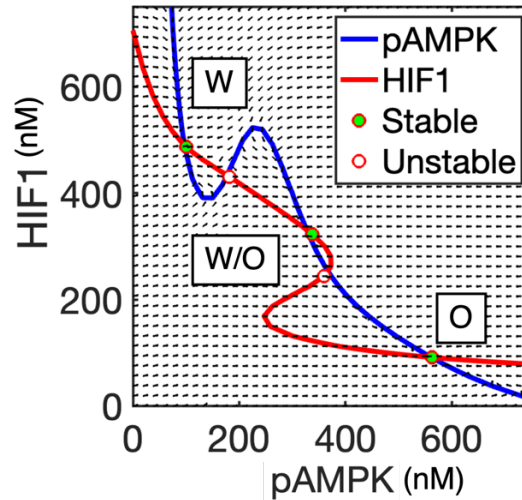


Computational modeling of cancer cell metabolism along the catabolic-anabolic axes

Javier Villela-Castrejon, Herbert Levine, Benny A. Kaiparettu, José N. Onuchic, Jason T. George, Dongya Jia

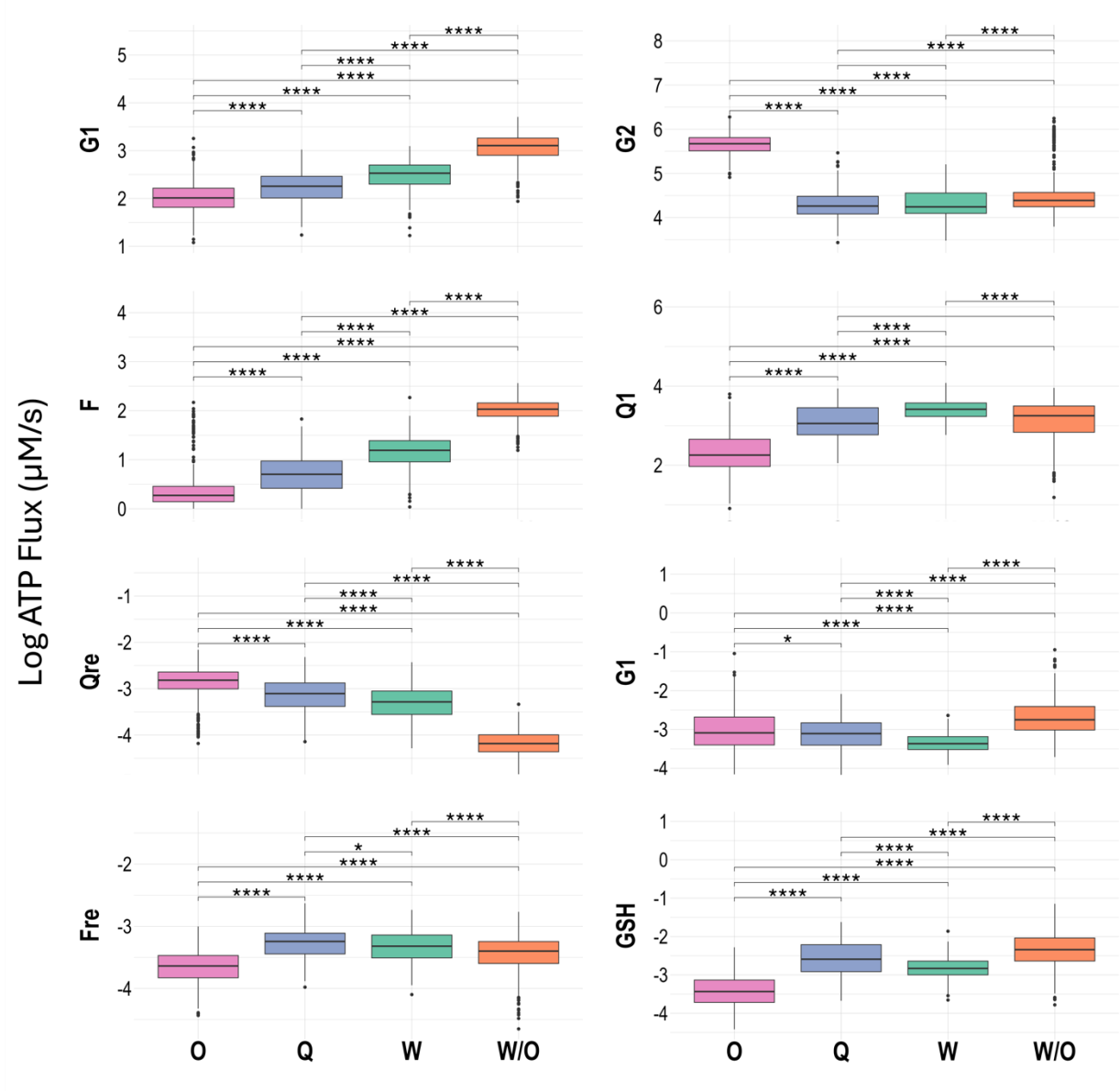
Supplementary Information

Supplementary Figure 1



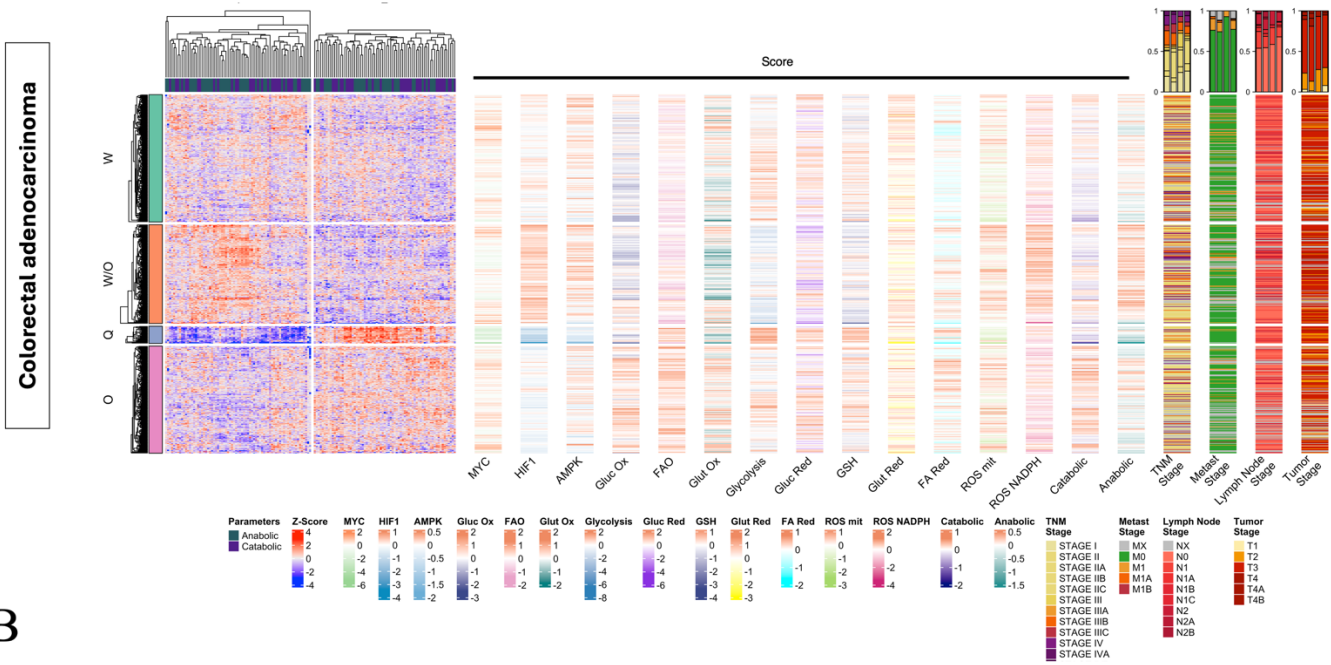
Supplementary Figure 1: The nullclines and steady states in the phase space of AMPK and HIF-1 when Myc = 1200 μ M. The red line represents the nullcline where the rate of change of HIF-1 (dH/dt) is zero, and the blue line represents the nullcline where the rate of change of AMPK (da/dt) is zero. Solid dots represent stable steady states while hollow dots represent unstable steady states. Each stable state is associated with a metabolic phenotype. With a low MYC expression, cells can acquire the Warburg phenotype, referred to as the state “W”, an OXPHOS phenotype, referred to as the state “O”, and a hybrid phenotype with intermediate activities of AMPK and HIF-1 called the state “W/O”.

30 **Supplementary Figure 2**

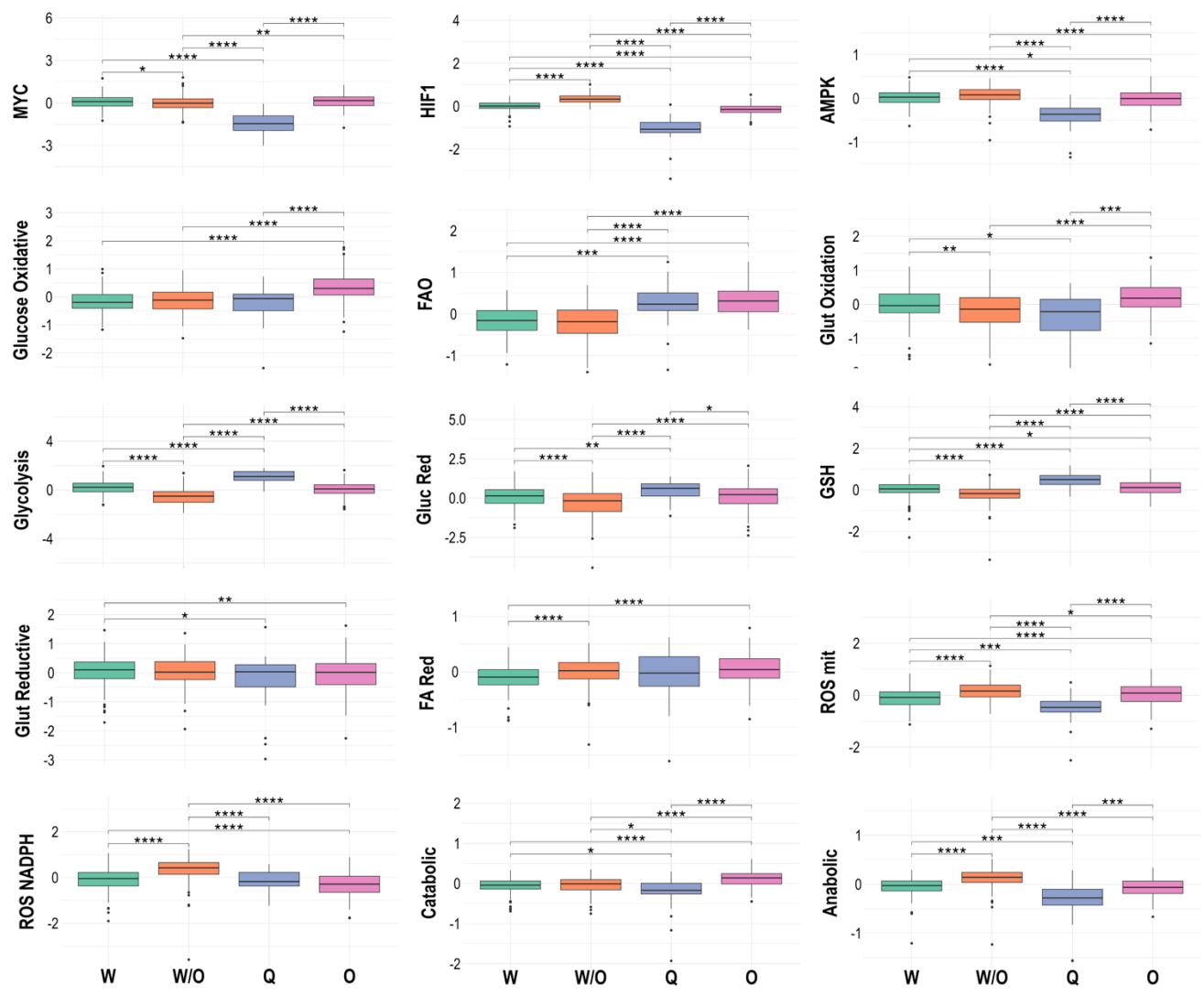


31 **Supplementary Figure 2: Log ATP flux of different metabolic pathways for the “O”, “W/O”,**
32 **“W”, and “Q” states.** Box plots summarizing and illustrating the differences in the log ATP flux
33 of various metabolic pathways for the different states. Positive rates indicate catabolic processes
34 where ATP is produced, while negative rates indicate anabolic processes where ATP is consumed.
35 Statistical significance is denoted as follows *, P < 0.05; **, P < 0.01; ***, P < 0.001; ****, P <
36 0.0001; *****, P < 0.0001.

