

Supplementary Materials for

**Molecular classification of geriatric breast cancer displays distinct
senescent subgroups of prognostic significance**

Xia Wu *et al.*

* Corresponding authors: Hao Ke at kehao@ncu.edu.cn;
Limin Zhao at zhaolimin@ncu.edu.cn

This PDF file includes:

Figures. S1 to S11

Other Supplementary Materials for this manuscript include the following:

Table S1 to S5

Figure S1. The analysis of 25 genes related to senescence in breast cancer.

(A) The network analysis was performed to reveal the interactions among these 25 genes in elderly breast cancer. Genes were grouped into four clusters (hcluster) based on their expression, with red lines indicate positive correlations and blue lines indicate negative correlations. The size of the circles reflects the P value representing the impact of the genes on patient survival. Two genes, HSPA8 and UBC, clustered together, while the remaining genes were distributed among three other clusters. (B) Displaying the expression levels of the 25 genes in both elderly breast cancer and normal samples. P value were determined using Student's t -test, with blue representing normal sample expression and red representing tumor sample expression. (C) Analysis of single nucleotide variations (SNVs) in the 25 senescence genes among 445 elderly breast cancer patients. (D) Co-occurrence analysis of genetic alterations in the 25 senescence genes among 445 elderly breast cancer patients. There are significant co-mutations between MDM2 and MAPKAPK5, as well as HMGA2 and CCNA2. (E) Univariate Cox analysis of the expression of the 25 senescence genes. HSPA8 and E2F2 were negatively correlated with patient survival, with a hazard ratio greater than 1 and statistical significance. $*P < 0.01$, $**P < 0.001$, $***P < 0.0001$, $****P < 0.00001$.

Figure S2. Unsupervised clustering analysis displays two distinct senescent clusters in elderly breast cancer.

(A) The ConsensusClusterPlus R package was used to calculate the optimal cutoff values for patients. Consistency Matrix (CM) plots values from white to blue on a color

scale for different K values. (B-H) Consensus matrix heatmaps represent sample matrices where values range from 0 to 1, indicating the likelihood of belonging to the same cluster, with colors from white to dark blue. (I) Consensus cumulative distribution function (CDF) plots use histograms with 100 bins to calculate cumulative distributions for each K corresponding to the consensus matrix. CDF plots help determine the optimal K value. (J) Delta area plot compares the relative changes in the area under the curve of the CDF between K and K-1. Points with minimal increase were selected as the optimal K value; in this case, K=2 was chosen. (K) Tracking plots show samples (rows) across different K values (columns) using heatmaps, allowing qualitative assessment of unstable clustering and sample stability. (L) PCA reduction of 25 senescence genes in 513 elderly breast cancer patients. Red represents Cluster1, and blue represents Cluster2.

Figure S3. Two senescent clusters show different gene enrichment pathways.

(A) Univariate Cox analysis of patient information (Gender, Stage, ER, PR, HER-2, and Cluster) (B) Multivariate Cox analysis of patient information (Gender, Stage, ER, PR, HER-2, and Cluster). (D-E) Illustrate the differential Gene Set Enrichment Analysis (GSEA) between Cluster1 and Cluster2.

Figure S4. Construction of the Sene_Signature model.

(A) Model Comparison: We conducted a comprehensive evaluation of machine learning models using accuracy parameters such as AUC, MCC, F1 score, recall, and

Positive predictive value (PPV). (B) Discrepancies in survival outcomes between the senescence score model and single genes, risk scores, and biological pathway enrichment scores.

Figure S5. Sene_Signature score associated with clinical features.

(A-B) Lollipop chart showing the correlation between 25 senescence genes and senescence scores in the TCGA (A) and METRBIC (B) data. The smaller the *P* value, the redder the color, and the size of the circle maps to the size of the correlation. (C) The Recurrence-Free Survival differences between the high and low evaluation groups in the GSE2990 dataset. (D) The sample information table is represented by the Sankey plot, which corresponds to cluster information, high and low scores, PAM50 typing information, and TMN tumor staging information. (E) The box chart of Sene_Signature difference between triple negative breast cancer and non-triple-negative breast cancer shows that there is significant difference between the two groups through Wilcoxon-test.

Figure S6. The correlation between Sene_Signature and genomic mutations

(A) The box plot of TMB scores in the high and low scoring groups in METABRIC shows that red represents the high scoring group and blue represents the low scoring group (Student's *t*-test). (B-C) Mutation information is provided for the top 20 genes with the highest number of mutations in high and low scoring patients in TCGA (B) and METABRIC (C).

Figure S7. Identification of characteristic genes for the single-cell transcriptomic data.

(A) Using the "FindAllMarkers" function to identify characteristic genes within 6 cell types from the single-cell transcriptomic data of 70 breast cancer patients. Columns represent cell types, rows represent genes, and the heatmap displays gene expression within each cell type.

Figure S8. The relationship between Sene_Signature and tumor immune infiltration from scRNA-seq data.

(A) Integration of 70 single-cell transcriptomic datasets, where different colors represent distinct patients. From the visual results, batch effects appear to have been removed. (B) UMAP dimensionality reduction results for the subdivision of T-cell subtypes, grouped into 12 clusters. (C) Mapping patient information onto the UMAP results for T-cell subtypes, with each color representing a different patient. No noticeable batch effects are observed in the data.

Figure S9. Drug sensitivity analysis for 25 senescence-related genes.

(A) The correlation between 25 senescence genes and drug IC50 was analyzed in the GDSC database, and the corresponding drug names were listed for the 25 genes. Red indicates that higher gene expression is associated with lower drug sensitivity, while blue indicates that higher gene expression is associated with greater drug sensitivity.

Addition, larger circles represent more significant *P* value.

Figure S10. Sene_Signature predicts drug sensitivity of elderly breast cancer.

(A-B) Differential analysis of IC50 values between high and low Sene_Signature groups in elderly breast cancer patients from the TCGA (A) and METABRIC (B) datasets. (C-D) Correlation analysis was conducted between drug sensitivity predictions and Sene_Signature scores in the TCGA (C) and METABRIC (D) datasets.

