimilar types of CNV profiles. This was further conformed when diagnostic CNVG and CNVL features were selected by means of machine learning using the correlation method, and employed as abundance markers to predict whether a given germline genomic sample belonged to the control group, the PMDD group, the V-type CNV group or the D-type CNV group, yielding average accuracies of prediction of 81.0-88.4% (Figure 3), which in turn validated the use of diagnostic CNVG and CNVL features to identify the genes and pathways that overlapped with such diagnostic features as potential contributors to the PMDD disorder.

449

450 In this regard, there exists overall accord between the cutree and the semi-supervised 451 methods in terms of diagnostic CNV features identified, replication-phase distribution and 452 pathway enrichments (Table S5, S12 and S13). As indicated in DSM-V, PMDD is defined by 453 a complex system of symptoms. In the present study, limited data allowed the analysis of 454 only the depression-type and invasion-type symptoms. Nevertheless, the Venn diagrams in 455 Figure 3 clearly showed that the CNVs underlying the D-type and V-type CNV profiles were 456 strikingly more divergent from one another than their separate divergences from the CNVs 457 underlying the C-type. This finding was also consistent with the results in Figure 2A, which 458 showed that there were more correlation-based or frequency-based CNV features that could 459 be employed to distinguish between D_G-vs-V_G or D_L-vs-V_L compared to CNV-features that could distinguish between D_G-vs-C, V_G-vs-C, D_L-vs-C or V_L-vs-C. As well, the mixed 460 461 distribution of control CNV profiles among depression- or invasion-type CNV profiles 462 (Figure S3) indicated that the difference between the CNVs in the two subtypes of PMDD 463 was larger than their individual differences from the control. This surprising genome 464 condition, as illustrated in Figure 7, raises the question of whether the depression-type and 465 invasion-type conditions of PMDD might represent two distinct clinical disorders.

466

467 A faithful temporal order of DNA replication is fundamental to normal cellular function, and

468 aberrant replication timings were observed in complex diseases including cancers (34, 35). 469 Accordingly, the relative abundances of diagnostic CNVG and CNVL features among 470 genomic DNA sequence regions preferentially replicating in each one of the six phases of cell 471 cycle, namely G1b, S1, S2, S3, S4 and G2 were examined in Figure 4. The peaks of C-472 favoring CNVL features in P-vs-C comparisons (downward hollow green bars in Figure 4A) 473 shifted clearly from the early S1 phase among the 50-kb features to the late G2 phase among 474 the 450-kb features, pointing to the enrichment of some small CNVL features in the early-475 replicating regions and larger CNVL features in the late-replicating regions among the 476 determinants of the C-type, viz. in the prevention of PMDD occurrence. As well, more D-477 favoring CNVG features were located in G2-replicating sequences compared to genomic 478 DNA sequences replicating in other cell-cycle phases within the D>C and D>V groups, 479 which was particularly notable in view of the enrichment of G2 phase-replicating sequences 480 in non-coding sequences (27, 29). In addition, the abundance of V-favoring 50-kb CNVL 481 features in the V>C and V>D comparisons (Figure 4B and D) suggests that small-size 482 CNVLs also played important roles in the development of V-type PMDD.

483

484 When diagnostic CNVs were analyzed for their genomic feature enrichment with reference to 485 replication phases, interesting observations were obtained (Figure 6; Table 3). It has been 486 revealed that the late-replicating S4-G2 phases in the gene-distal zones are found to be 487 depleted of functional genomic features (27). However, the present study observed 488 associations of open chromatin signals, regulatory elements and epigenetic regulation sites 489 with the diagnostic CNV features in these late-replicating sequences (Table 3), indicating that 490 the diagnostic CNV features might represent pivotal genomic sites in the late-replicating 491 sequences that sequence alterations may give raise to functional perturbations underlying 492 PMDD and its two subtypes. As illustrated herein, genomic feature content analysis,

implemented with replication phase information, has pointed to the likelihood of genomic events underlying the subtyping of PMDD and hence a genomic nature of the disorder and its clinical diversity. Since genomic features included in the analysis were broad in spectrum and well beyond the boundary of known genes, the feature enrichment analysis performed herein may complement with and surpass genetic pathway analysis as a powerful tool for genomic studies on complex traits and disorders.

499

500 Previously, a number of genes was proposed to be PMDD suspectable genes, including those 501 of steroid hormone biosynthesis (2, 3), and estrogen signaling (36, 37), and these proposals 502 were supported by the presence of these genes in Table 1. The overlaps of genes of nicotine 503 addiction, glutamatergic synapses, olfactory transduction, alcoholism, systemic lupus 504 erythematosus, hypogonadism, premature ovarian failure, and breast cancer with PMDD might be suggestive of hitherto hidden aspects of central nervous system or endocrine system 505 506 involvements with PMDD. The GRIA4 gene, overlapping with the 100-kb CNV features for 507 the C>D and V>D comparisons, groups, has also been found to be associated with 508 schizophrenia (38), in accordance with the shared CNVs between schizophrenia and PMDD 509 (14).

510

In conclusion, through CNV profiling, the present study provided evidence for strong correlation of the clinical depression-subtype or invasion-subtype with the D-type and V-type germline genomes, marked by the overlaps between their CNVs and the machine-selected diagnostic CNV features that favored one or another type of genomes. On account of this correlation, the diagnostic CNV features could be employed as frequency markers to predict the propensity to PMDD and one of its clinical subtypes, as well as position markers to identify candidate PMDD genes and pathways. Moreover, the genetic difference between the

depression-favoring and invasion-favoring CNV profiles was found to exceed their individual divergences from the normal controls (Figure 7), raising the question of how this outcome might have been evolved. Future studies will be required to determine how many of the array of PMDD symptoms besides the depression-subtype and invasion-subtype ones could be significantly correlated with CNVs, and what complex diseases other than PMDD would embody CNV-symptom correlations as strong as those encountered with PMDD.

524

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536 **Conflict of Interest**

The authors declare that the research was conducted in the absence of any commercial orfinancial relationships that could be construed as a potential conflict of interest.

539

540 Author Contributions

HX and MQ conceived and designed the experiments, ZW, XLo, AU, SC and WM performed
the AluScan sequencing related experiments and analysis of the sequencing data. PS, MG, JW,

- 543 HW, XLi, WS and MQ coordinated the collection of PMDD and control cohorts, and HX,
- 544 ZW, XLo, SC and MQ wrote the paper.
- 545

546 Supplementary Information

- 547 Supplementary materials are available online, including Figures S1-S8 and Table S1-S15.
- 548

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654

655 **Figure Legends**

Figure 1. Hierarchical clustering of PMDD samples based on their pairwise similarities

657 in genome wide CNV profiles. For all 127 P-group samples, all CNVs were identified from

658 AluScan sequencing data with 100-kb non-overlapping scanning windows across the genome 659 and used in the plots of similarity scores for CNVGs (A) and CNVL (B), respectively. The 660 dendrograms on top of the heat maps were bootstrapped 1,000 times. The color of each 661 square in the heat map indicates the correlation coefficient (r) of a pair of samples according 662 to the blue-red thermal scale. The semi-supervised classification of samples based on (A) 663 CNVGs and (B) CNVLs was indicated by the red dendrogram branches for V-type and blue 664 ones for D-type genomes. The bands below the dendrograms and on the left-hand side of the 665 heat maps portrayed the subtyping of PMDD samples based on clinical symptoms, with purple bands representing the clinically determined invasion subtype (n = 56) and orange 666 667 bands the depression subtype (n = 71). Each of the square diagonal boxes in panels (A) and 668 (B) enclosed a group of genomes with close correlations between each other in the group, 669 such that they could be identified as a coherent block of genomes belonging to either the V-670 type or D-type CNV profiles depending on their enrichment in the invasion- or depression-671 subtype samples (see 'Clustering of patient samples based on CNV profiles' in Methods). 672 Comparable heat maps obtained using sequence window sizes of 50 to 500 kb for CNV-673 calling are shown in Figure S3.