A

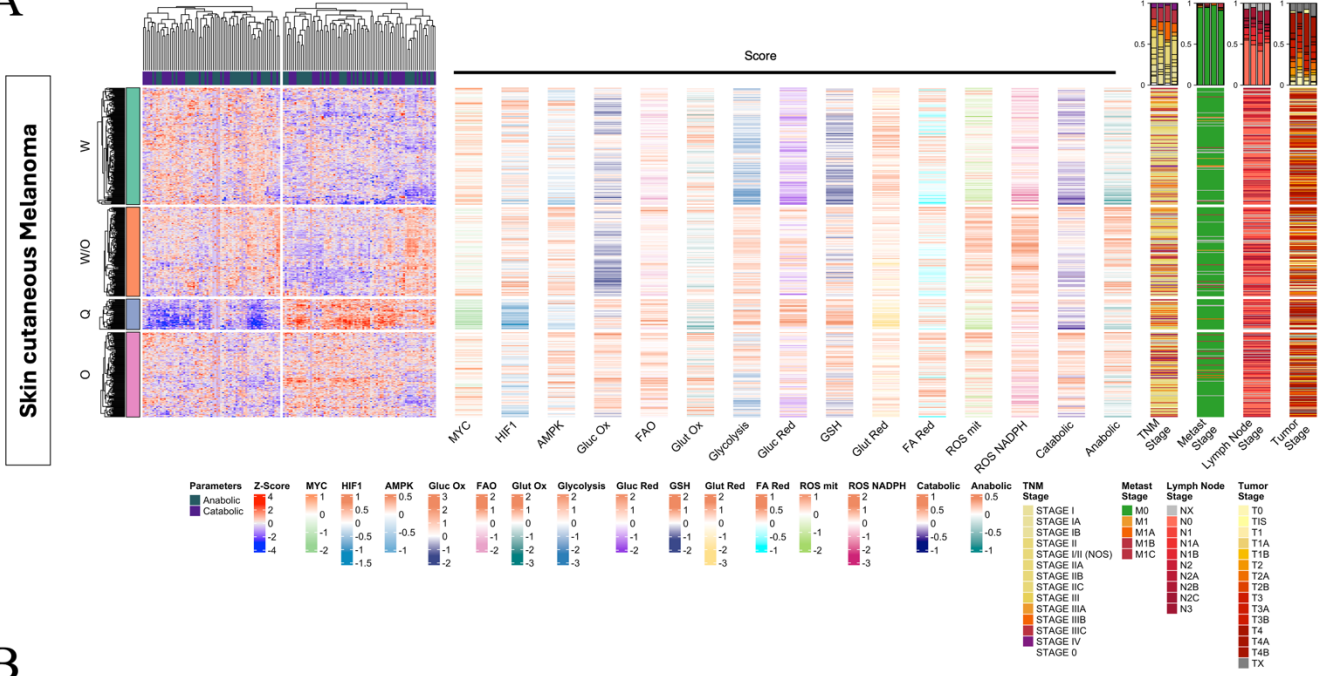


B

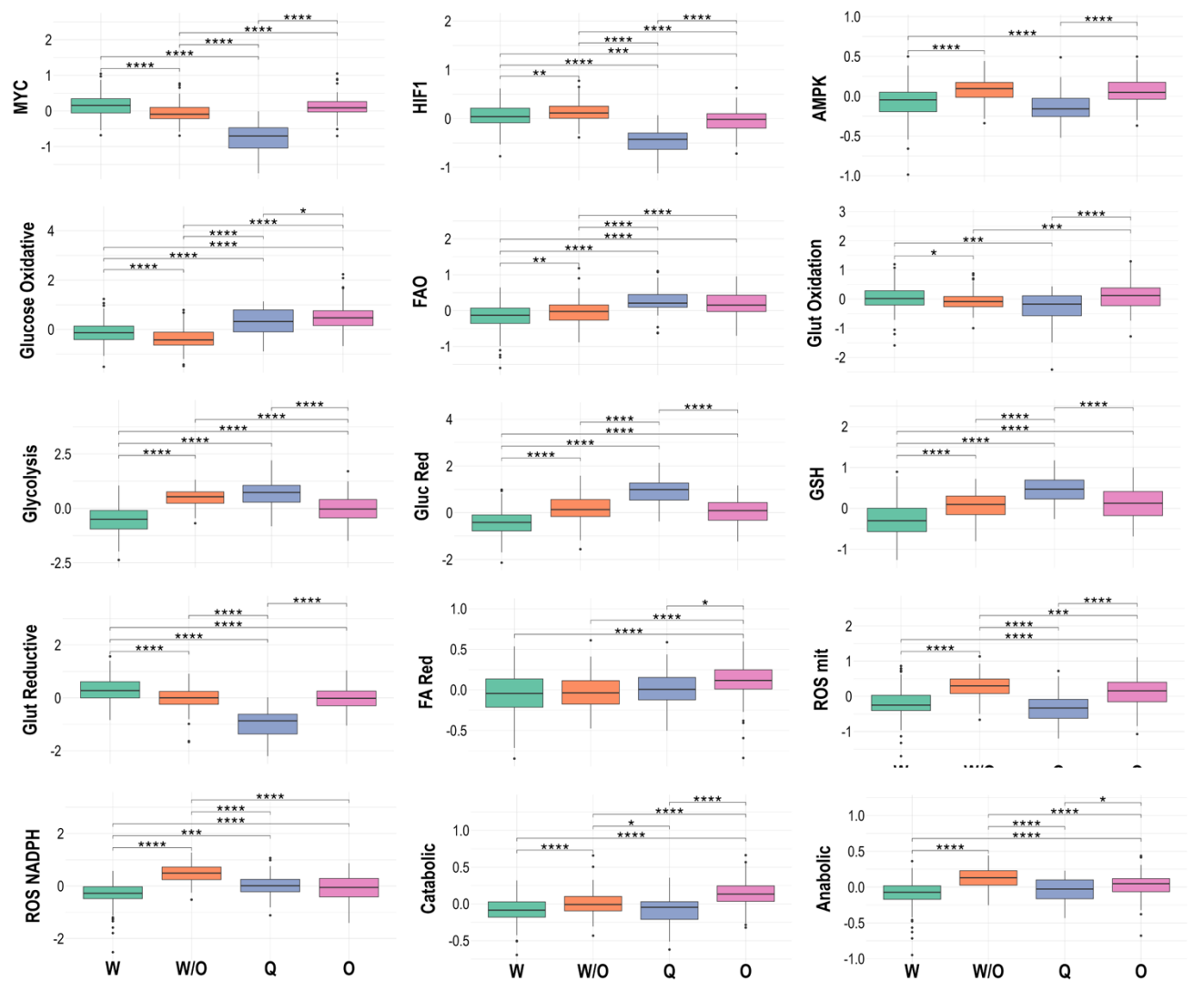


Supplementary Figure 3. The association between gene activity and metabolic pathway activity for colorectal carcinoma. **A.** Heatmap of RNA-seq data. Each row represents a patient sample, and each column represents the expression of selected genes, which are divided according to their metabolic or anabolic activities. Four distinct clusters can be identified in the heatmap. The adjacent one-column heatmaps represent the scores for Myc, HIF-1, AMPK, glycolysis, glucose oxidation, FAO, glutamine oxidation, glycolysis, glucose reduction, GSH, glutamine reduction, FA reduction, ROS mitochondrial, ROS NADPH, overall catabolic, and overall anabolic activities, respectively, we also included some of the phenotypic data of cancer: TNM stage, metastasis stage, lymph node stage, and tumor stage. **B.** Box plots summarizing and showing the differences in the scores according to each identified cluster. A t-test was used to test the significance of each pair of clusters. Significance levels are indicated as follows: *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$; ****, $P < 0.0001$.