FigureS11. EGFR inhibitor sensitivity analysis in high and low Sene_Signature groups.

(A) Eight breast cancer patients in GSE33658 predicted the high and low scores through the senescence model, and checked the patients' drug response to EGFR inhibitor Gefitinib.

Figure S1

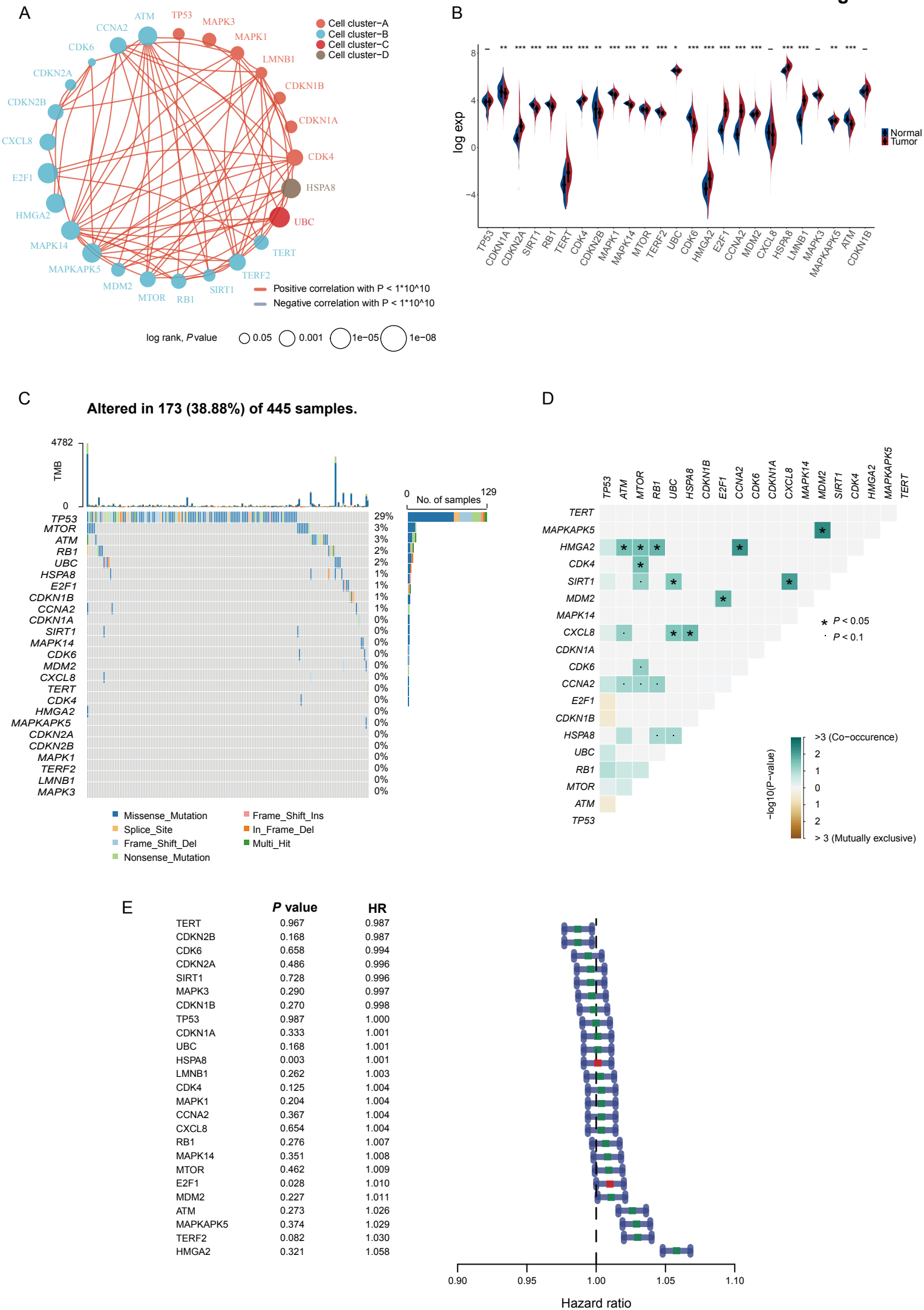


Figure S2

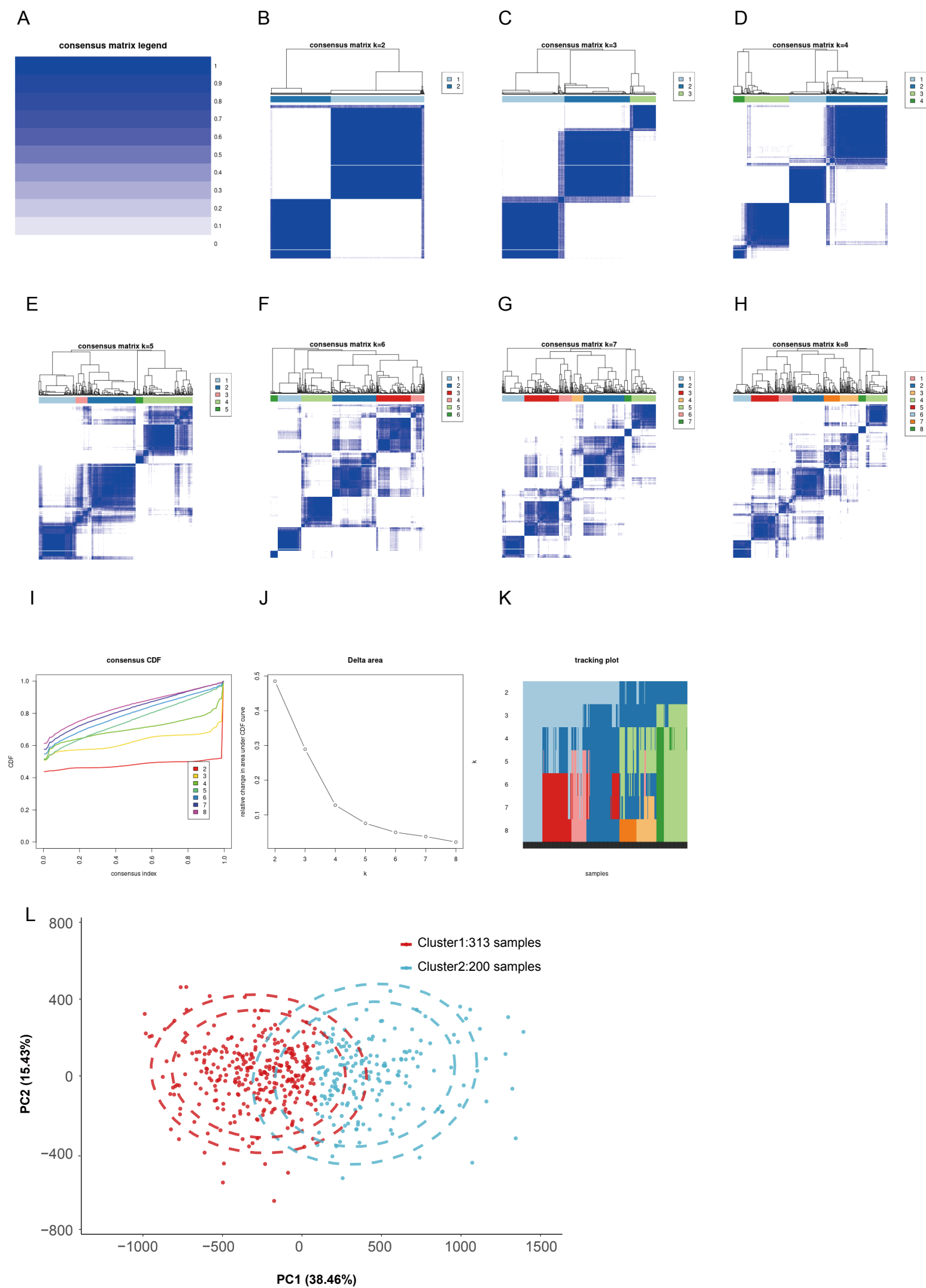
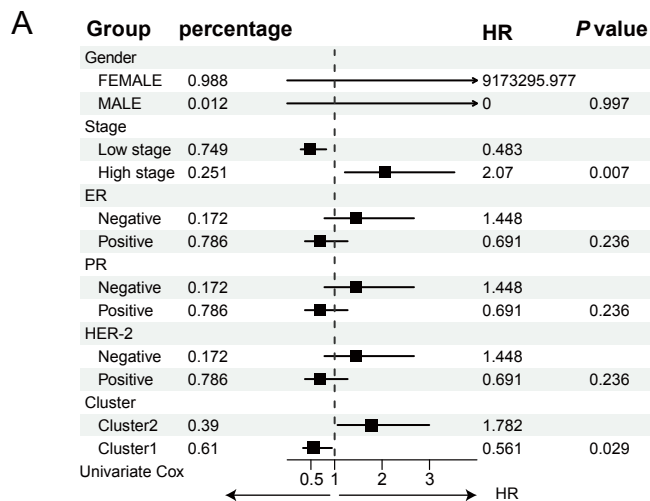
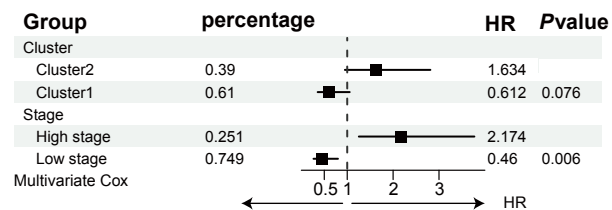
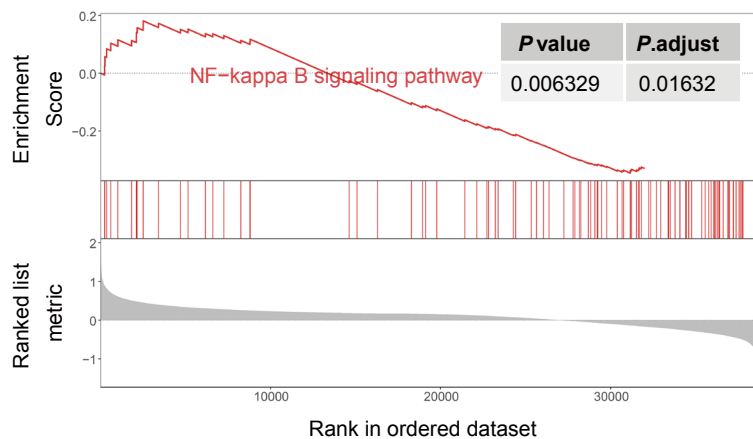
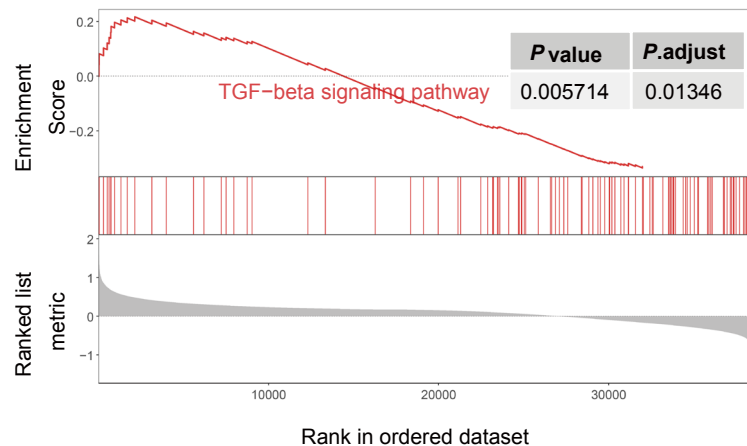
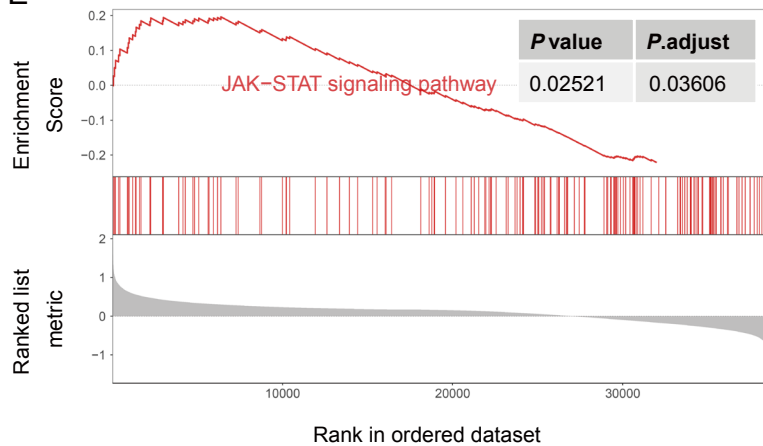