674

675 Figure 2. Occurrence frequencies of diagnostic CNV features and their prediction 676 accuracies for seven pairs of sample groups. Panel (A) shows the frequency distribution of 677 diagnostic CNV features for different pairs of sample groups. The x-axis represents the 678 frequency of CNVs in the first-named group (Group 1 as shown on x-axis), and y-axis the 679 frequency of CNVs in the second-named group (Group 2 as shown on y-axis) in a given pair 680 of sample groups. Diagnostic CNV features with higher frequencies in Group 1 relative to 681 Group 2 (located in lower right crescent) are referred to as 'Group 1-favoring' features, 682 whereas diagnostic CNV features with higher frequencies in Group 2 relative to Group 1

683 (located in upper left crescent) are 'Group 2-favoring' features. Black circles are CNV 684 features selected using the frequency-based method with FDR < 0.01 (Fisher's exact tests), 685 and red triangles are CNV features selected using the correlation-based method. Panel (B) 686 shows the prediction accuracies (estimated using Eqn.2 in Methods) of sample classification 687 in seven sample-pairs based on CNV features selected using the correlation method. For each 688 of the seven pairs, prediction accuracy was estimated 1,000 times and the average accuracy (Av.) was given in the pertinent panel. Subscript G denotes that the D- or V-type samples 689 690 were derived from the dendrogram of CNVGs (Figure 1A), while subscript L denotes that the 691 D- or V-type samples were derived from the dendrogram of CNVLs (Figure 1B).

692

693 Figure 3. Overlaps between the diagnostic CNV features differentiating the two 694 subtypes of PMDD collectively and individually from the control. CNV features identified 695 using (A) correlation-based method, and (B) frequency-based method. Circled 'G' indicates 696 CNVG features and circled 'L' indicates CNVL features. The '>' and '<' signs portray the 697 relative frequencies of the CNV features for a pair of sample groups, e.g. P>C represents diagnostic CNV features that occurred in higher frequencies in P-group compared to C-698 699 group. Subscript G denotes that the D- or V-type samples were derived from the CNVG 700 dendrogram in Figure 1A, whereas subscript L denotes that the D- or V-type samples were 701 derived from the CNVL dendrogram in Figure 1B.

702

Figure 4. Distribution of frequency-based diagnostic CNV features among genomic sequences of different DNA replication phases. Number of base pairs of the CNV features called using 50, 100 and 450-kb windows for (A) P-vs-C, (B) D_G -vs-C, (C) V_G -vs-C, and (D) D_G -vs- V_G groups. The solid bars represent CNVG features and hollow bars represent CNVL features in each panel. The replication phases G1b to G2 are color coded as shown. The '>' or

708 '<' sign portrays larger or smaller frequencies of the CNV features in favor of the first-named 709 group over the second-named one. L/G represents the ratio of the number of CNVLs over the 710 number of CNVGs. Significant enrichment of CNV features in a particular replication phase 711 in the genome is indicated by asterisks that are color coded according to the replication phase, or in black asterisks for comparison between an L/G value in the upper half of a panel 712 and an L/G value in the lower half (Bonferroni-corrected, *** p < 0.005, ** p < 0.01, * p < 0.713 714 0.05). Numerical *p*-values are shown in Table S14. Subscript G denotes that the D- or V-type 715 samples were derived from the CNVG dendrogram in Figure 1A. See Figure S7 for the 716 results obtained based on the D- or V-type samples derived from the CNVL dendrogram in 717 Figure 1B.

718

Figure 5. Selected genes overlapping with frequency-based diagnostic CNV features. 719 720 Expanded views of chromosomal segments on (A) chromosomes 2 and 7 for steroid 721 biosynthesis pathway genes, (B) chromosomes 5, 11, 12, 16 and 17 for GRI-genes of the 722 glutamatergic synapse and nicotine addiction pathways, and (C) chromosomes 6 and X for the non-pathway TRERF1 and POF1B genes with color-coded representation of the DNA 723 724 replication phase in the 'Phase' track, and aligned gene sequence(s) in blue (e.g. UGT1A8 or 725 TRERF1) as described in RefSeq Genes in UCSC Genome Browser. Green rectangular boxes 726 either below the genes indicate the presence of diagnostic CNVG or CNVL feature(s). Inside 727 each box, colored stripes are indicative of CNVL features(s), and solid coloring is indicative 728 of CNVG features(s): purple for predominantly V-favoring features, orange for D-favoring 729 features, and green for C-favoring features.

730

Figure 6. Enrichment analysis of genomic-feature contents in different replication
 phases for control and PMDD subtypes. Frequency-based CNV features diagnostic for C

733 group, i.e., control, as well as that for D and C groups of PMDD samples clustered by CNVG 734 dendrogram, identified with 100-kb scanning windows, were used in the analysis. 735 Enrichment analysis results were plotted for CNVG features in the upper two panels and that 736 for CNVL features in the bottom two panels. A similar analysis performed in parallel for 737 clustered by CNVL dendrogram can be found in Figure S8. Fold-change of each genomic 738 feature in the diagnostic CNV features relative to the non-diagnostic-CNV regions was estimated according to 'Genomic-feature content of diagnostic CNV features in different 739 740 replication phases' in Methods, and was color-coded based on the thermal scale. Fold-change 741 greater than 2-fold was capped at 2 in the heat map. 'Group 1' indicated the first-named 742 group and 'Group 2' the second-named group in a given pair of samples. Genomic features 743 were grouped into Retrotransposon (SVAef, SVAcd, SVAab, AluYy, AluYy, AluS, AluJ, 744 FLAM, L1vy, L1y, L1m, L1o, MIR, L2), Genetic markers (RecD, RecH, RecK, GWAS, 745 ClinVar, GV hotspot, Cluster, CNVG), Regulatory sites (H3k27me3, H4k20me1, H3k9me1, 746 H2az, H3k79me2, H3k36me3, H3k4me3, H3k9ac, H3k4me2, H3k27ac, H3k4me1, H3k9me3, 747 MeMRE, MeDIP, MeBS, CpGi, CpGe, Me450, TFBS, REG, FAIRE, DNase) and Gene/Transcription (Gene, EXPS, LRNA+, LRNA-, LINC) groups on the x-axis based on 748 749 their sequence and functional properties. The descriptions of genomic features and numeric 750 data were available in Table S11.

751

Figure 7. Genetic distances between the two subtypes of PMDD and the control. Pairwise distances were estimated based on the abundance of diagnostic CNV features between C-, D- and V-type genomes. The numbers of frequency-based CNV features were employed as an approximate index of the genetic distance between the D-vs-C, V-vs-C or Dvs-V sample pairs in Table S15, which comprised the 50-500 kb frequency-based CNV

757 features. Notably, the D-vs-V distance was larger than the D-vs-C distance or the V-vs-C

758 distance.