A

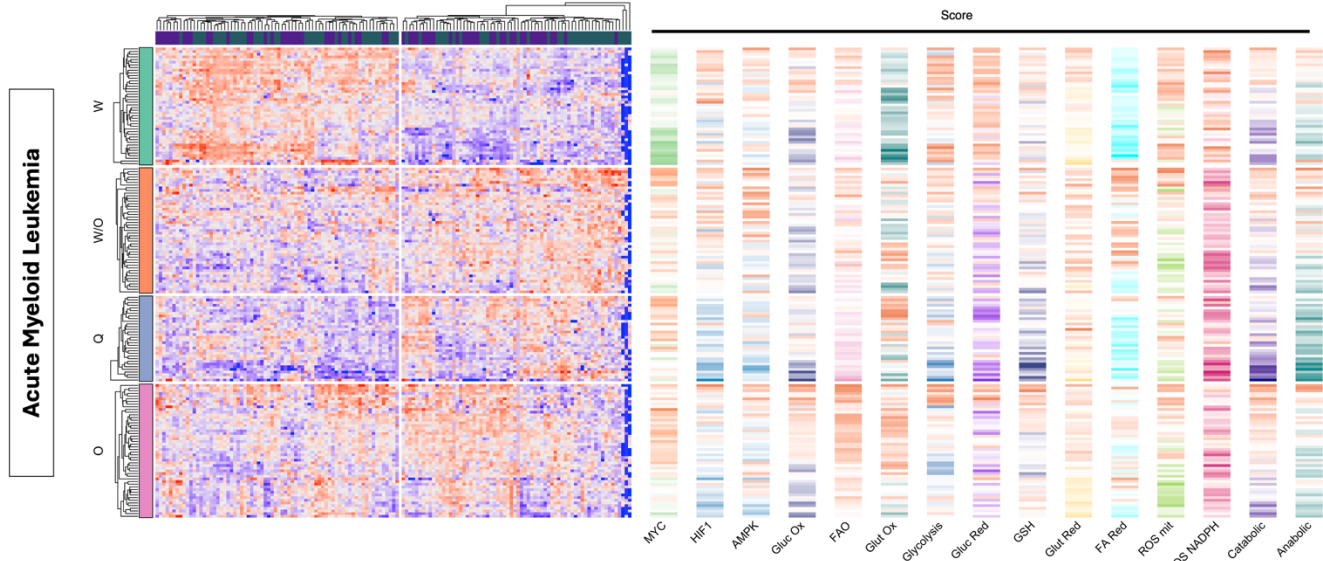


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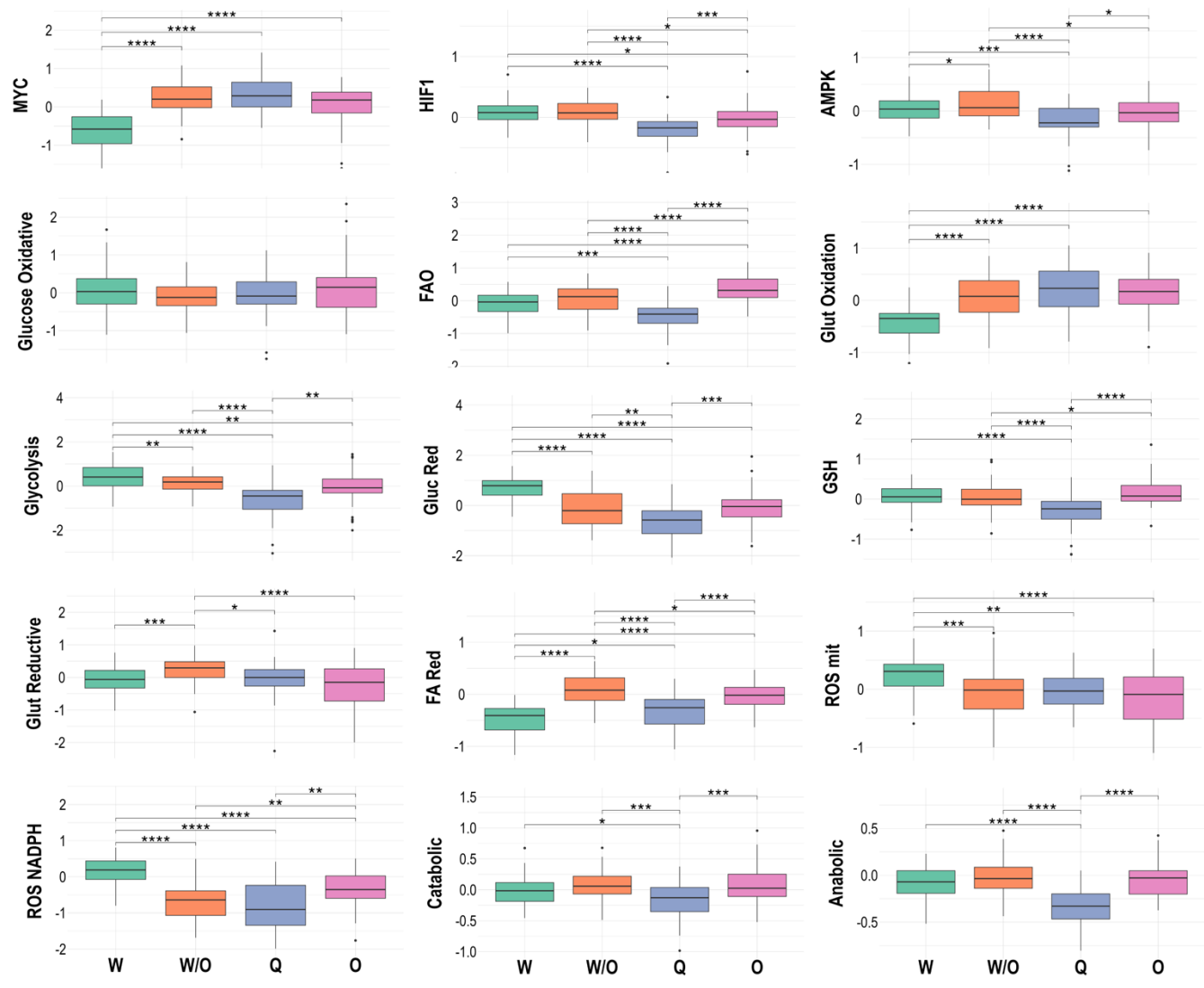


Supplementary Figure 4. The association between gene activity and metabolic pathway activity for skin cutaneous melanoma. **A.** Heatmap of RNA-seq data. Each row represents a patient sample, and each column represents the expression of selected genes, which are divided according to their metabolic or anabolic activities. Four distinct clusters can be identified in the heatmap. The adjacent one-column heatmaps represent the scores for Myc, HIF-1, AMPK, glycolysis, glucose oxidation, FAO, glutamine oxidation, glycolysis, glucose reduction, GSH, glutamine reduction, FA reduction, ROS mitochondrial, ROS NADPH, overall catabolic, and overall anabolic activities, respectively, we also included some of the phenotypic data of cancer: TNM stage, metastasis stage, lymph node stage, and tumor stage. **B.** Box plots summarizing and showing the differences in the scores according to each identified cluster. A t-test was used to test the significance of each pair of clusters. Significance levels are indicated as follows: *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$; ****, $P < 0.0001$.

A

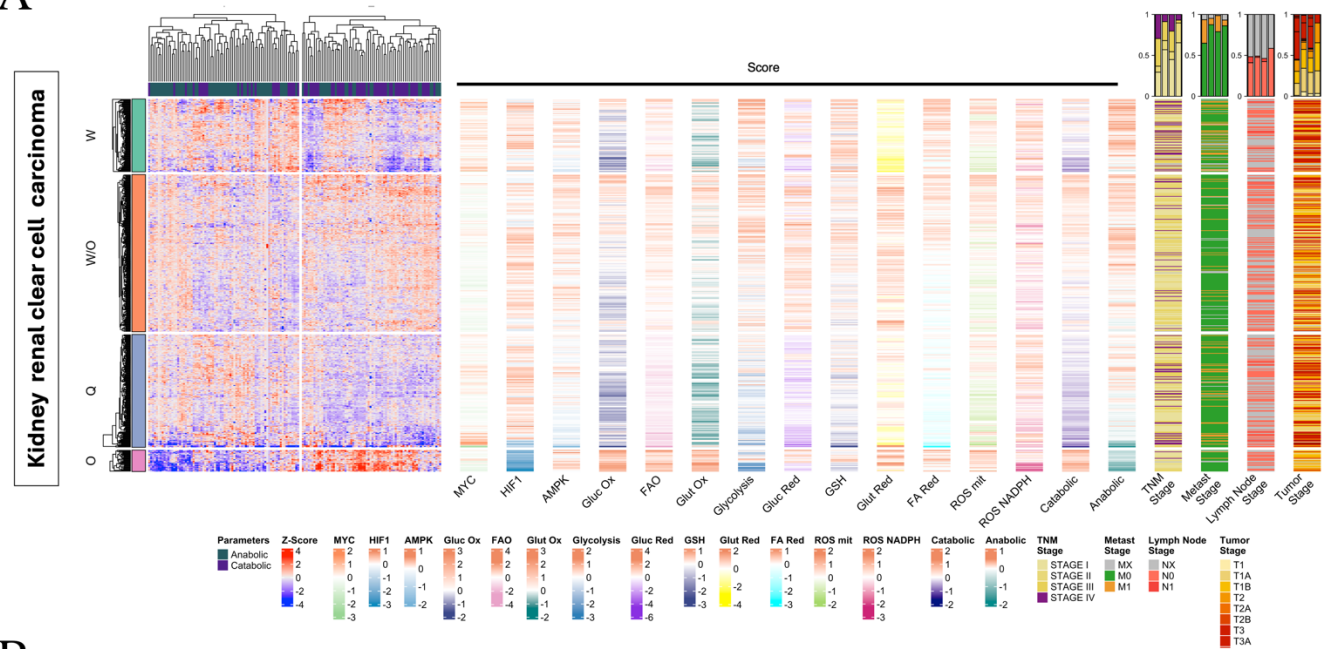


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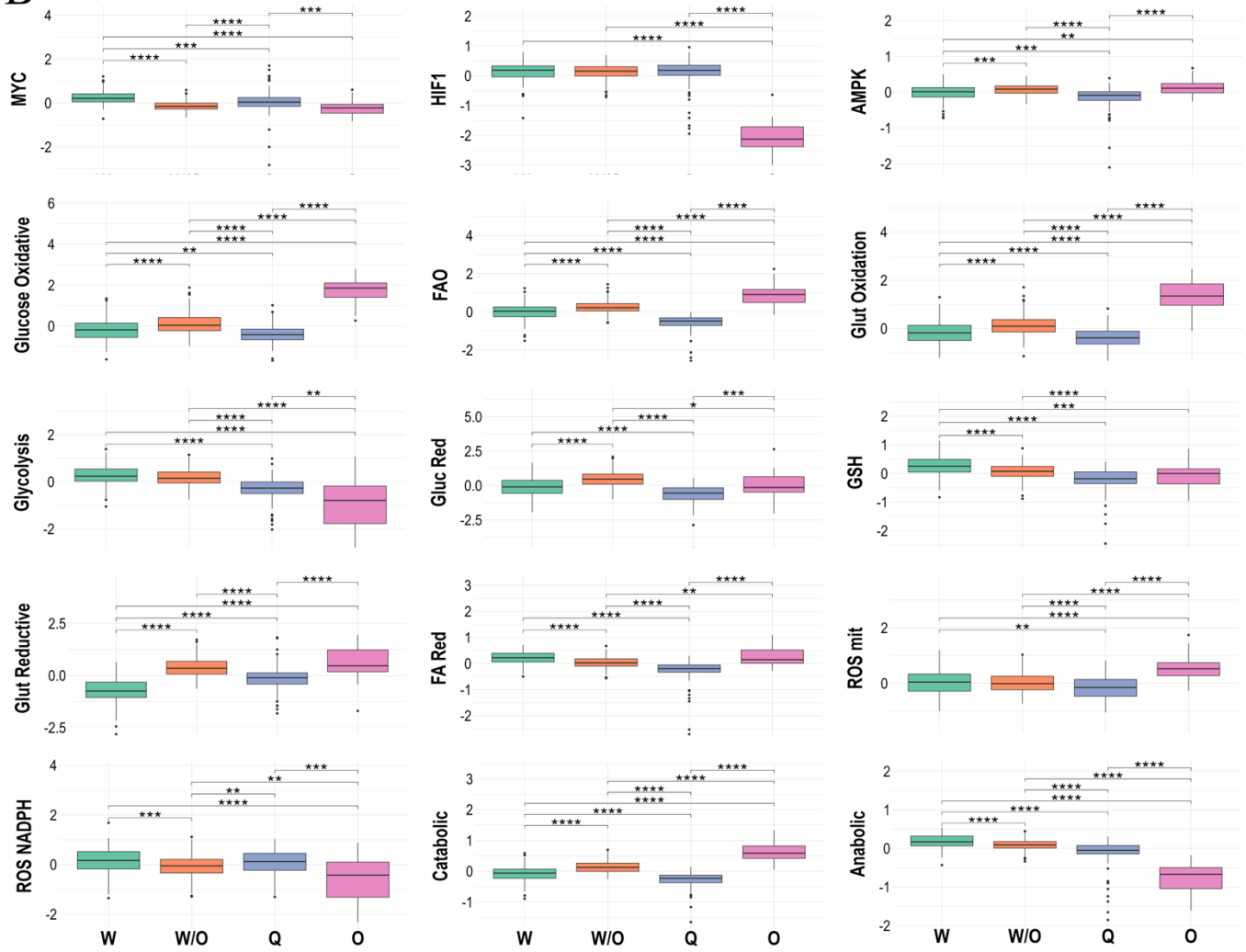


Supplementary Figure 5. The association between gene activity and metabolic pathway activity for acute myeloid leukemia. A. Heatmap of RNA-seq data. Each row represents a patient sample, and each column represents the expression of selected genes, which are divided according to their metabolic or anabolic activities. Four distinct clusters can be identified in the heatmap. The adjacent one-column heatmaps represent the scores for Myc, HIF-1, AMPK, glycolysis, glucose oxidation, FAO, glutamine oxidation, glycolysis, glucose reduction, GSH, glutamine reduction, FA reduction, ROS mitochondrial, ROS NADPH, overall catabolic, and overall anabolic activities, respectively, this data set did not include the phenotypic data analyzed for the rest of the cancers. **B.** Box plots summarizing and showing the differences in the scores according to each identified cluster. A t-test was used to test the significance of each pair of clusters. Significance levels are indicated as follows: *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$; ****, $P < 0.0001$.