Figure S3

**B****C****Cluster1 VS Cluster2****D****Cluster1 VS Cluster2****E****Cluster1 VS Cluster2**

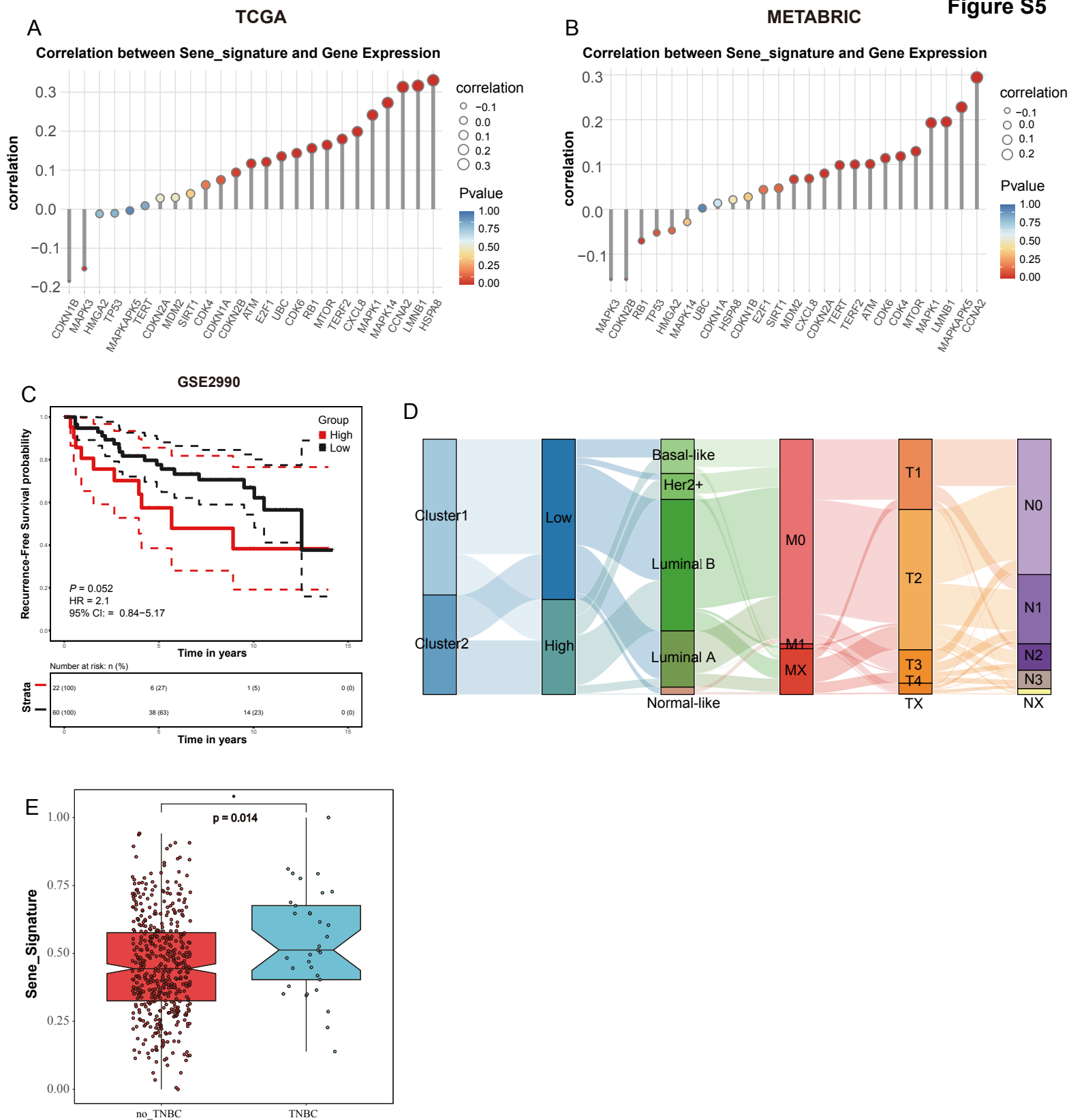
A

Method	AUC	MCC	F1Score	Recall	PPV
OneClassDetection	0.65330	0.2170231	0.5784314	0.7375	0.4758065
GradientBoostingRegressor	0.63555	0.2161001	0.5573770	0.6375	0.4951456
DecisionTreeRegressor	0.60975	0.2150721	0.5433526	0.5875	0.5053763
KNeighborsRegressor	0.68885	0.2100731	0.5512821	0.5375	0.5657895
LinearRegressor	0.61940	0.1896500	0.5502646	0.6500	0.4770642
SupportVectorRegression	0.73080	0.1705952	0.3589744	0.2625	0.5675676