Gene	Ratio	H% ²	L% ³	CNV	CNV location	<i>p</i> -value ⁵	CNV in replication phase (%) ⁶					
					$(x \ 100 \ kb)^4$	<i>p</i> -value	G1b	S1	S2	S3	S4	G2
GABA _A Receptor Fa	•	Nicotine a	ddiction)									
GABRR1, 2	$C > D_G$	26	2	L	6:899-900	2.05E-04	0	0	99	0	0	0
GABRG3	$C > D_G$	61	27	L	15:275-276	5.55E-04	0	0	0	0	0	100
GABRG3	$V_G > D_G$	59	27	L	15:275-276	3.46E-03	0	0	0	0	0	100
Glutamate Metabotr	opic Receptor	(KEGG:	Glutamat	ergic syna	pse)							
GRM4	$D_L > V_L$	80	51	L	6:339-340	6.99E-03	0	87	0	0	0	0
GRM8	$D_L > V_L$	91	45	L	7:1,267-1,268	1.08E-06	0	0	0	37	45	0
GRM5	$V_G > D_G$	16	0	L	11:882-883	3.98E-03	0	90	0	0	0	0
Glutamate Ionotropi	c Receptor (K	EGG: Glu	tamaterg	ic synapse.	, Nicotine addiction)							
GRIA1	$V_G > D_G$	31	0	L	5:1,530-1,531	6.10E-06	0	0	0	12	78	0
GRIK2	$V_G > D_G$	16	0	L	6:1,025-1,026	3.29E-03	0	0	0	0	0	100
GRIA4	$V_G > D_G$	25	3	L	11:1,057-1,058	3.98E-03	0	0	0	0	100	0
GRIN2B	$V_G > D_G$	23	0	L	12:138-139	2.56E-04	0	0	0	0	100	0
GRIN2A	$V_G > D_G$	39	6	L	16:98-99	1.61E-04	0	0	0	77	16	0
GRIN2A	$V_G > D_G$	26	5	L 16:99-100		6.84E-03	0	0	0	94	0	0
GRIN2C	$V_G > D_G$	39	12	L	17:728-729	4.36E-03	3	92	0	0	0	0
UDP Glucuronosyltr	ansferase 1 Fa	mily (KE	GG: Ster	oid hormo	ne biosynthesis)							
UGT1A1, 3-10	$V_L > D_L$	36	11	L	2:2,346-2,347	6.62E-03	0	0	98	0	0	0
Cytochrome P450 (K	EGG: Steroid I	hormone b	biosynthe	sis)								
CYP3A4, 5, 7	$C > D_G$	30	5	G	7:993-994	3.05E-04	0	100	0	0	0	0
CYP3A4, 5, 7	$C > D_L$	30	9	G	7:993-994	6.15E-03	0	100	0	0	0	0
CYP3A4, 5, 7	$V_L > D_L$	55	9	G	7:993-994	6.37E-07	0	100	0	0	0	0
CYP11B1, 2	$V_L > D_L$	19	0	G	8:1,439-1,440	6.55E-04	0	1	68	0	0	0
CYP11A1	$V_L > D_L$	51	22	L	15:746-747	7.80E-03	100	0	0	0	0	0
Premature Ovarian l	Failure Protein	n 1B										
POF1B	C > P	29	9	G	X:845-846	2.13E-03	0	0	0	0	6	92
POF1B	$C > D_G$	29	0	G	X:845-846	2.19E-06	0	0	0	0	6	92
POF1B	$V_G > D_G$	18	0	G	X:845-846	1.20E-03	0	0	0	0	6	92
POF1B	$D_G > C$	23	5	G	X:846-847	2.94E-03	0	0	0	0	0	100
POF1B	$D_G > V_G$	23	2	G	X:846-847	1.67E-03	0	0	0	0	0	100
Transcriptional Regu	lating Factor	1 (Breast	cancer ar	nti-estroge	n resistance 2)							
TRERFI	$\tilde{C} > D_G$	20	0	LŬ	6:423-424	5.55E-04	8	92	0	0	0	0
TRERF1	$V_G > D_G$	16	0	L	6:423-424	3.98E-03	8	92	0	0	0	0
TRERF1	$D_I > V_I$	42	15	G	6:424-425	7.63E-03	97	0	0	0	0	0

Table 1. Selected genes overlapping with 100-kb frequency-based CNVG and CNVL features¹ with adjusted *p*-values less than 0.01.

Opioid Binding Protein/Cell Adhesion Molecule Like (Hypogonadotropic Hypogonadism 14)														
$D_G > C$	100	79	L	11:1,331-1,332	3.17E-04	0	0	0	0	0	100			
$D_G > V_G$	100	85	L	11:1,331-1,332	7.57E-03	0	0	0	0	0	100			
$D_G > C$	61	24	L	11:1,332-1,333	1.07E-04	0	0	0	0	0	100			
$D_G > V_G$	61	15	L	11:1,332-1,333	6.24E-06	0	0	0	0	0	100			
MACRO Domain Containing 2 (Mono-ADP Ribosylhydrolase 2, Hypogonadotropic Hypogonadism 21)														
$C > D_G$	21	2	G	20:158-159	7.43E-04	0	0	0	31	34	0			
$D_G > C$	97	77	G	20:151-152	1.45E-03	0	0	0	100	0	0			
$C > D_G$	64	35	G	20:144-145	2.07E-03	0	0	0	74	15	0			
$C > D_G$	64	24	L	20:156-157	2.82E-05	0	0	0	75	23	0			
$D_G > V_G$	97	62	G	20:151-152	8.43E-06	0	0	0	100	0	0			
$V_G > D_G$	31	2	G	20:158-159	2.79E-05	0	0	0	31	34	0			
$V_G > D_G$	21	2	G	20:145-146	2.03E-03	0	0	0	100	0	0			
$V_G > D_G$	64	35	G	20:144-145	6.56E-03	0	0	0	74	15	0			
$V_G > D_G$	74	24	L	20:156-157	1.17E-06	0	0	0	75	23	0			
$V_G > D_G$	15	0	L	20:146-147	7.25E-03	0	0	0	100	0	0			
	$\begin{array}{c} D_{G} > C \\ D_{G} > V_{G} \\ D_{G} > V_{G} \\ \hline D_{G} > V_{G} \\ \hline \textbf{ontaining 2 (Mood C} \\ C > D_{G} \\ V_{G} > D_{G} \\ \end{array}$	$\begin{array}{cccc} D_G > C & 100 \\ D_G > V_G & 100 \\ D_G > C & 61 \\ D_G > V_G & 61 \\ \hline \mbox{ontaining 2 (Mono-ADP} \\ C > D_G & 21 \\ D_G > C & 97 \\ C > D_G & 64 \\ C > D_G & 64 \\ D_G > V_G & 97 \\ V_G > D_G & 31 \\ V_G > D_G & 21 \\ V_G > D_G & 64 \\ V_G > D_G & 64 \\ V_G > D_G & 74 \\ \hline \end{array}$	$\begin{array}{c ccccc} D_G > C & 100 & 79 \\ D_G > V_G & 100 & 85 \\ D_G > C & 61 & 24 \\ D_G > V_G & 61 & 15 \\ \hline \mbox{ontaining 2} (Mono-ADP Ribosylh) \\ C > D_G & 21 & 2 \\ D_G > C & 97 & 77 \\ C > D_G & 64 & 35 \\ C > D_G & 64 & 24 \\ D_G > V_G & 97 & 62 \\ V_G > D_G & 31 & 2 \\ V_G > D_G & 64 & 35 \\ V_G > D_G & 74 & 24 \\ \hline \end{array}$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$										

¹ See Table S7 for data on 50-500 kb CNV features;
 ² CNV frequency in first-named, higher frequency group (H), e.g. C-group of C>P pair;
 ³ CNV frequency in second-named, lower frequency group (L), e.g. P-group of C>P pair;

⁴ Chromosome number with start and end coordinates (to be multiplied by 100 kb);

⁵ FDR-corrected *p*-value obtained using Fisher's exact test on counts of CNV features in the two groups compared, as specified in the 'Ratio' column;

⁶ % base pairs in 6 replication phases; the % in genomic regions with unknown replication timing are not shown.