A

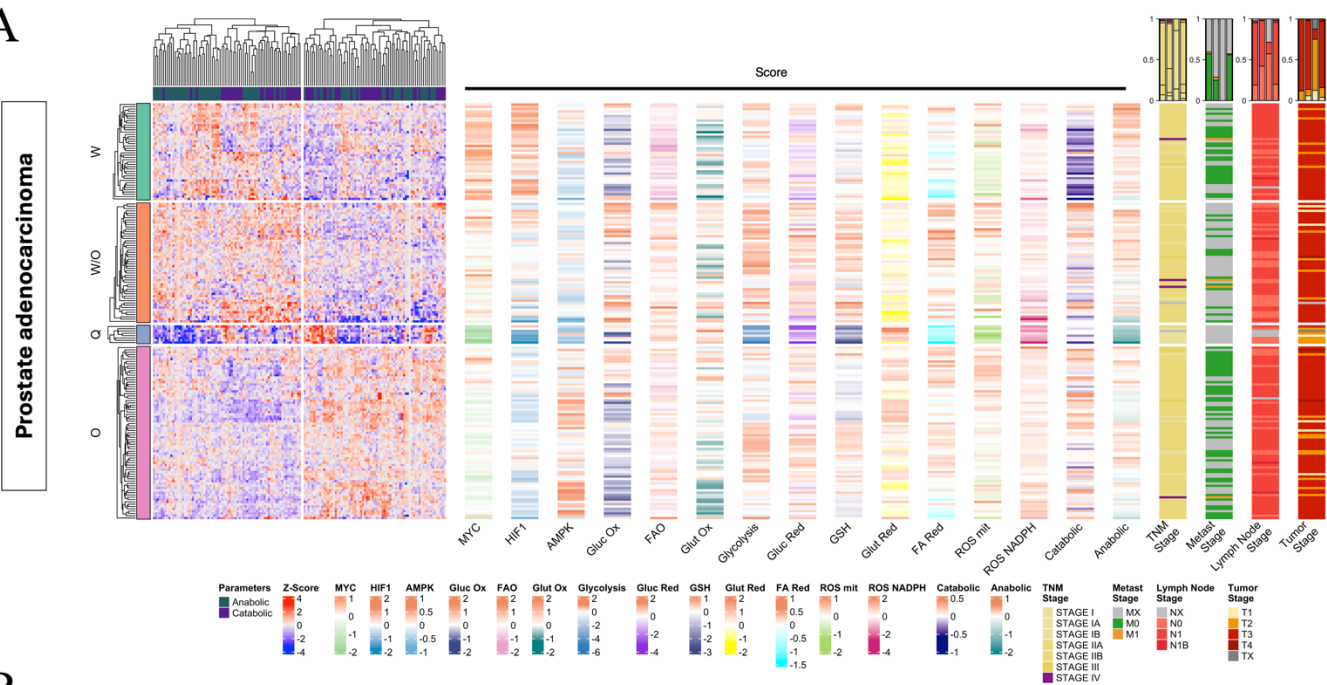


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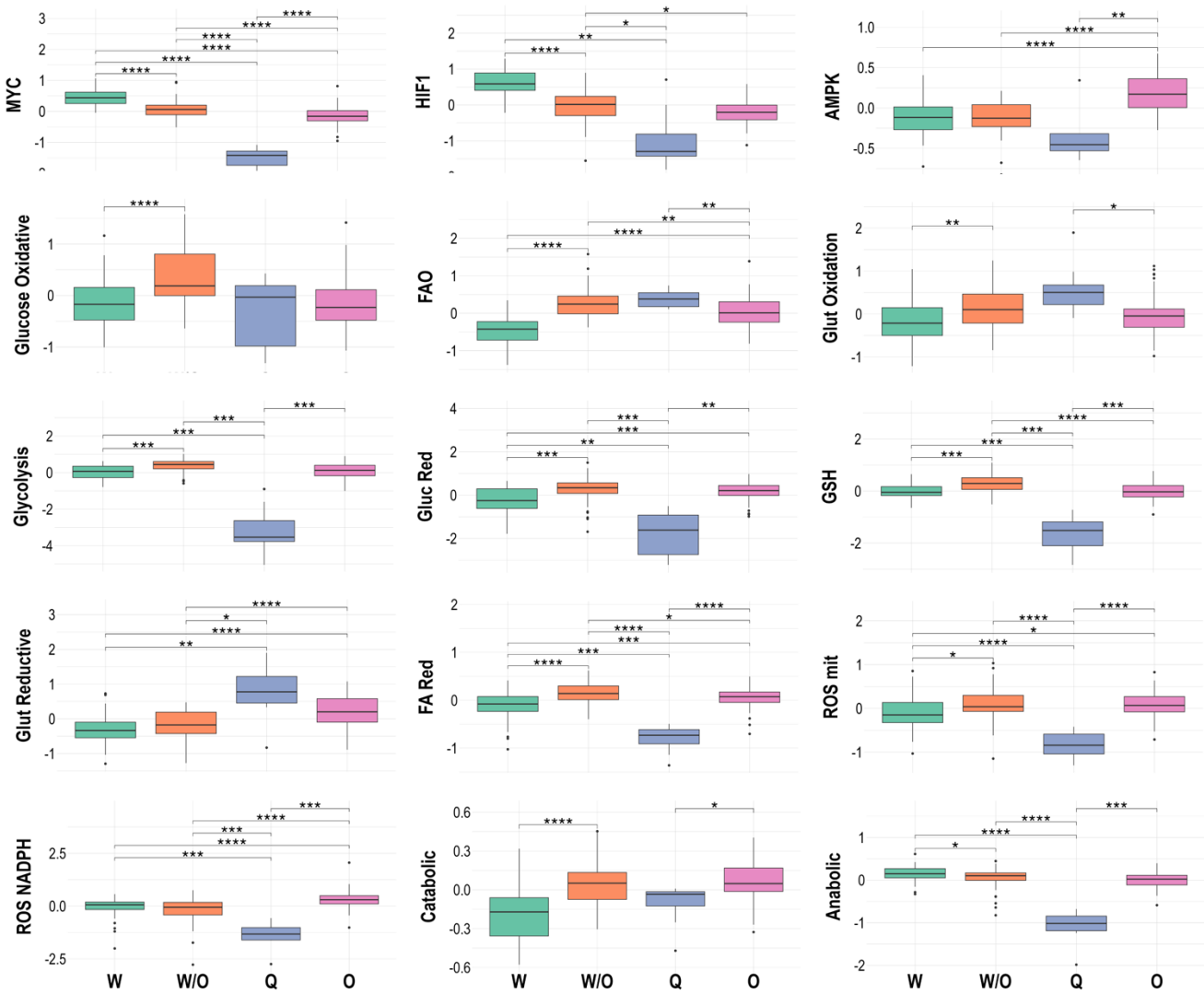


Supplementary Figure 6. The association between gene activity and metabolic pathway activity for Kidney renal clear cell carcinoma. A. Heatmap of RNA-seq data. Each row represents a patient sample, and each column represents the expression of selected genes, which are divided according to their metabolic or anabolic activities. Four distinct clusters can be identified in the heatmap. The adjacent one-column heatmaps represent the scores for Myc, HIF-1, AMPK, glycolysis, glucose oxidation, FAO, glutamine oxidation, glycolysis, glucose reduction, GSH, glutamine reduction, FA reduction, ROS mitochondrial, ROS NADPH, overall catabolic, and overall anabolic activities, respectively, we also included some of the phenotypic data of cancer: TNM stage, metastasis stage, lymph node stage, and tumor stage. **B.** Box plots summarizing and showing the differences in the scores according to each identified cluster. A t-test was used to test the significance of each pair of clusters. Significance levels are indicated as follows: *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$; ****, $P < 0.0001$.

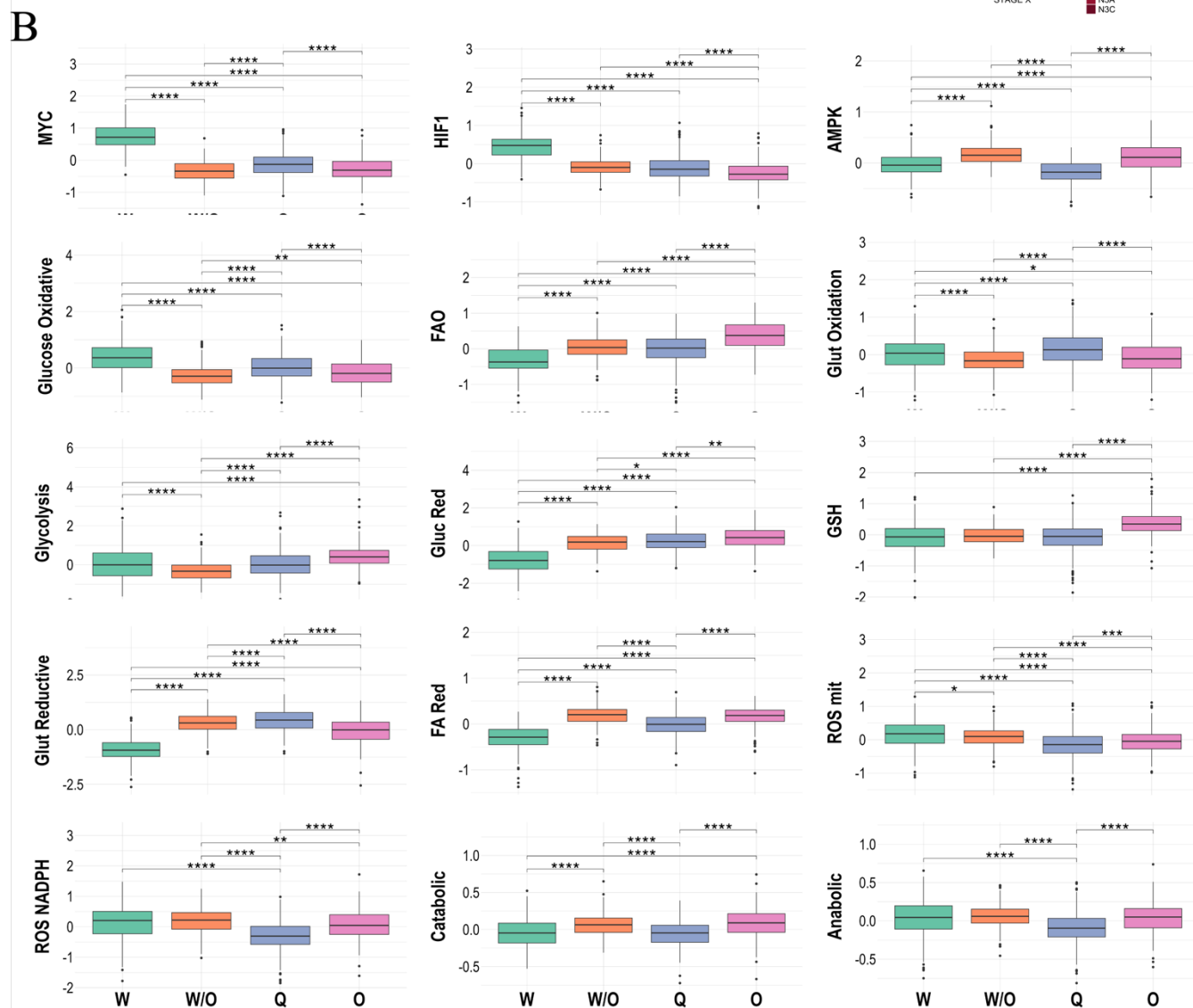
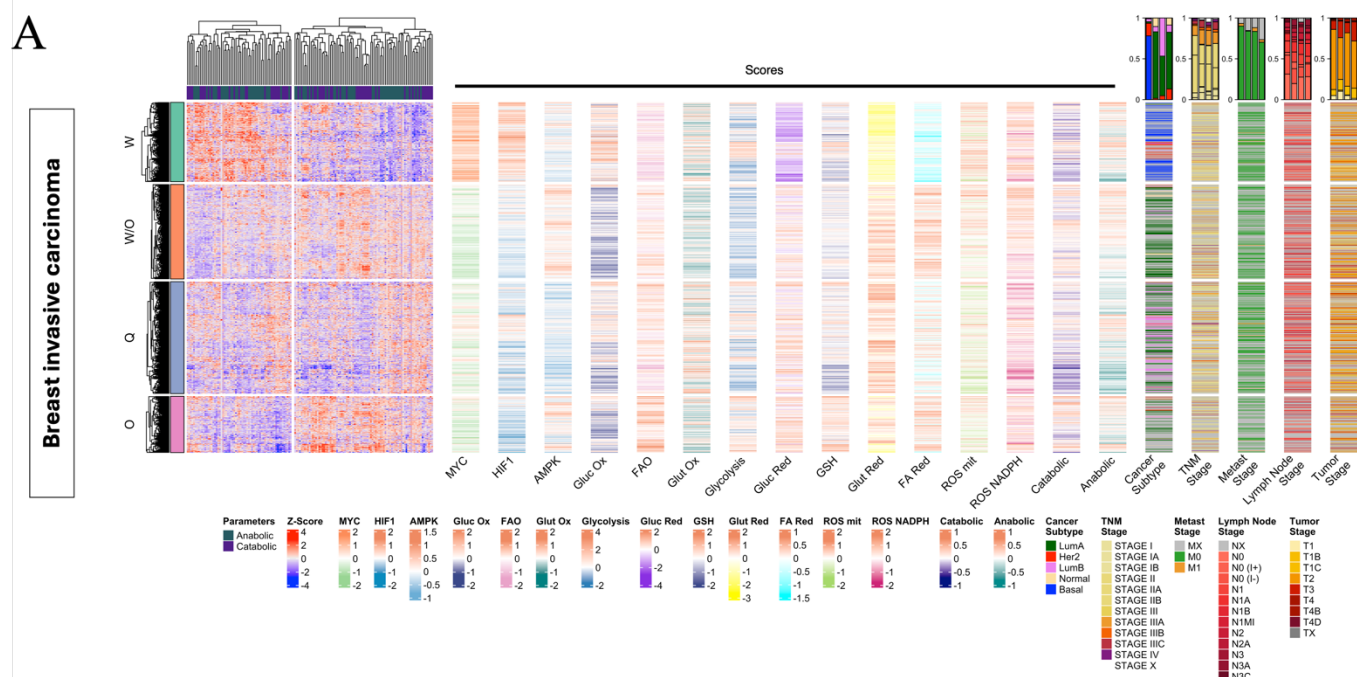
A