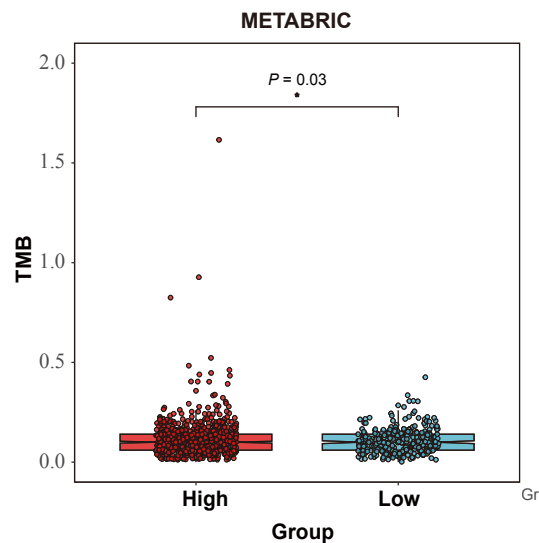
B

Models	HR	<i>P</i> value	Low	Upper
Sene_Signature	5.783	0.017	1.375	24.317
SERPINE1.Sig	1.001	0.382	0.999	1.002
ASF1B.Sig	1.004	0.033	1.000	1.008
ORC6.Sig	1.060	0.004	1.019	1.103
SKP2.Sig	1.034	0.250	0.977	1.095
8_DNA_Repair.Sig	1.273	0.000	1.144	1.415
13_Epigenetic.Sig	1.003	0.283	0.997	1.009
Immune_Score	1.342	0.565	0.493	3.654
CD8 T effector	0.891	0.393	0.684	1.161
APM	1.082	0.676	0.749	1.563
Immune checkpoint	1.040	0.756	0.814	1.327
EMT	1.238	0.158	0.920	1.665
Pan-F-TBRS	0.861	0.092	0.723	1.025
Angiogenesis	0.858	0.218	0.672	1.095
Cell cycle	0.939	0.636	0.724	1.218
DNA replication	1.153	0.222	0.917	1.449
NER	1.151	0.353	0.855	1.549
DNA damage repair	0.923	0.558	0.706	1.207
Homologous recombination	1.281	0.059	0.990	1.656
Mismatch repair	1.202	0.133	0.945	1.528
WNT target	0.871	0.291	0.674	1.125
TMEscore	1.208	0.086	0.974	1.498
Courtois-Cox et al.	1.765	0.045	1.012	3.077
de Magalhães et al.	1.220	0.667	0.494	3.013
Fridman et al.	0.339	0.052	0.114	1.007
GOBP_AGING	0.529	0.409	0.116	2.404
Regulski et al.	1.099	0.878	0.331	3.653
CellAge	1.200	0.793	0.308	4.678
HumanAge	1.334	0.657	0.374	4.755
Kyng et al.	0.921	0.862	0.365	2.325
Lee et al.	0.662	0.546	0.173	2.529
Lu et al.	0.938	0.905	0.329	2.677
Rodwell et al.	0.554	0.272	0.194	1.588
Monet et al.	2.309	0.009	1.231	4.332
Visala et al.	1.085	0.865	0.427	2.757