Na	Gro	oup ¹	CNV ²	KECC notheror ³	Chromosom o ⁴	Gen	e distri	ibution in r	eplicat	ion phas	ses ⁵	Proportion	
No.	Н	L		KEGG pathway ³	Chromosome ⁴	G1b	S1	S2	S 3	S4	G2	(%) ⁶	<i>p</i> -value ⁷
1	С	Р	G	Steroid hormone biosynthesis	2	-	-	++++++	-	-	-	> 0 - 100	[5.7E-04, 1.5E-09]
2	С	V_{G}	G	Steroid hormone biosynthesis	2	-	-	++++++	-	-	-	> 0 - 100	[2.7E-04, 9.3E-10]
3	С	V_{L}	G	Steroid hormone biosynthesis	2	-	-	++++++	-	-	-	> 0 - 100	[2.7E-04, 1.3E-09]
4	С	D_G	G	Steroid hormone biosynthesis	2,7	-	++	++++	-	-	-	> 0 - 100	[5.6E-05, 1.4E-11]
5	С	D_L	G	Steroid hormone biosynthesis	2,7	-	++	++++	-	-	-	> 0 - 100	[3.1E-05, 7.6E-12]
6	V_{L}	D_L	L	Steroid hormone biosynthesis	2,15	+	-	+++++	-	-	-	> 0 - 100	[4.8E-02, 6.7E-05]
7	V_L	D_L	G	Steroid hormone biosynthesis	7,8,1	-	+++	++	-	-	-	60	[4.9E-02, 4.9E-02]
8	D_G	V_{G}	L	Ovarian steroidogenesis	15,10,14,16,7	+++	+	+	+	-	-	40	[4.8E-02, 4.8E-02]
9	С	D_G	L	Nicotine addiction	6,11,12,15,16,17,5	-	+	++	+	++	+	> 0 - 20	[3.2E-02, 1.9E-02]
10	С	D_L	L	Nicotine addiction	6,11,12,15,16,17,5	-	+	++	+	++	+	> 0 - 20	[4.9E-02, 1.2E-02]
11	С	D_G	L	Circadian entrainment	11,17,12,16,20,5,8	+	+	-	+	++++	+	20	[2.9E-02, 2.9E-02]
12	V_{G}	D_G	L	Serotonergic synapse	1,11,15,12,17,20,21,5,6,7	+	+	+	+++	-	+	> 0 - 30	[3.8E-02, 1.2E-02]
13	V_{G}	D_G	L	Glutamatergic synapse	11,15,17,1,12,16,20,5,6	+	++	+	+	++	+	> 0, 10	[4.6E-02, 3.6E-02]
14	V_{G}	D_G	L	Nicotine addiction	15,11,12,16,17,5	-	+	-	++	+++	+	10	[4.6E-02, 4.6E-02]
15	V_{G}	D_G	L	Dopaminergic synapse	1,11,12,16,17,2,20,21,4,5,7,8	+	-	++	++	++	+	> 0 - 20	[4.4E-02, 3.0E-02]
16	V_{G}	D_G	L	Circadian entrainment	1,11,17,12,16,20,21,4,5	+	+	++	+	++	+	> 0 - 20	[3.0E-02, 1.7E-02]
17	V_{G}	D_{G}	L	cAMP signaling pathway	1,11,5,10,12,16,17,3,4,6,7	+	+	+	++	++	-	20	[3.3E-02, 3.3E-02]

Table 2. Representative pathways enriched in 100-kb frequency-based CNV features.

¹ Significant difference in CNV frequencies between compared groups, with 'H' and 'L' indicating higher- and lower-frequency group respectively. The subscripts 'G' and 'L' indicate sample groups clustered based on CNVG and CNVL respectively;

² 'G' indicates copy-number-gains and 'L' indicates copy-number-losses;

³ KEGG pathway IDs are, in order of appearance in table, hsa00140, hsa04913, hsa05033, hsa04713, hsa04726, hsa04724, hsa04728 and hsa04024;

⁴ Chromosomes where pathway genes overlapped with CNV feature(s);

⁵ Approximate distribution of pathway genes in different replication phases, with '-' indicating 0%, and one '+' indicating 0-20%, up to six '+' indicating 100%;

⁶ Proportion of gene sequence overlapping with the CNV feature(s) ranging from > 0% to 100%;

⁷ Range of Benjamini-adjusted *p*-values of pathway enrichment pertaining to bottom and top figures referred to in footnote 6.

H L CNV G1b S1 S2 S3 S4 G2 CpGi (CpG island) C P G -0.32 0.06 -0.06 1.62 -0.18 1.15 C P L -0.18 0.05 0.39 0.46 1.10 2.20 C D G -0.45 0.02 -0.08 0.59 1.18 0.57 C VG L 0.14 0.06 0.69 0.71 0.47 1.42 P C L -0.34 0.12 -0.02 0.38 -0.23 1.08 Me450 (Methylation status using HumanMethylation450) C C P L -0.29 0.23 -0.02 0.33 1.16 1.05 C P L -0.29 0.23 -0.02 0.33 1.16 1.05 C P L -0.29 0.23 1.02 1.35 C 1.55 C 0.4 0.	Gro	un ¹		F	old-chang	e in differø	ent renlica	tion nhase	s ³			
$\begin{array}{c c c c c c c c c c c c c c c c c c c $		L	- CNV ² $-$									
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $		i (Cp	G island)	010	51	5-	50	5.	0-			
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	_			-0.32	0.06	-0.06	1.62	-0.18	1.15			
$\begin{array}{cccccccccccccccccccccccccccccccccccc$												
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$\begin{array}{c c c c c c c c c c c c c c c c c c c $												
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$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Me4	50 (M	lethvlation									
$\begin{array}{cccccccccccccccccccccccccccccccccccc$								-0.01	0.43			
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	С	Р	L	-0.29	0.23	-0.02	0.33	1.16	1.05			
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	С	V _L	G	1.00	0.04	-0.02	-0.35	-0.48	-0.25			
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	MeĿ	BS (cy	tosine met	hylation ı	using bisul	fite sequen	cing)					
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	С	Р	L	-0.12	0.45	0.12	0.49	1.53	1.55			
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	С	D_L	G	-0.53	0.10	0.06	0.64		0.59			
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	С	V_{G}	L	0.27	0.26	0.69	0.94	1.51	0.29			
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	D_G	С	L	1.03	0.54	0.35	0.24	1.20	-0.39			
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	D_L	С		1.38	0.20	0.25	0.37	0.13	-0.34			
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	D_G	V_{G}	L	1.15	0.41	0.37	0.46	1.69	-0.24			
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	D_L	V_L	L	0.82	0.45	0.53	0.59	1.47	-0.15			
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	VL	D_L	G	0.15	-0.17	-0.14	0.45	1.35	1.21			
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	MeMRE (Methylation using MRE-											
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		Р	G		0.23				-0.19			
$\begin{array}{c c c c c c c c c c c c c c c c c c c $		Р			-0.06	0.31			0.90			
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Р	С	L	-0.13	0.10	0.10	0.33	-0.22	1.70			
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	DNa		Nase I hy									
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		-	_									
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$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	D_L											
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	V_{G}											
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$									-0.66			
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$ \begin{array}{cccccccccccccccccccccccccccccccccccc$												
$D_{G} V_{G} L 0.22 0.17 0.11 0.11 1.15 0.92$												
	DL											
$D_L V_L L 0.20 0.21 0.02 0.03 0.77 2.08$												
	D_L	V_L	L	0.20	0.21	0.02	0.03	0.77	2.08			