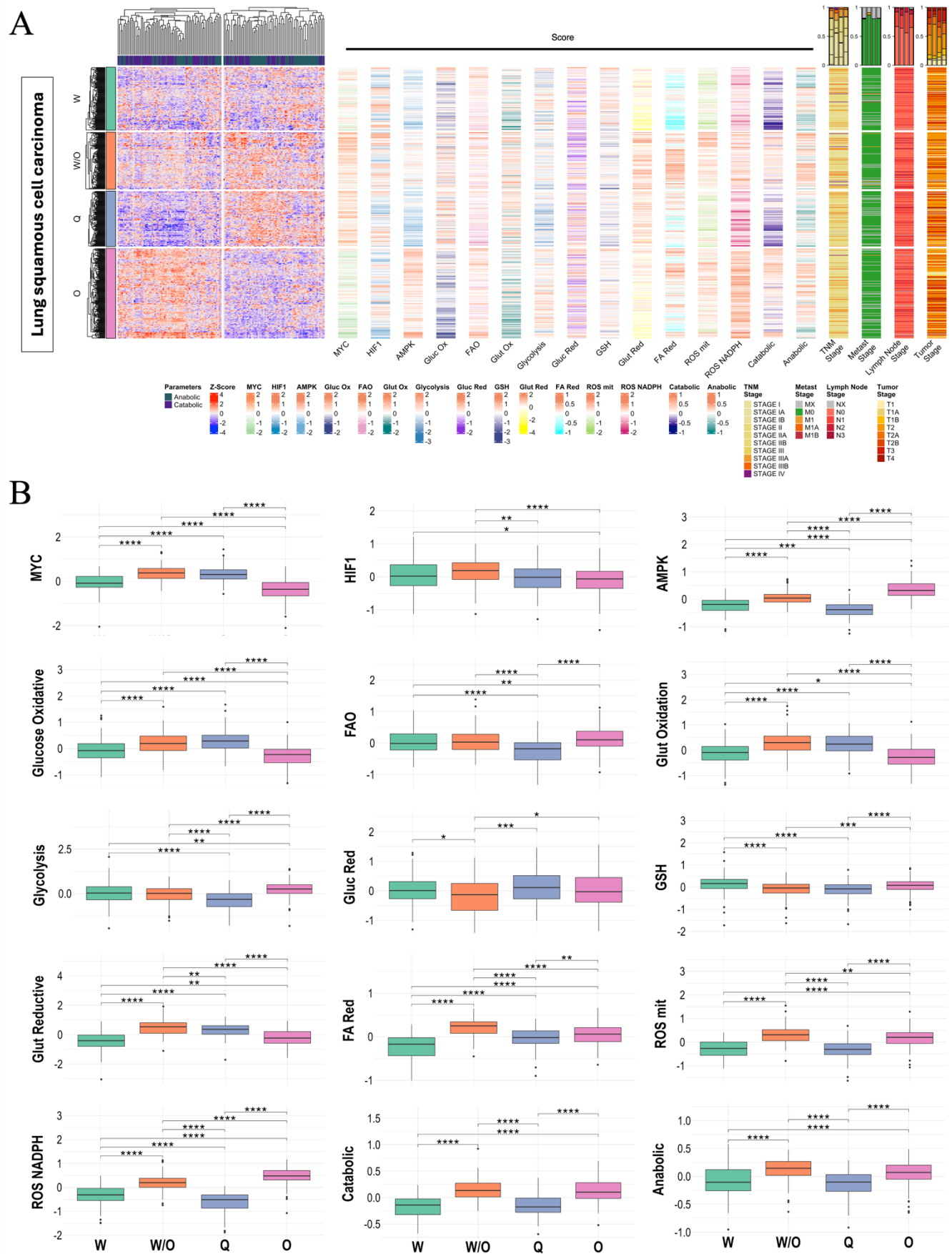
B



Supplementary Figure 7. The association between gene activity and metabolic pathway activity for prostate adenocarcinoma. A. Heatmap of RNA-seq data. Each row represents a patient sample, and each column represents the expression of selected genes, which are divided according to their metabolic or anabolic activities. Four distinct clusters can be identified in the heatmap. The adjacent one-column heatmaps represent the scores for Myc, HIF-1, AMPK, glycolysis, glucose oxidation, FAO, glutamine oxidation, glycolysis, glucose reduction, GSH, glutamine reduction, FA reduction, ROS mitochondrial, ROS NADPH, overall catabolic, and overall anabolic activities, respectively, we also included some of the phenotypic data of cancer: TNM stage, metastasis stage, lymph node stage, and tumor stage **B.** Box plots summarizing and showing the differences in the scores according to each identified cluster. A t-test was used to test the significance of each pair of clusters. Significance levels are indicated as follows: *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$; ****, $P < 0.0001$.



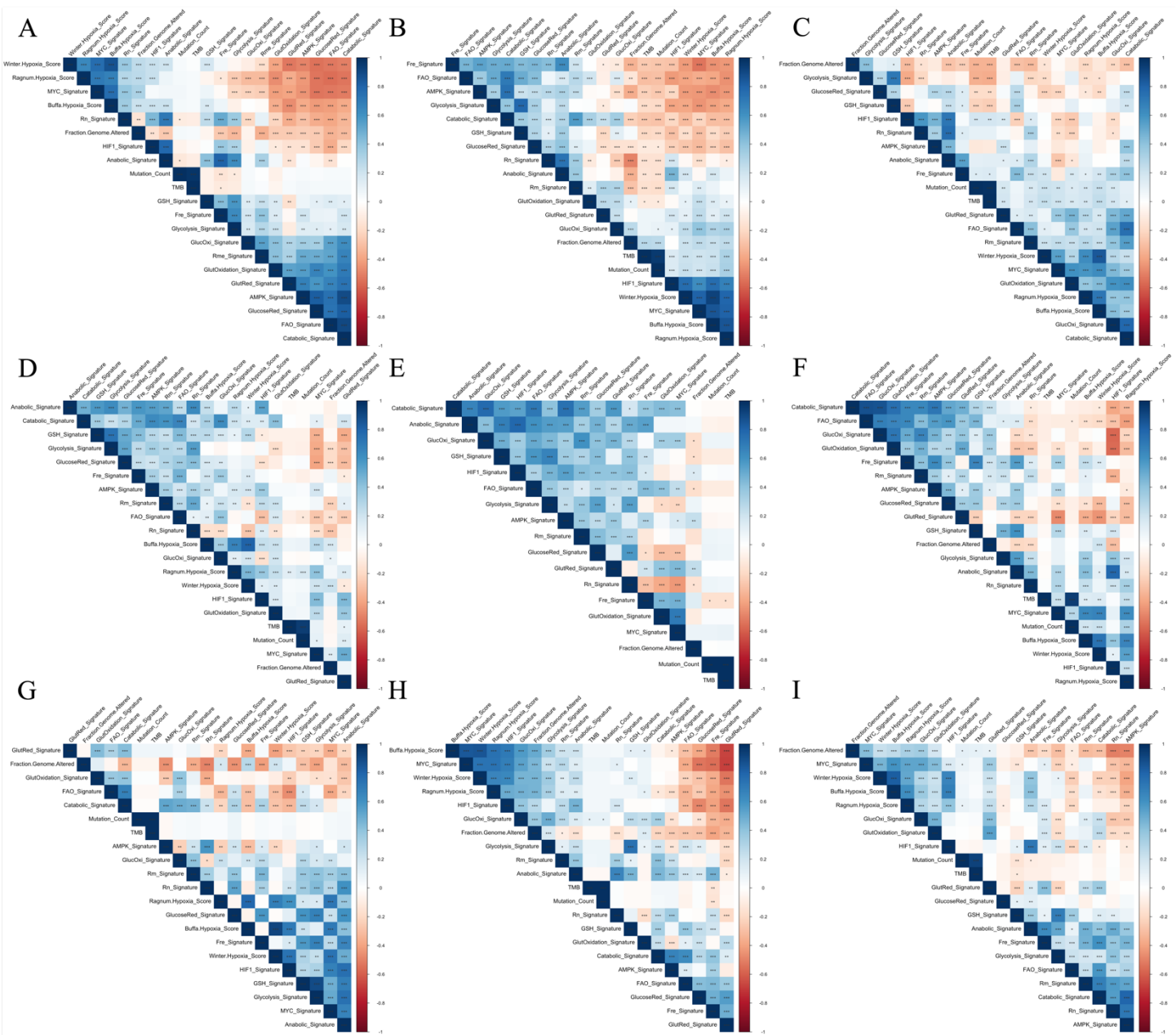
Supplementary Fig 8: The association between gene activity and metabolic pathway activity for breast invasive carcinoma. A. Heatmap of RNA-seq data. Each row represents a patient sample, and each column represents the expression of selected genes, which are divided according to their metabolic or anabolic activities. Four distinct clusters can be identified in the heatmap. The adjacent one-column heatmaps represent the scores for Myc, HIF-1, AMPK, glycolysis, glucose oxidation, FAO, glutamine oxidation, glycolysis, glucose reduction, GSH, glutamine reduction, FA reduction, ROS mitochondrial, ROS NADPH, overall catabolic, and overall anabolic activities, respectively, we also included some of the phenotypic data of cancer: cancer, subtype, TNM stage, metastasis stage, lymph node stage, and tumor stage **B.** Box plots summarizing and showing the differences in the scores according to each identified cluster. A t-test was used to test the significance of each pair of clusters. Significance levels are indicated as follows: *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$; ****, $P < 0.0001$.



Supplementary Figure 9. The association between gene activity and metabolic pathway activity for lung squamous cell carcinoma. **A.** Heatmap of RNA-seq data. Each row represents a patient sample, and each column represents the expression of selected genes, which are divided according to their metabolic or anabolic activities. Four distinct clusters can be identified in the heatmap. The adjacent one-column heatmaps represent the scores for Myc, HIF-1, AMPK, glycolysis, glucose oxidation, FAO, glutamine oxidation, glycolysis, glucose reduction, GSH, glutamine reduction, FA reduction, ROS mitochondrial, ROS NADPH, overall catabolic, and overall anabolic activities, respectively, we also included some of the phenotypic data of cancer: TNM stage, metastasis stage, lymph node stage, and tumor stage. **B.** Box plots summarizing and showing the differences in the scores according to each identified cluster. A t-test was used to test the significance of each pair of clusters. Significance levels are indicated as follows: *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$; ****, $P < 0.0001$.