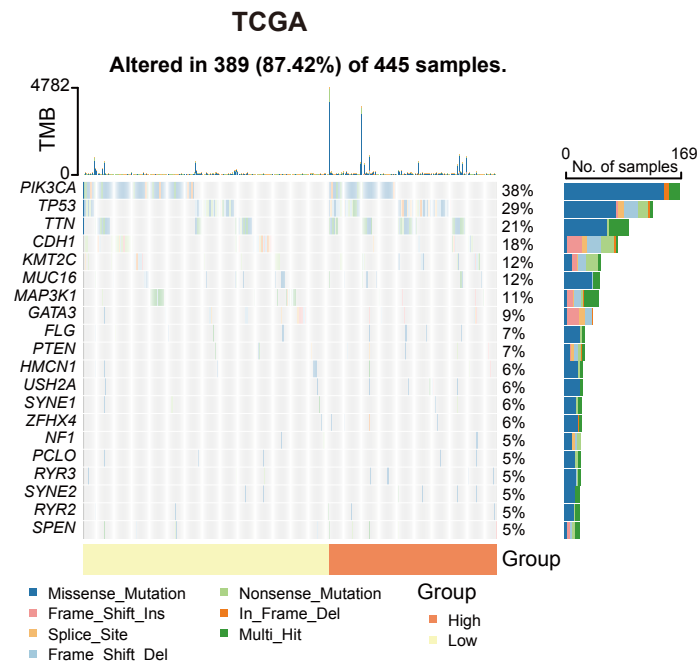
Figure S5



A



B



C

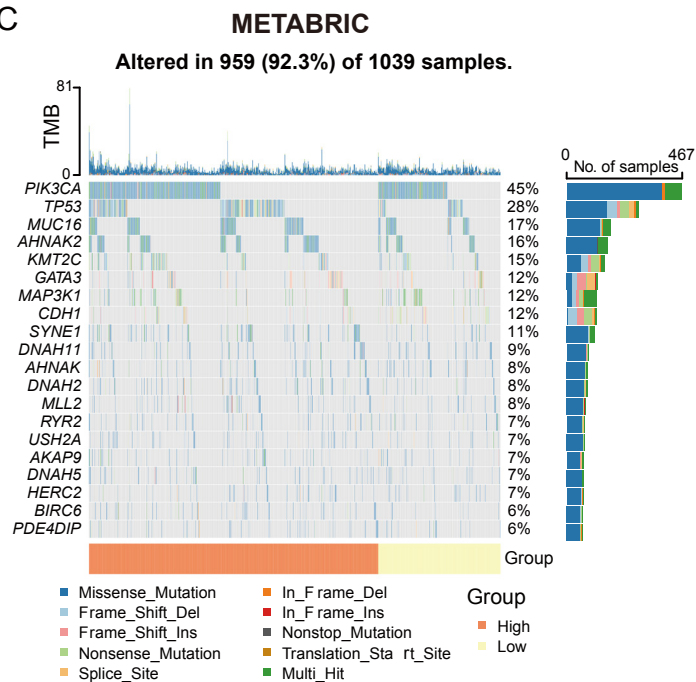
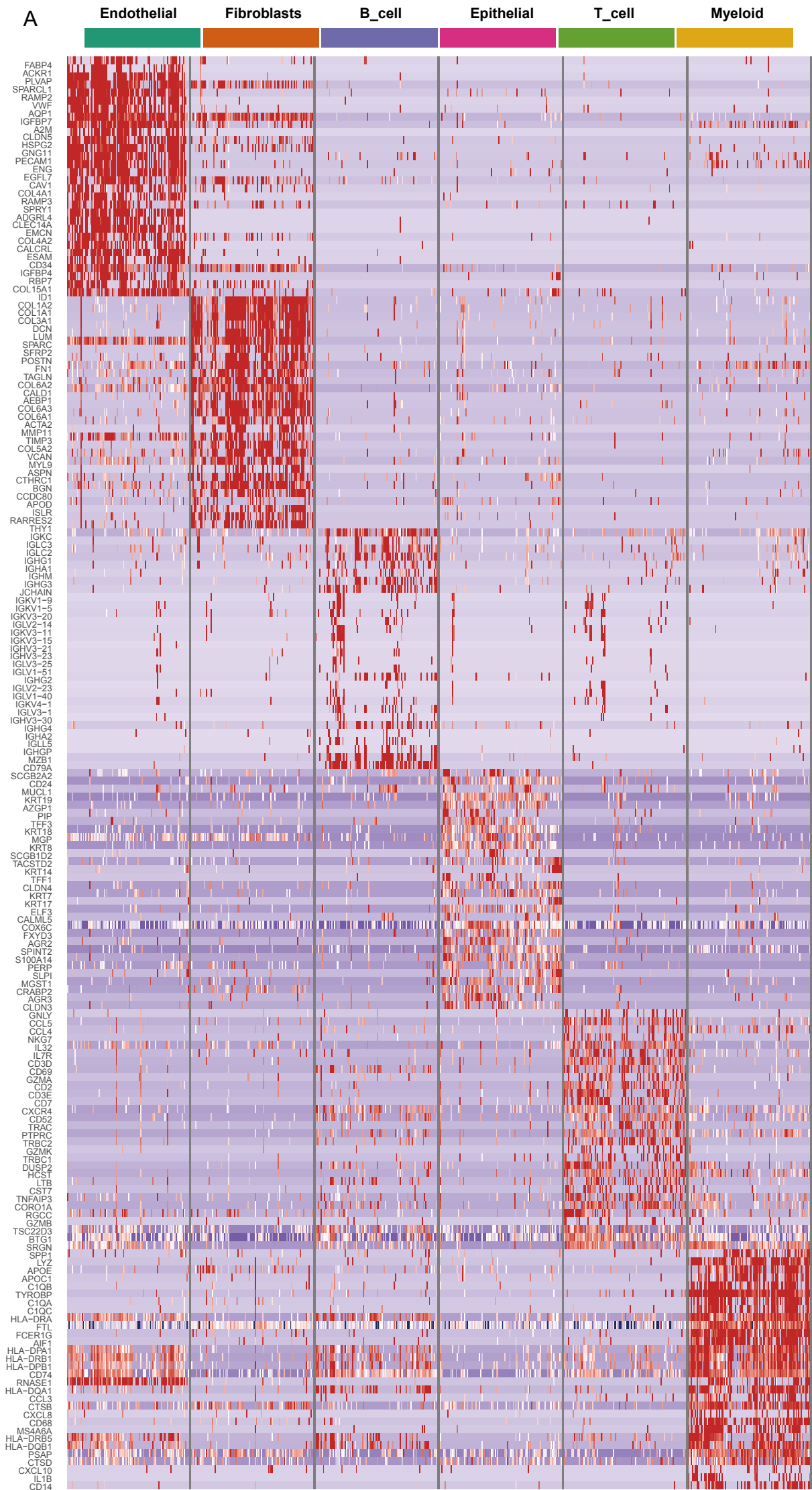