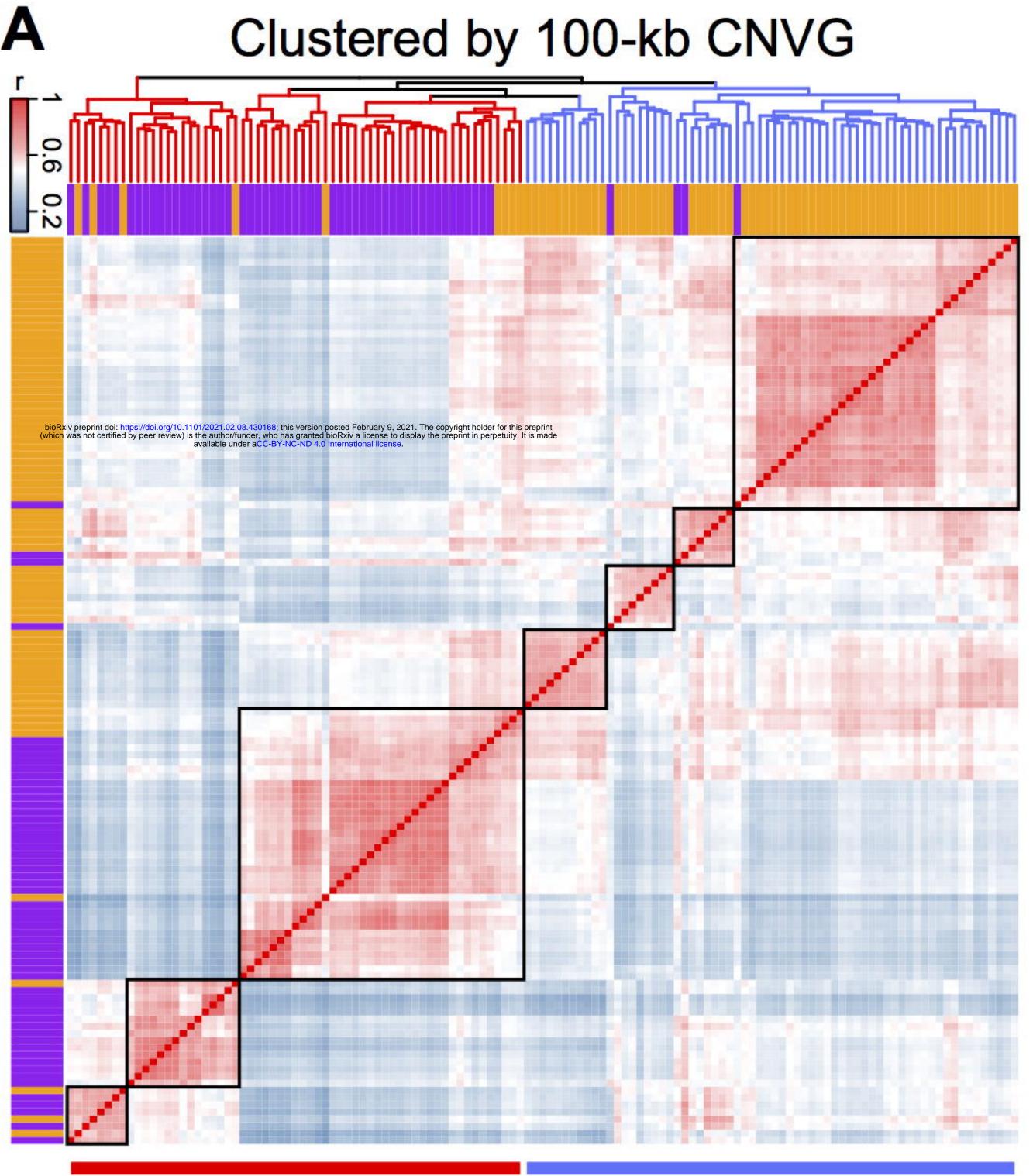
Gro	up ¹	- CNV ² -	I	Fold-change in different replication phases ³									
Н	L	- CNV ² -	G1b	S1	S2	S 3	S4	G2					
LIN	C (La	rge interg	enic non-	coding RN	(A)								
Cont	tinuea	1											
С	Р	G	-0.97	-0.52	18.30	4.23	0.32	-0.11					
С	Р	L	-0.99	1.05	0.17	1.02	-0.73	0.92					
С	V _L	G	0.11	-0.96	0.03	1.75	-0.55	2.42					
С	V_{G}	L	-1.00	-0.77	-0.79	-0.93	-0.47	1.59					
С	V _L	L	-0.98	-0.74	-0.72	-0.87	-0.50	1.06					
V_{G}	Ċ	L	0.48	-0.70	0.32	2.14	1.61	1.36					
V_L	С	L	0.31	-0.75	-0.02	1.80	1.01	0.74					
V _G	D_G	L	0.37	-0.67	1.19	0.52	0.33	1.34					
<u>Recl</u>) (Sex	x-averaged	d rates of	recombina	<u>tion)</u>								
Р	С	L	1.31	0.39	0.26	0.44	0.36	0.97					
D _G	С	L	0.23	0.16	0.43	0.42	0.35	1.24					
D_L	С	L	0.40	0.30	0.52	0.50	0.51	1.56					
D_L	V_L	L	0.25	0.13	0.24	0.22	0.45	1.06					
<u>GWAS (GWAS-identified SNPs)</u>													
С	V_{G}	L	2.08	-0.01	-0.02	-0.35	0.18	0.60					
С	V_L	L	1.63	-0.13	-0.01	-0.23	0.10	0.38					
Р	С	G	-0.26	5.48	-0.38	0.27	-0.26	-0.34					
D_G	С	G	-0.16	1.61	-0.13	-0.28	-0.05	-0.01					
D_L	С	G	-0.08	1.78	-0.17	-0.22	-0.03	-0.16					
V_{G}	С	L	-0.34	-0.20	-0.22	-0.23	2.78	-0.14					
V_L	С	L	-0.28	-0.37	-0.29	-0.17	2.00	0.01					
D_G	V_{G}	G	-0.16	1.25	-0.02	0.33	-0.28	-0.25					
D_L	V_L	G	-0.08	1.27	-0.03	0.24	-0.24	-0.11					
					nt hotspot)								
C	V_{G}	G	1.97	-0.34	-0.21	-0.27	-0.15	1.22					
С	VL	G	1.63	0.01	-0.27	-0.09	-0.28	0.69					
Р	С	L	0.12	-0.01	-0.11	0.70	1.58	0.29					
D _G	V_{G}	G	-0.03	-0.23	-0.44	0.14	0.20	1.03					
DL	VL	G	0.01	-0.31	-0.43	0.28	0.00	1.06					
D _G	V _G	L	0.30	0.27	0.09	0.42	0.61	1.22					
			-	riant hotsp		0.07	0.00						
C	DL	L	0.03	-0.84	0.38	-0.87	-0.30	2.42					
C	V _G	G	3.68	-1.00	-1.00	0.42	-0.15	-0.29					
C	VL	G	2.90	-1.00	-1.00	0.37	-0.21	-0.52					
C	V _G	L	-0.23	1.42	0.03	0.24	0.26	0.83					
Р	C	L	-1.00	-1.00	-0.27	4.33	4.26	-1.00					
D _G	C	L	2.15	0.73	-0.05	0.57	1.34	-1.00					
D_L	С	L	2.46	0.90	0.07	0.73	1.11	-1.00					

Table 3. Selected genomic features in 100-kb frequency-based diagnostic CNV features with fold-change greater than 1 in at least one replication phase(s).