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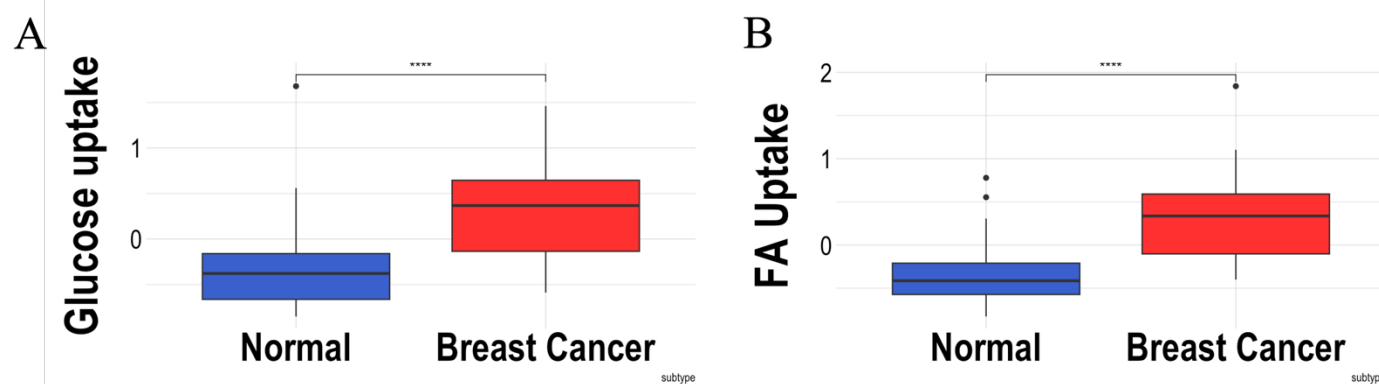
Supplementary Figure 10



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Supplementary Figure 10. Correlograms of Metabolic Scores Across Various Cancer Types. Correlograms between the metabolic scores for each cancer dataset were analyzed. The analysis includes the following cancer types: A. Hepatocellular carcinoma (LIHC), B. Lung adenocarcinoma (LUAD), C. Colorectal adenocarcinoma (COAD), D. Skin cutaneous melanoma (SKCM), E. Acute myeloid leukemia (LAML), F. Kidney renal clear cell carcinoma (KIRC), G. Prostate adenocarcinoma (PRAD), H. Breast invasive carcinoma (BRCA), and I. Lung squamous cell carcinoma (LUSC). The correlation matrix was computed, and the statistical significance of the correlations was assessed at a 95% confidence level. Significance levels are indicated as follows: *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$.

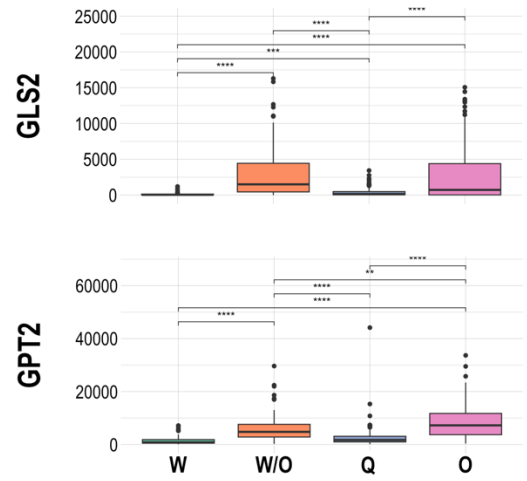
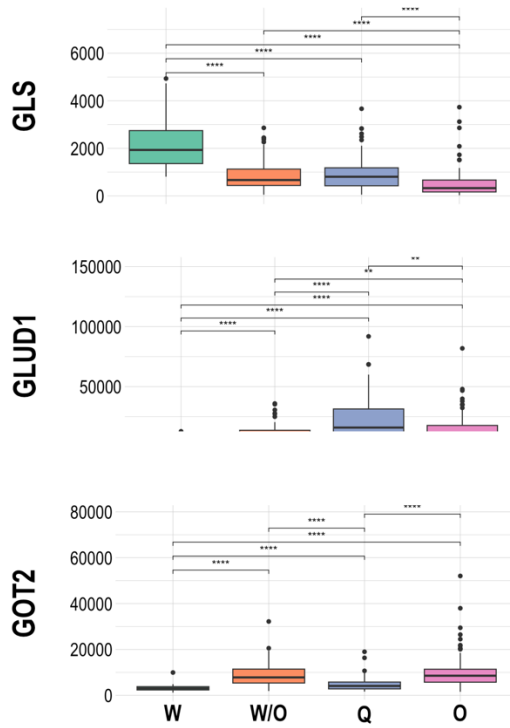
143 **Supplementary Figure 11**



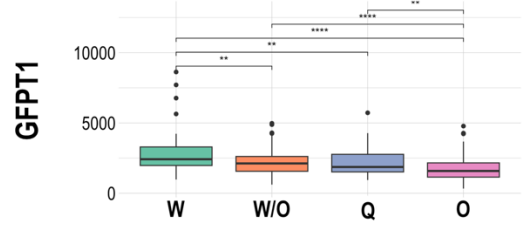
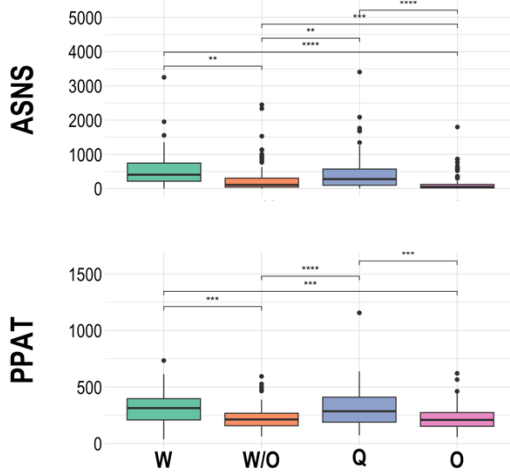
144 **Supplementary Figure 11:** Glucose uptake signature (A) and Fatty acid uptake score (B)were applied to a
145 normal versus breast cancer dataset (1). T-test was used to test the significance *, $P < 0.05$; **, $P < 0.01$; ***, P
146 < 0.001 ; ****, $P < 0.0001$. From the genes associated with both glucose and fatty acid (FA) uptake signatures, a
147 differential gene expression analysis was performed as a first step to identify those specifically overexpressed in
148 this specific cancer. The plots were generated using only the subset of genes that were overexpressed in cancer.
149 While the original list included genes typically overexpressed in cancer, not all of them were applicable to this
150 specific breast cancer dataset.

Hepatocellular carcinoma

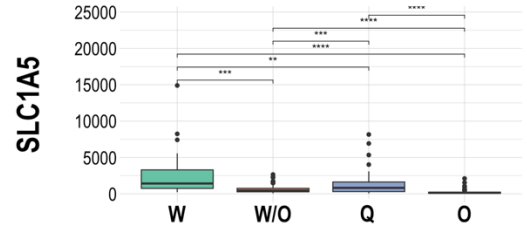
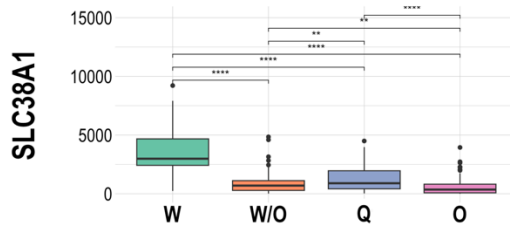
Glutamine Oxidation



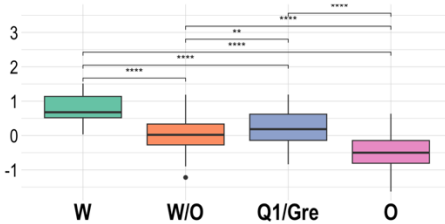
Biosynthesis



Transporter genes



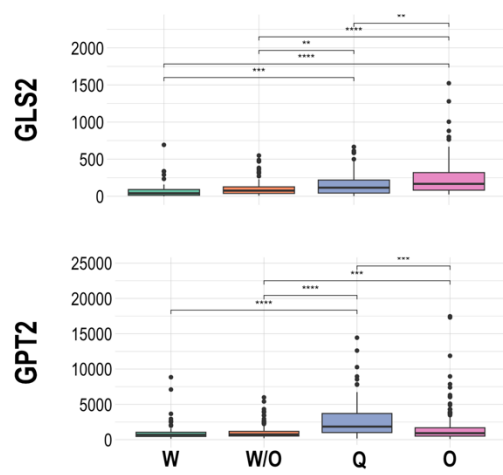
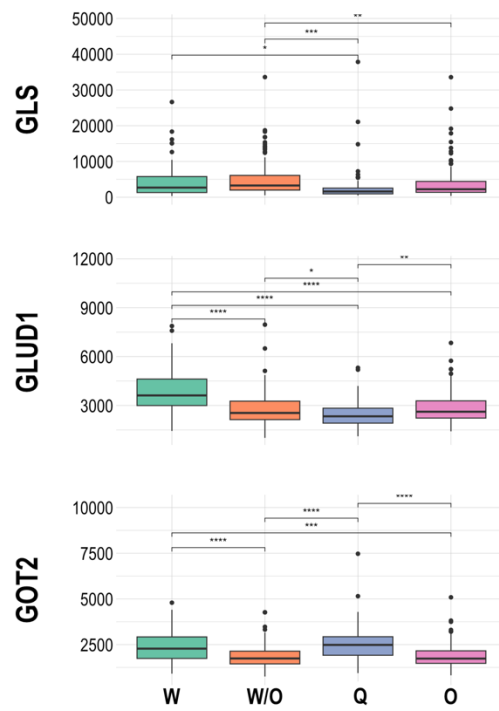
GMGS Score



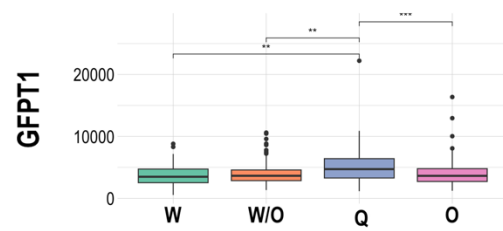
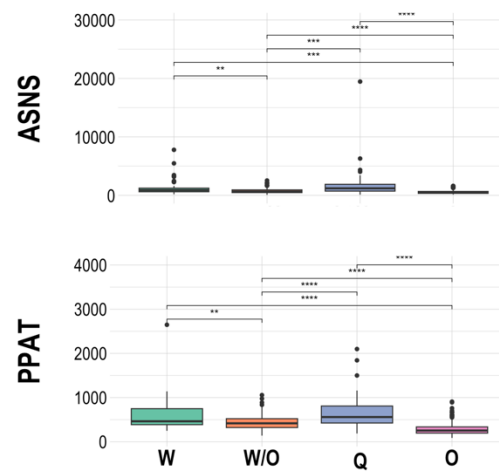
Supplementary Figure 12. Comparison of glutamine metabolism relevant genes in the “O”, “W”, “W/O” and “Q” states in the hepatocellular carcinoma samples. The glutamine metabolism relevant genes can be largely classified into three categories: oxidation genes (GLS, GLS2, GOT2, GLUD1 and GPT2), biosynthesis genes (ASNS, GFPT1, PPAT), and transporter genes (SLC38A1/2, SLC1A5), the gene signature (GMGS) is also included. T-test was used to test the significance *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$; ****, $P < 0.0001$.