Figure S7



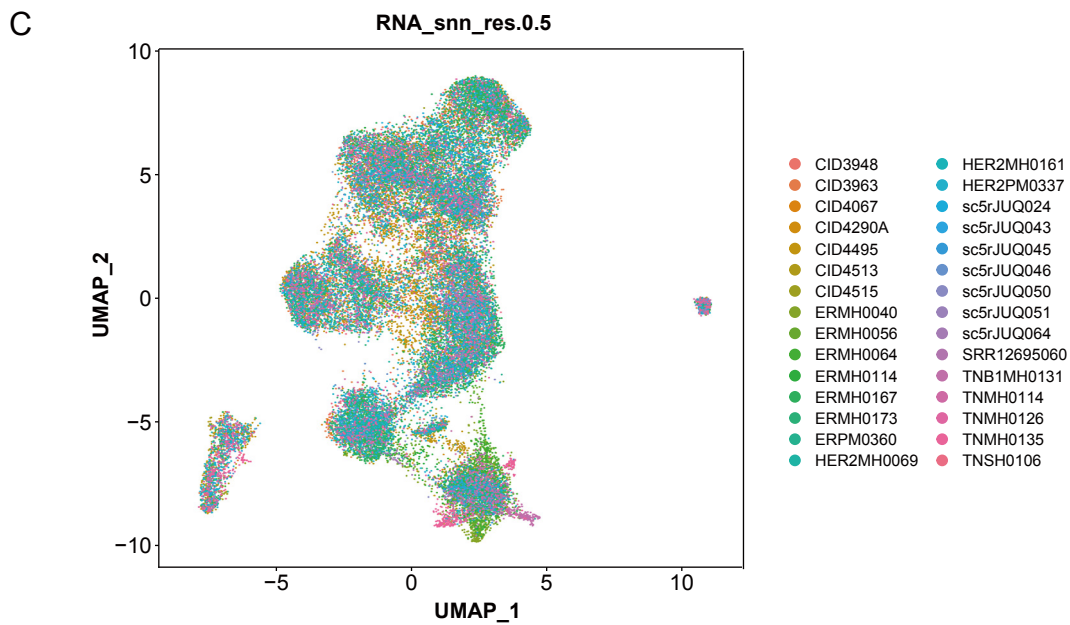
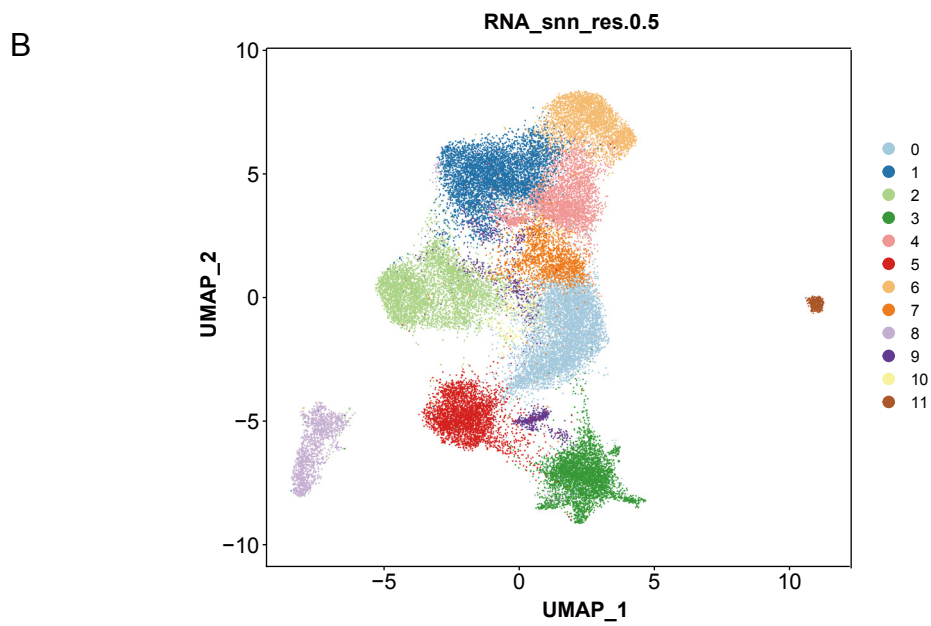
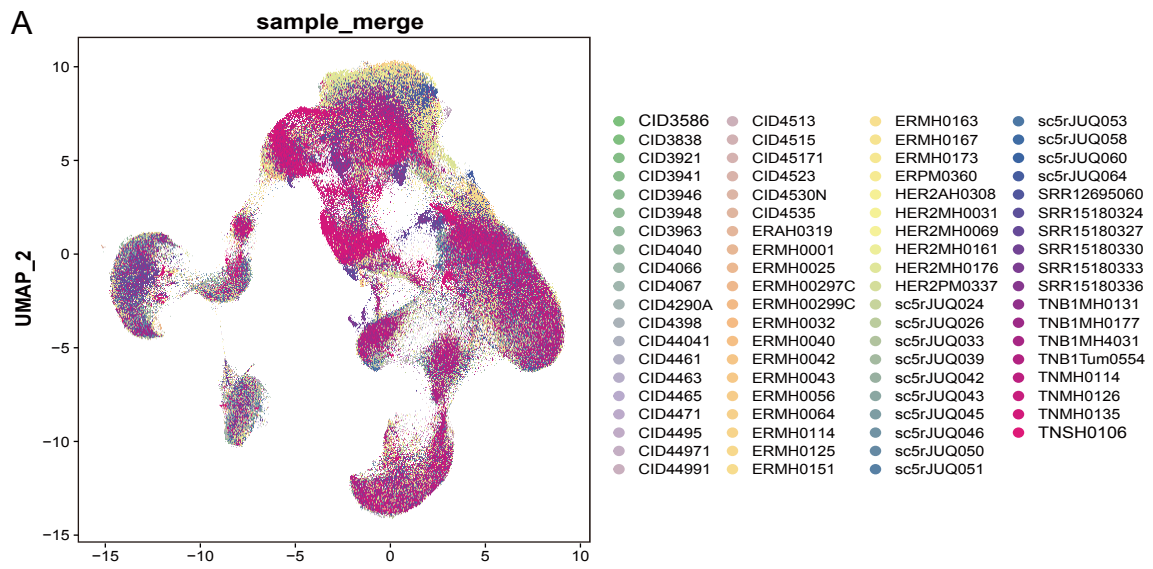
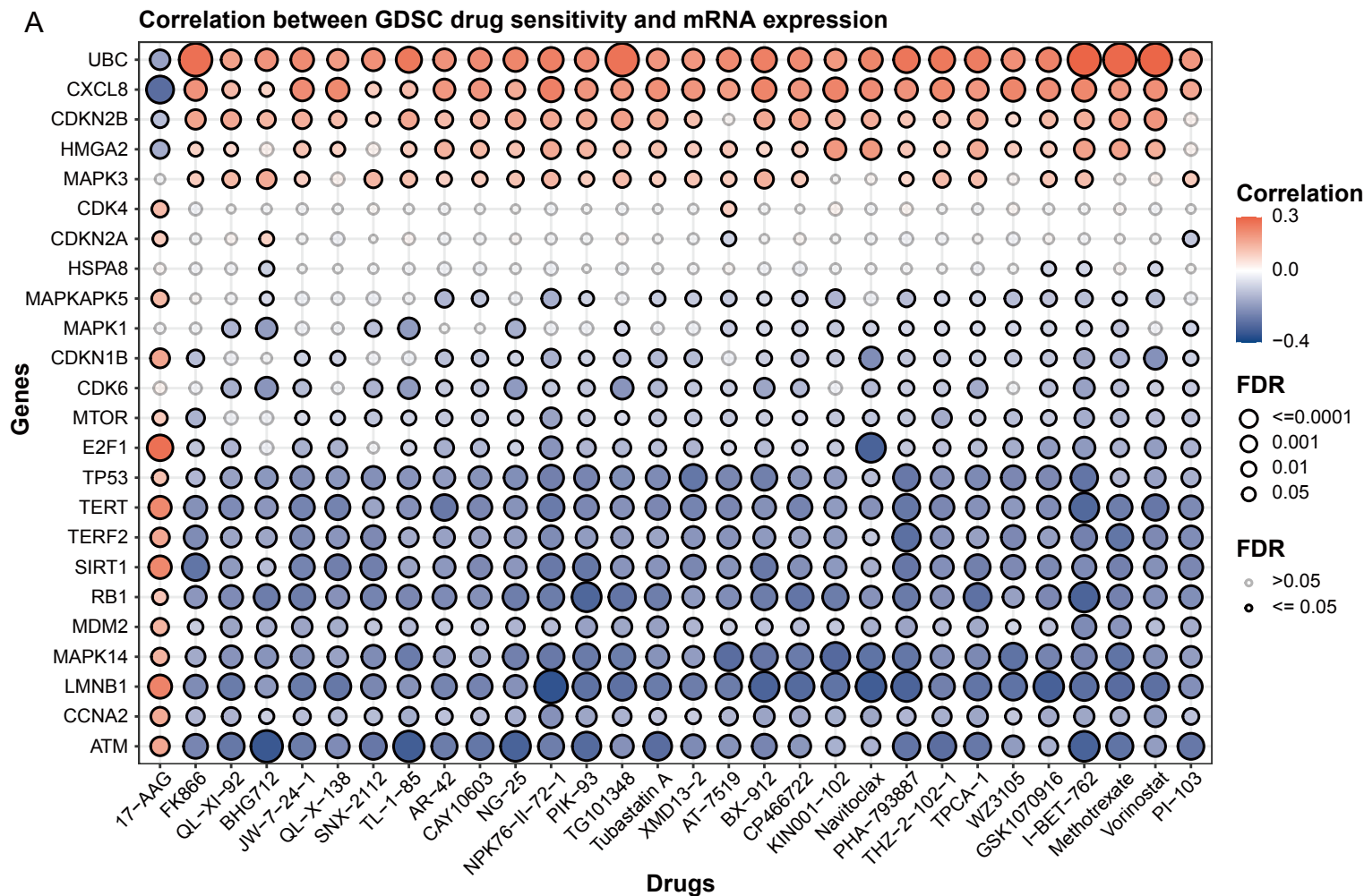