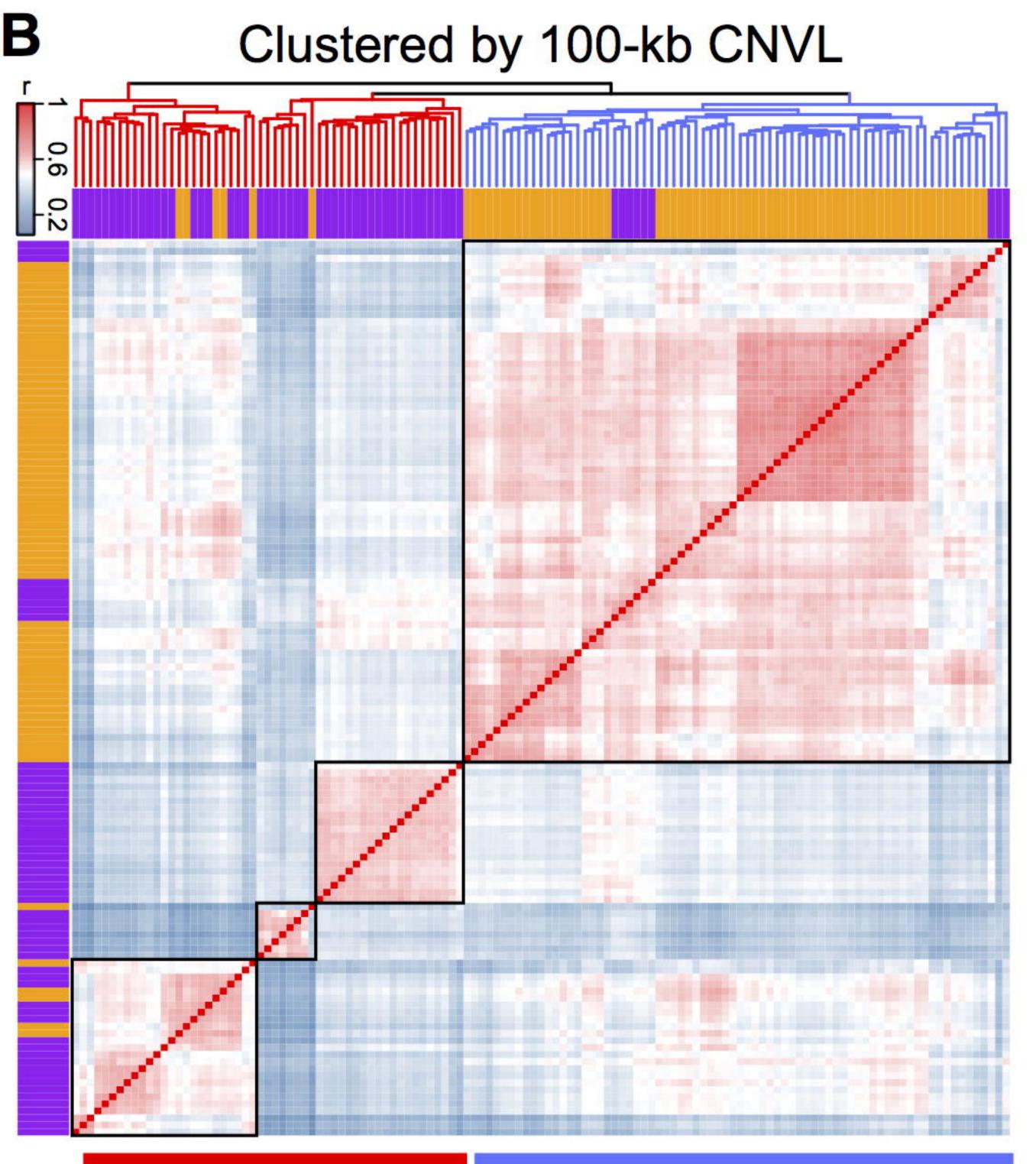
LINC (Larg	e inter	genic non-o	oding RN	<u>A)</u>				V _G	С	G	-1.00	-0.26	1.48	0.46	0.12	-0.83
C D _G	G	0.50	-0.64	7.56	1.38	1.46	0.11	V_L	С	G	-1.00	1.45	0.72	0.19	-0.08	-0.38
C D _L	G	-0.98	-0.76	8.90	1.53	1.51	0.16	V_{G}	С	L	-0.41	-0.72	-0.70	1.68	0.46	-0.97
C D _G	L	-0.86	0.44	0.46	-0.79	-0.88	3.10	V_L	С	L	-0.21	-0.78	-0.41	1.20	0.27	-0.89
D _G C	G	1.84	-0.92	-0.68	0.21	-0.99	-0.80	D_G	V_{G}	G	0.02	-0.65	-0.55	-0.50	1.52	0.89
D _G C	L	-0.85	-0.84	-0.95	1.89	-1.00	-1.00	D_L	V_L	G	-0.05	-0.64	-0.55	-0.53	1.41	0.95
D _L C	L	-0.81	-0.82	-0.95	1.85	-1.00	-1.00	D_G	V_{G}	L	0.91	0.42	0.43	0.64	1.71	1.25
V _G D _G	G	0.87	-0.74	4.34	-0.66	0.81	0.16	V_{G}	D _G	L	-0.64	-0.36	3.00	0.50	0.12	0.20
$V_L D_L$	G	0.76	-0.75	3.45	-0.69	0.65	-0.08	V_L	DL	L	-0.44	-0.52	-0.15	0.41	-0.38	1.07

¹ Significant difference in CNV frequencies between compared groups, with 'H' and 'L' indicating higher- and lower-frequency group respectively. The subscripts 'G' and 'L' indicate sample groups clustered based on CNVG and CNVL respectively; ² 'G' indicates copy-number-gains and 'L' indicates copy-number-losses; ³ Fold-change (> 1-fold in bold) of genomic feature density or intensity in diagnostic CNV features relative to non-diagnostic-CNV regions in replication

phase.