Lung Adenocarcinoma

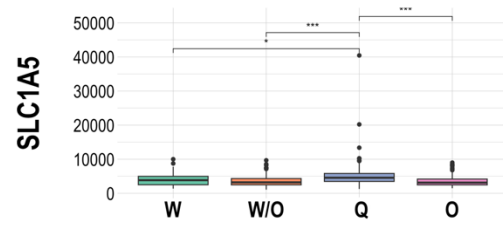
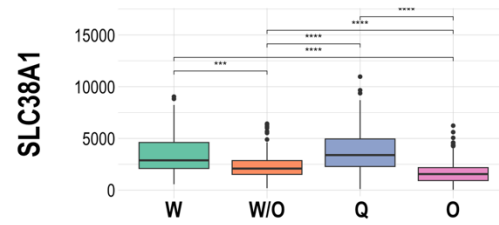
Glutamine Oxidation



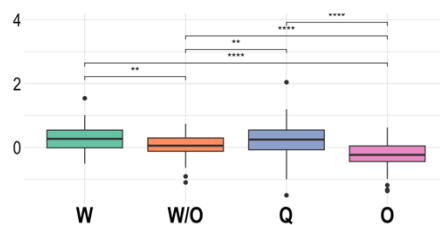
Biosynthesis



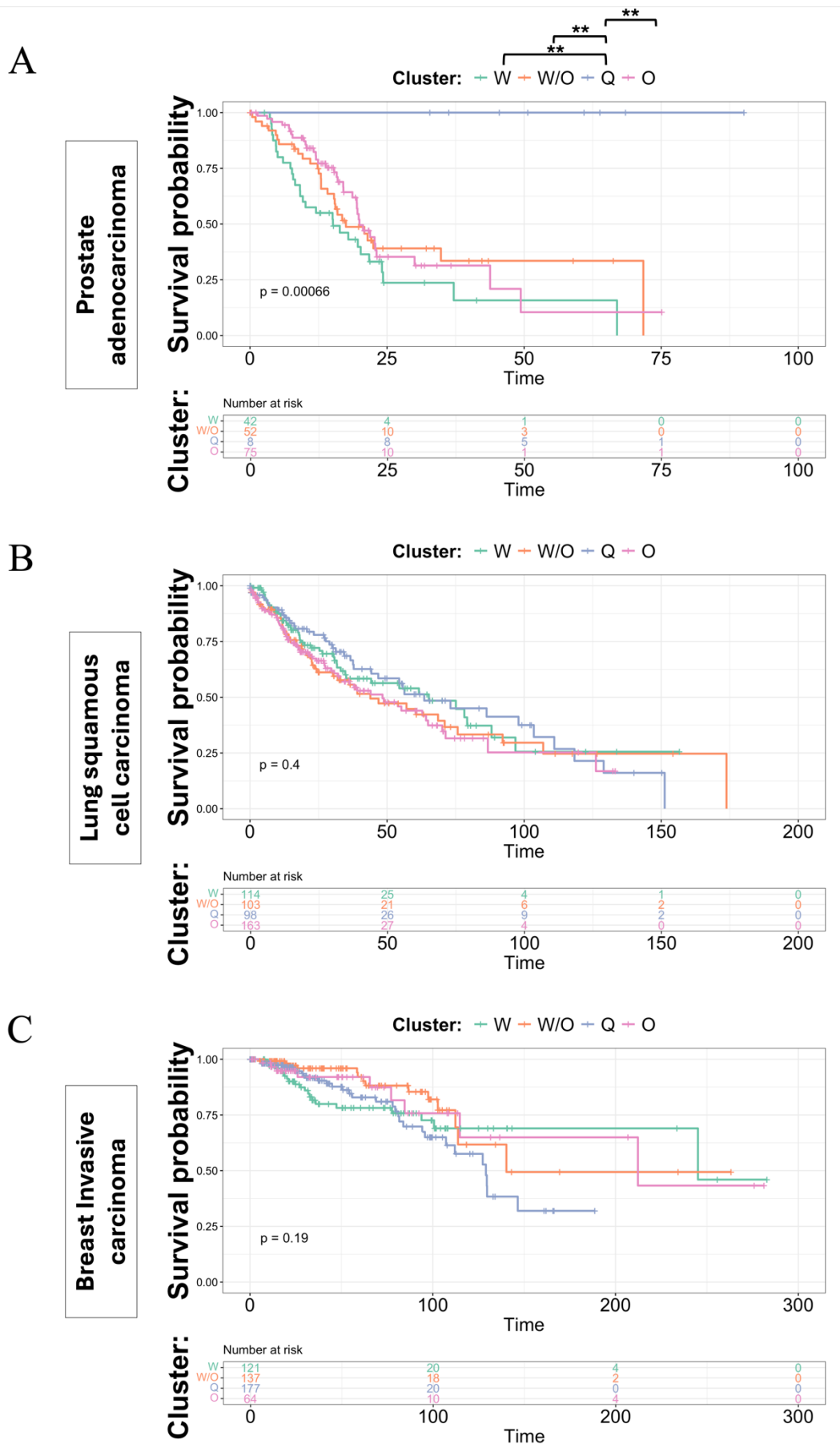
Transporter genes



GMGS Score

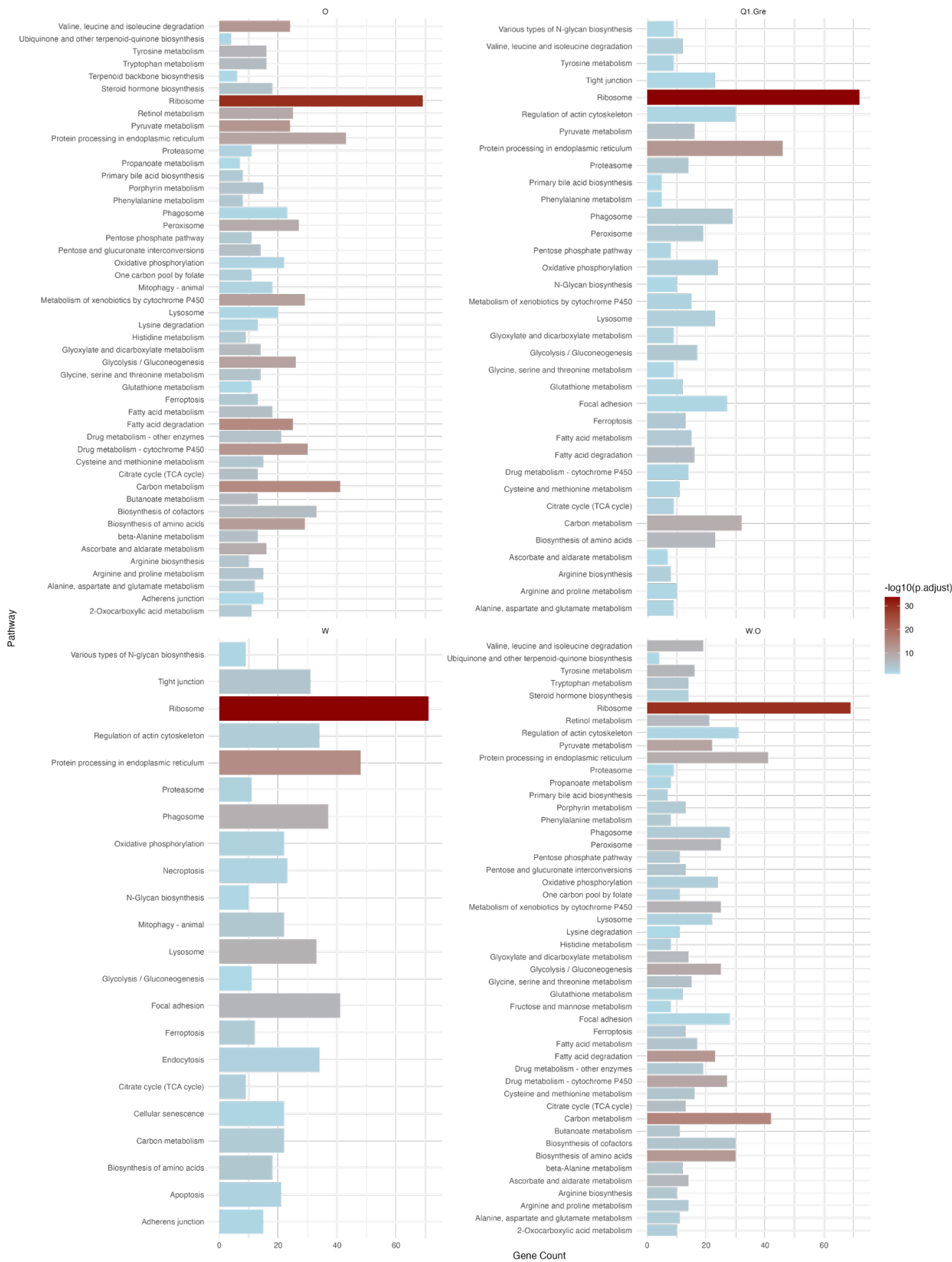


Supplementary Figure 13. Comparison of glutamine metabolism relevant genes in the “O”, “W”, “W/O” and “Q” states in the Lung adenocarcinoma samples. The glutamine metabolism relevant genes can be largely classified into three categories: oxidation genes (GLS, GLS2, GOT2, GLUD1 and GPT2), biosynthesis genes (ASNS, GFPT1, PPAT), and transporter genes (SLC38A1/2, SLC1A5), the gene signature (GMGS) is also included. T-test was used to test the significance *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$; ****, $P < 0.0001$.



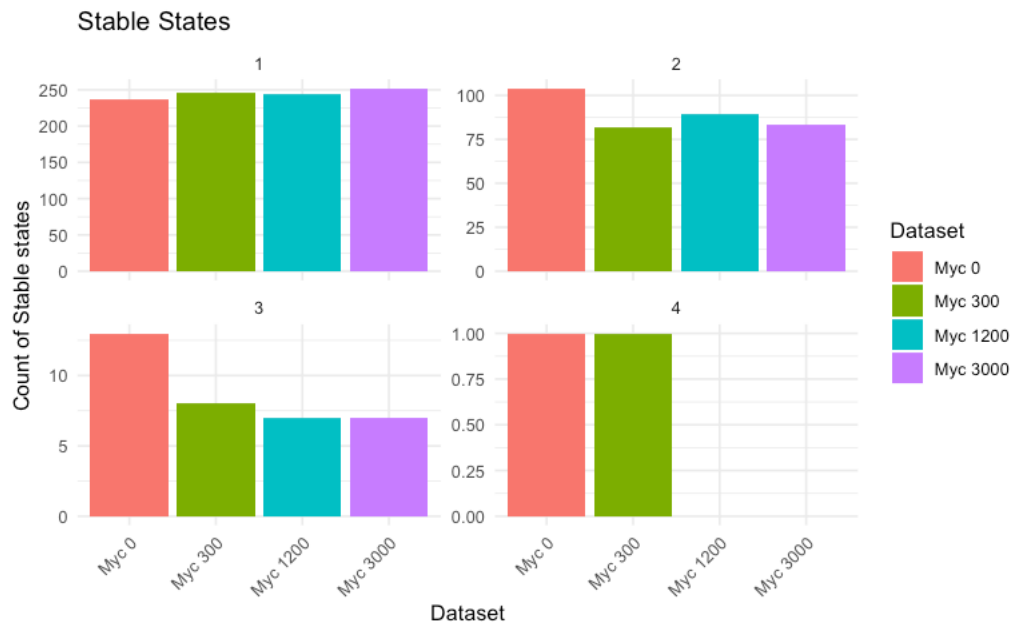
Supplementary Figure 14 Survival curves stratified by cluster. Survival curves for prostate adenocarcinoma (A), lung squamous cell carcinoma (B), and breast invasive carcinoma (C) datasets. Each dataset was separated in the four distinct phenotypes according to their metabolic or anabolic activities. The survival curves were estimated using the Kaplan-Meier method and compared using the log-rank test. Pairwise comparisons of survival distributions stratified by cluster are displayed above the survival curve for each pair of clusters. Significance levels are indicated as follows: *, $P < 0.05$; **, $P < 0.01$.

Pathway Enrichment Analysis by Cluster



Supplementary Figure 15 Pathway Enrichment Analysis by Cluster. Bar plots show the results of KEGG pathway enrichment analysis for genes from different clusters (W, W/O, Q, O) from the LIHC data set. The x-axis represents the gene count in each enriched pathway, and the y-axis lists the pathways. The fill color of the bars corresponds to the significance of the enrichment, with darker red indicating stronger statistical significance (lower adjusted p-value). The values were obtained by first identifying the top 1000 most highly expressed genes from each cluster, followed by performing the KEGG enrichment analysis using the clusterProfiler package.