Figure S9



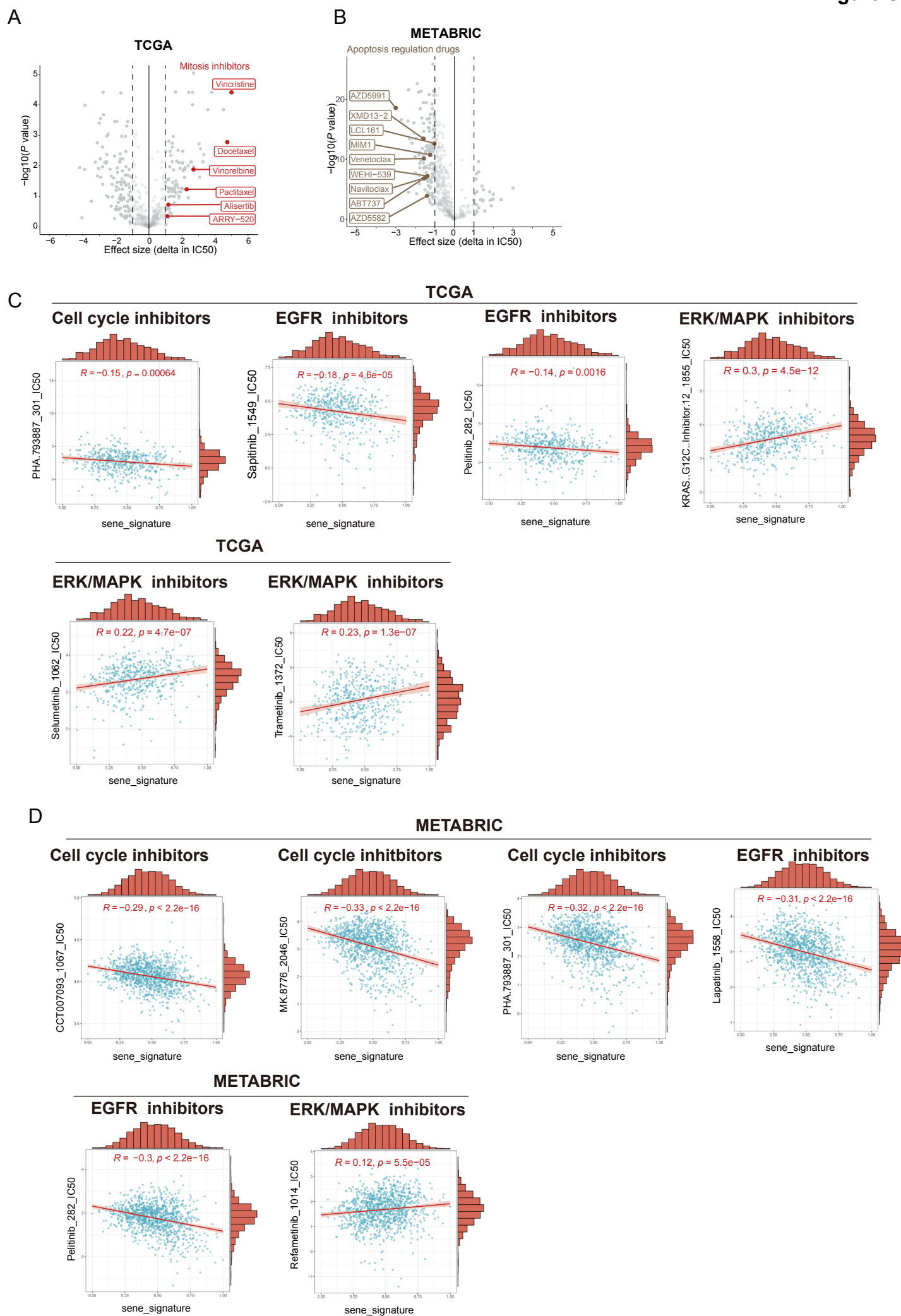


Figure S11