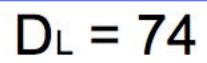


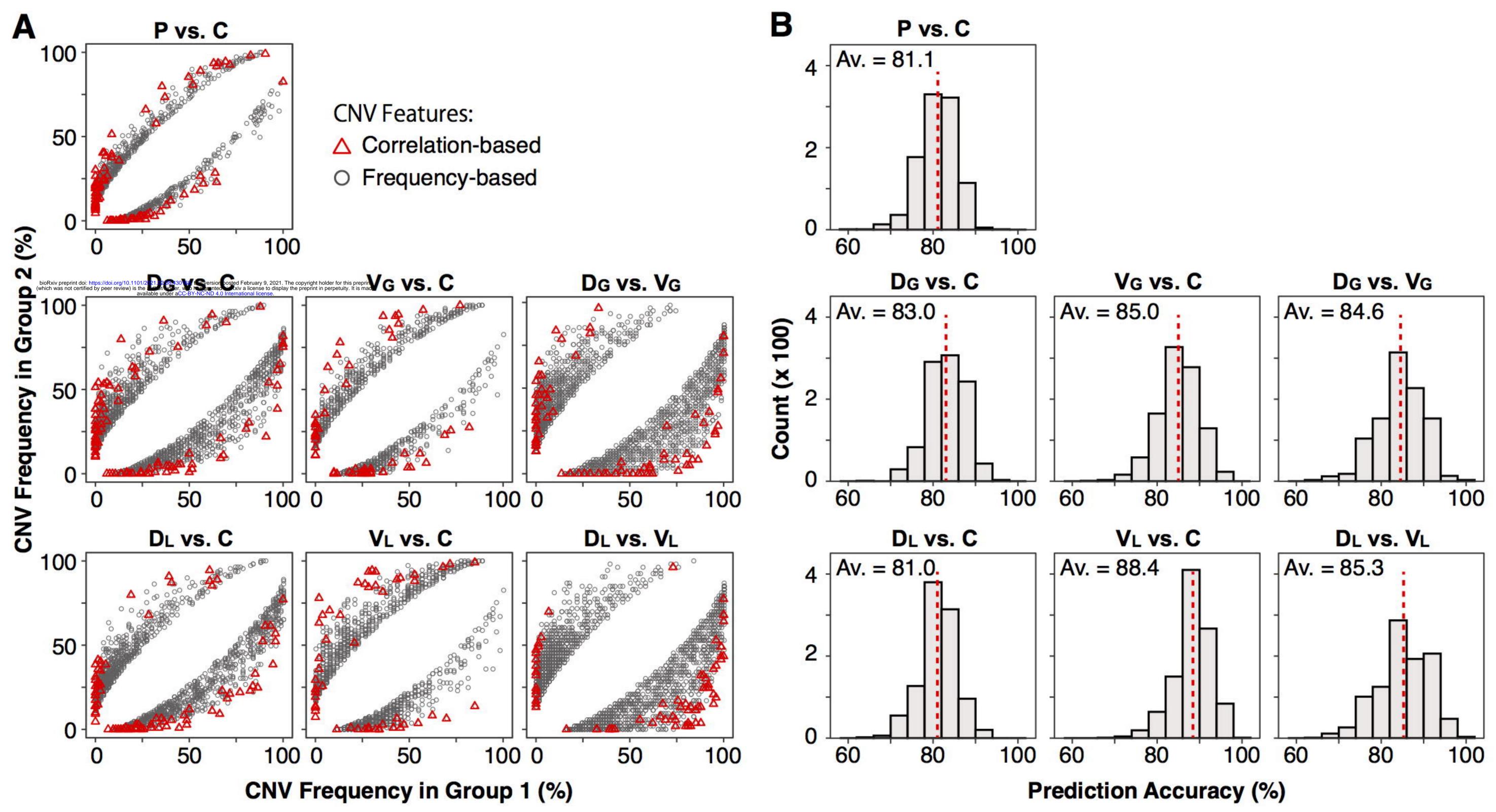
 $D_{G} = 66$

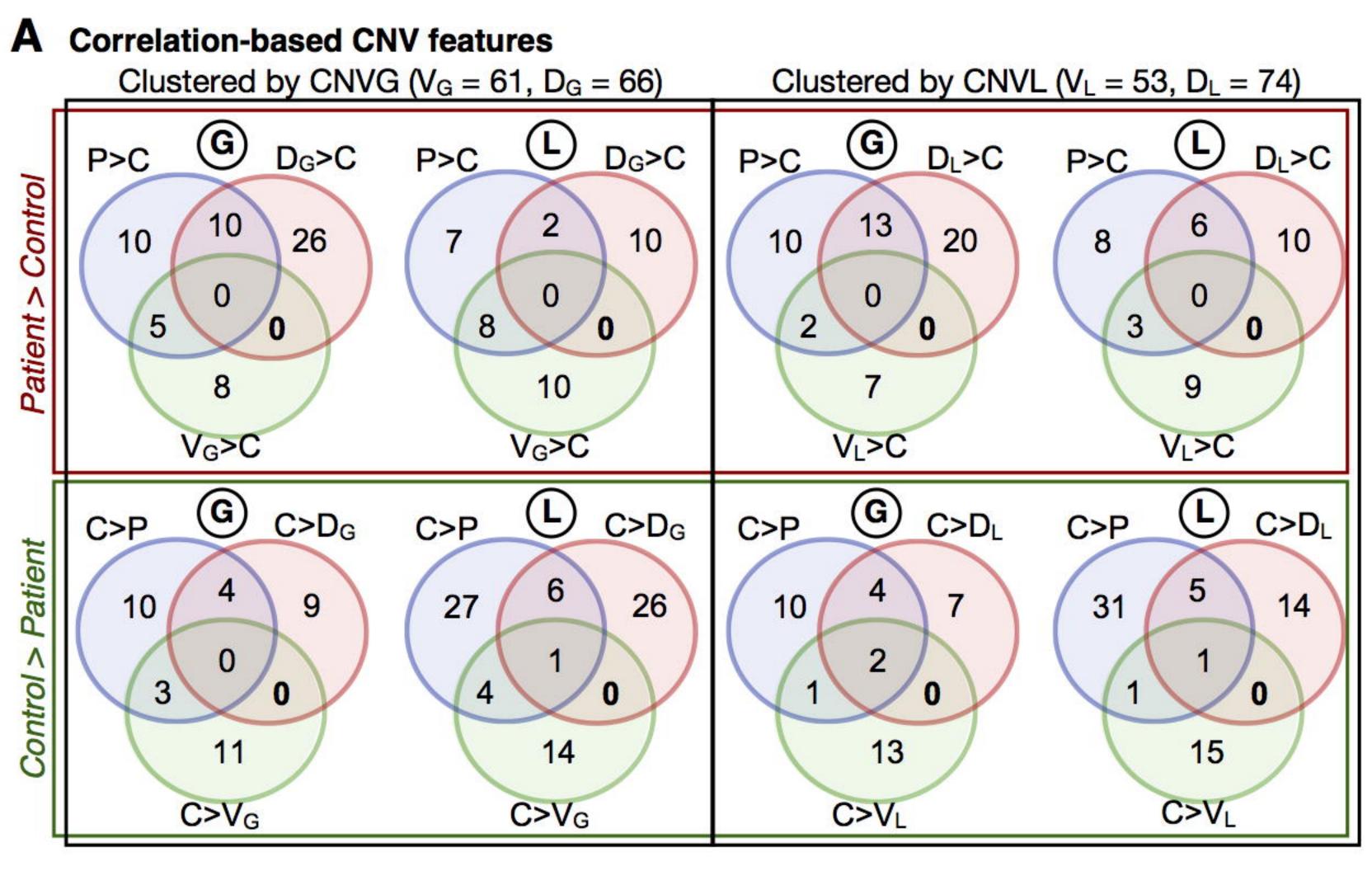


V∟ = 53







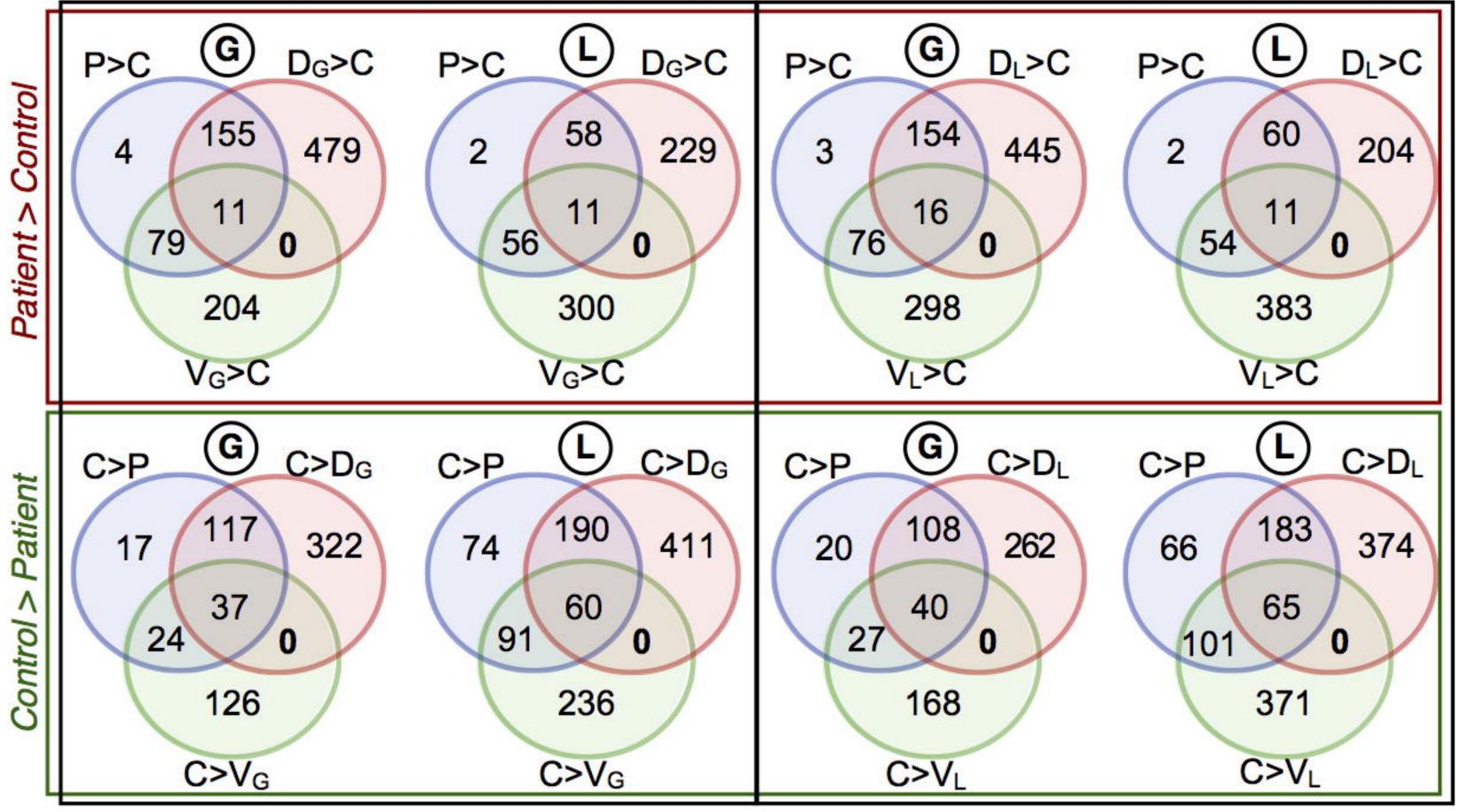


B Frequency-based CNV features

Clustered by CNVG ($V_G = 61$, $D_G = 66$)

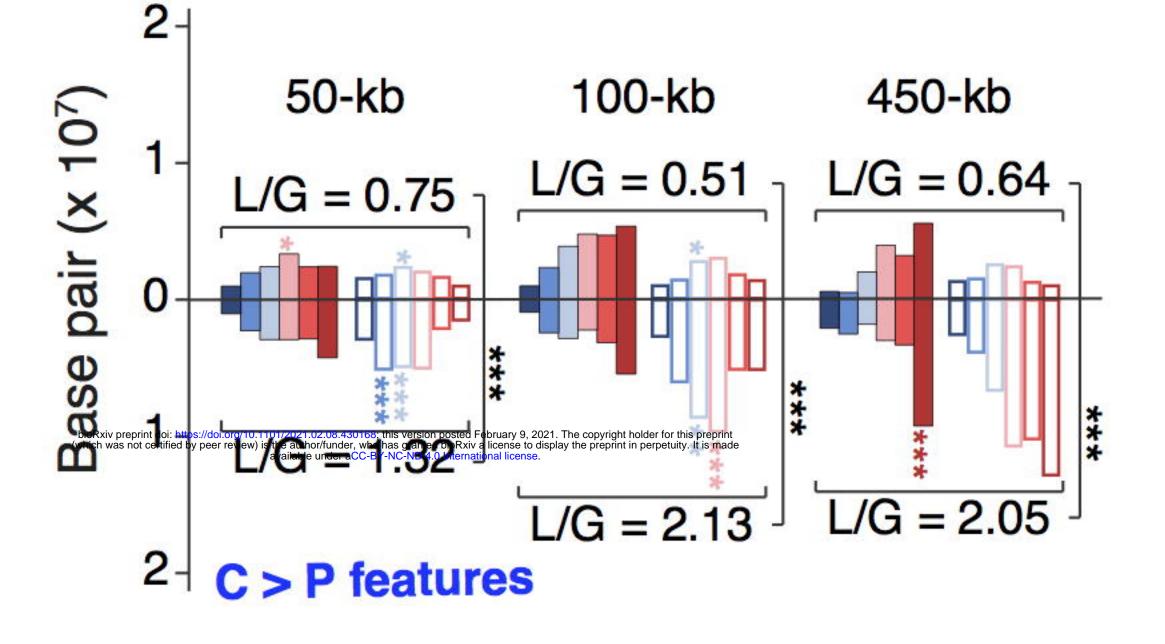
Clustered by CNVL ($V_L = 53$, $D_L = 74$)

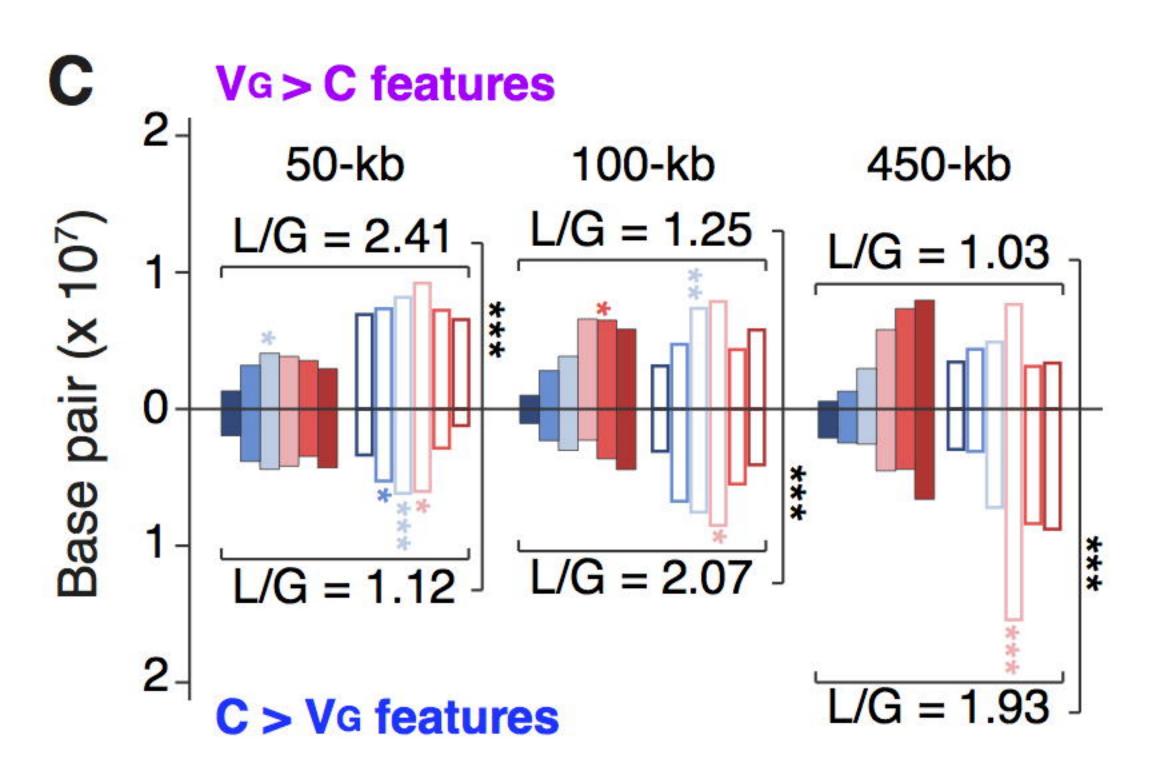




Α

P > C features





DG > C features

B