193 **Supplementary Figure 16**



196 **Supplementary Figure 16 Count of the stable states obtained after the parameter randomization for each**
197 **Myc level.** It highlights both monostable and multi-stable states. Although the occurrence of four stable states is
198 less frequent, it remains a possibility within our model. The respective number of stable states per MYC level is
199 as follows: 487 for MYC level 0, 438 for MYC level 300, 448 for MYC level 1200, and 439 for MYC level
200 3000

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Supplementary Table 1. The values of parameters

Parameters	Value	Unit	Description	Ref
$g_{R_{mt}}$	0.9	$nmol \cdot L^{-1} \cdot h^{-1}$	Production rate of mtROS	
γ_{G_I}	50	-	mtROS production in glucose oxidation	
γ_F	$\gamma_{G_I} * 9/2$	-	mtROS production in fatty acid oxidation	
γ_{Q_I}	10	-	mtROS production in glutamine oxidation	
$k_{R_{mt}}$	5	min^{-1}	Degradation rate of mtROS	(2,3)
$A_{R_{mt}}^0$	350	$nmol \cdot L^{-1}$	Threshold of mtROS inhibition by AMPK	(4)
$\lambda_{A,R_{mt}}$	2	-	Fold change of mtROS inhibition by AMPK	
$n_{A,R_{mt}}$	2	-	Hill coefficient	
$G_{GSH,R}^0$	10	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Threshold of mtROS clearance by AMPK	
$\lambda_{GSH,R}$	1.2	-	Fold change of mtROS clearance by AMPK	
$n_{GSH,R}$	2	-	Hill coefficient	
$g_{R_{nox}}$	40	$\mu mol \cdot L^{-1} \cdot min^{-1}$	Production rate of noxROS	(2,3)
g_0	1	-	Basal noxROS	
$g_{H,R_{nox}}$	5	-	Fold-change of noxROS activation by HIF-1	(5)
$H_{R_{nox}}^0$	250	$nmol \cdot L^{-1}$	Threshold of noxROS activation by HIF-1	
$n_{H,R_{nox}}$	2	-	Hill coefficient	(5)

$g_{A,R_{nox}}$	0.2	-	Fold change of noxROS inhibition by AMPK	(5)
$A_{R_{nox}}^0$	150	$nmol \cdot L^{-1}$	Threshold of noxROS inhibition by AMPK	(4)
$n_{A,R_{nox}}$	2	-	Hill coefficient	(5)
$k_{R_{nox}}$	5	min^{-1}	Degradation rate of noxROS	(2,3)
g_A	40	$nmol \cdot L^{-1} \cdot h^{-1}$	Production rate of AMPK	
$R_{T,A}^0$	250	$\mu mol \cdot L^{-1}$	Threshold of AMPK activation by ROS	
$\lambda_{R_{T,A}}$	8	-	Fold change of AMPK activation by ROS	(6)
$n_{R_{T,A}}$	4	-	Hill coefficient	(5)
H_A^0	150	$nmol \cdot L^{-1}$	Threshold of AMPK inhibition by HIF-1	
$\lambda_{H,A}$	0.1	-	Fold-change of AMPK inhibition by HIF-1	(5)
$n_{H,A}$	1	-	Hill coefficient	(5)
$\lambda_{X_{ATP,A}}$	0.25	-	Fold-change of AMPK inhibition by ATP	
$X_{ATP,A}^0$	2000	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Threshold of AMPK inhibition by ATP	
$n_{X_{ATP,A}}$	2	-	Hill coefficient	(5)
k_A	0.2	h^{-1}	Degradation rate of AMPK	(5)
g_H	15	$nmol \cdot L^{-1} \cdot h^{-1}$	Production rate of HIF-1	(7)
A_H^0	150	$nmol \cdot L^{-1}$	Threshold of HIF-1 inhibition by AMPK	
$\lambda_{A,H}$	0.1	-	Fold-change of HIF-1 inhibition by AMPK	(5)

$n_{A,H}$	1	-	Hill coefficient	
k_H	0.25	h^{-1}	Degradation rate of HIF-1	(7)
$G_{2,H}^0$	250	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Threshold of HIF-1 activation by glycolysis	
$\lambda_{G_2,H}$	0.1	-	Fold-change of HIF-1 activation by glycolysis	
$n_{G_2,H}$	4	-	Hill coefficient	
M	0-3000	$\mu mol \cdot L^{-1}$	Myc Level	
$M_{M,H}^0$	150	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Threshold of MYC inhibiting HIF-1 degradation	
$\lambda_{M,H}$	0.8	-	Fold change of MYC inhibiting HIF-1 degradation	
$n_{M,H}$	2	-	Hill coefficient	
$\lambda_{R_T,H}$	0.2	-	Fold-change of HIF-1 stabilization by ROS	(5)
$R_{T,H}^0$	40	$\mu mol \cdot L^{-1}$	Threshold of HIF-1 stabilization by ROS	
$n_{R_T,H}$	4	-	Hill coefficient	(5)
g_{H,G_0}	20	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Basal glucose uptake rate	
$H_{G_0}^0$	150	$nmol \cdot L^{-1}$	Threshold of glucose uptake regulated by HIF-1	
λ_{H,G_0}	6	-	Fold-change of glucose uptake regulated by HIF-1	
n_{H,G_0}	4	-	Hill coefficient	
g_{A,G_0}	20	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Basal glucose uptake rate	
$A_{G_0}^0$	200	$nmol \cdot L^{-1}$	Threshold of glucose uptake regulated by AMPK	

λ_{A,G_0}	4	-	Fold-change of glucose uptake regulated by AMPK	
n_{A,G_0}	2	-	Hill coefficient	
$M_{G_0}^0$	150	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Threshold of glucose uptake regulated by MYC	
λ_{M,G_0}	2	-	Fold change of glucose uptake regulated by MYC	
n_{M,G_0}	2	-	Hill coefficient	
$M_{Q_0}^0$	150	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Threshold of glutamine uptake regulated by MYC	
λ_{M,Q_0}	2	-	Fold-change of glutamine uptake regulated by MYC	
n_{M,Q_0}	2	-	Fold-change of glucose uptake regulated by MYC	
g_{A,C_0}	15	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Basal utilization rate of acetyl-CoA for OXPHOS	
$A_{C_0}^0$	250	$nmol \cdot L^{-1}$	Threshold of acetyl-CoA utilization regulated by AMPK	
λ_{A,C_0}	8	-	Fold-change of acetyl-CoA utilization regulated by AMPK	
n_{A,C_0}	4	-	Hill coefficient	
g_{G_1}	100	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Basal glucose oxidation rate	
λ_{G,G_1}	0.1	-	Restriction of glucose oxidation rate by glucose uptake rate	
n_{G,G_1}	2	-	Hill coefficient	
λ_{C,G_1}	0.1	-	Restriction of glucose oxidation by acetyl-CoA utilization rate	
n_{C,G_1}	4	-	Hill coefficient	
g_{G_2}	150	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Basal glycolysis rate	

λ_{G,G_2}	0.1	-	Restriction of glycolysis rate by glucose uptake rate	
n_{G,G_2}	2	-	Hill coefficient	
$H_{G_2}^0$	200	$nmol \cdot L^{-1}$	Threshold of glycolysis upregulation by HIF-1	
λ_{H,G_2}	8	-	Fold-change of glycolysis upregulation by HIF-1	
n_{H,G_2}	4	-	Hill coefficient	
g_{Gr}	60	$nmol \cdot L^{-1} \cdot h^{-1}$	Basal reductive glucose metabolic rate	
λ_{G,Gr_e}	0.1	-	Restriction of reductive glucose metabolic rate by glucose uptake rate	
n_{G,Gr_e}	2	-	Hill coefficient	
$A_{Gr_e}^0$	200	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Threshold of reductive glucose metabolism regulation by AMPK	
λ_{A,Gr_e}	0.25	-	Fold-change of reductive glucose metabolism regulation by AMPK	
n_{A,Gr_e}	2	-	Hill coefficient	
$M_{Gr_e}^0$	150	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Threshold of reductive glucose metabolism regulation by MYC	
$\lambda_{M,Gr_e'}$	2	-	Fold-change of reductive glucose metabolism regulation by MYC	
n_{M,Gr_e}	2	-	Hill coefficient	
g_f	3	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Basal FAO rate	
$\lambda_{C,F}$	0.1	-	Restriction of FAO rate by acetyl-CoA utilization rate	
$n_{C,F}$	2	-	Hill coefficient	
$A_{F_I}^0$	200	$nmol \cdot L^{-1}$	Threshold of FAO upregulation by AMPK	

λ_{A,F_I}	6	-	Fold-change of FAO upregulation by AMPK	
n_{A,F_I}	4	-	Hill coefficient	
g_{F0}	5	$mol \cdot L^{-1} \cdot s^{-1}$	Basic fatty acid update rate	
A_{F0}^0	200	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Threshold of fatty acid uptake regulation by AMPK	
n_{A,F_0}	2	-	Hill coefficient	
λ_{A,F_0}	4	-	Fold-change of fatty acid uptake regulation by AMPK	
λ_{F,F_I}	0.8	-	Restriction of FAO rate by fatty acid uptake rate	
n_{F,F_I}	2	-	Hill coefficient	
H_F^0	200	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Threshold of FAO regulation by HIF-1	
λ_{H,F_I}	0.8	-	Fold-change of FAO regulation by HIF-1	
$n_{H,F}$	4	-	Hill coefficient	
$\gamma_{G,F}$	0.1	-	Lipogenesis rate of glucose	
$\gamma_{G,Q}$	0.1	-	Lipogenesis rate of glutamine	
g_{F_r}	75	$nmol \cdot L^{-1} \cdot h^{-1}$	Basal reductive fatty acid metabolic rate	
λ_{F,F_r}	0.1	-	Restriction of FAO rate by fatty acid uptake rate	
n_{F,F_r}	2	-	Hill coefficient	
g_{Q_I}	30	$nmol \cdot L^{-1} \cdot h^{-1}$	Basal glutamine oxidation rate	
γ_{GSH}	0.1	-	Effect of glutathione (GSH) on ROS.	

$H_{Q_I}^0$	350	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Threshold of glutamine oxidation regulation by HIF-1	
λ_{H,Q_I}	0.2	-	Fold change of glutamine oxidation regulation by HIF-1	
n_{H,Q_I}	4	-	Hill coefficient	
λ_{Q,Q_I}	0.5	-	Restriction of glutamine oxidation rate by glutamine uptake rate	
n_{Q,Q_I}	2	-	Hill coefficient	
g_{Q_0}	10	$nmol \cdot L^{-1} \cdot h^{-1}$	Basal glutamine update rate	
$M_{Q_0}^0$	150	$nmol \cdot L^{-1}$	Threshold of glutamine uptake regulation by MYC	
λ_{M,Q_0}	2	-	Fold change of glutamine uptake regulation by MYC	
n_{M,Q_0}	2	-	Hill coefficient	
$M_{Q_I}^0$	150	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Threshold of glutamine oxidation regulation by MYC	
λ_{M,Q_I}	2	-	Fold change of glutamine oxidation regulation by MYC	
n_{M,Q_I}	2	-	Hill coefficient	
$g_{Q_{GSH}}$	30	$nmol \cdot L^{-1} \cdot h^{-1}$	Basal glutathione synthesis rate	
$\lambda_{Q,Q_{GSH}}$	0.5	-	Restriction of glutathione synthesis rate by glutamine uptake rate	
$n_{Q,Q_{GSH}}$	2	-	Hill coefficient	
$M_{Q_{GSH}}^0$	150	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Threshold of glutathione synthesis regulation by MYC	
$\lambda_{M,Q_{GSH}}$	0.9	-	Fold change of glutathione synthesis regulation by MYC	
$n_{M,Q_{GSH}}$	2	-	Hill coefficient	

k_{GSH}	1	h^{-1}	The decay rate of glutathione	
g_{Q_r}	20	$nmol \cdot L^{-1} \cdot h^{-1}$	Basal reductive glutamine metabolic rate	
λ_{Q,Q_r}	0.5	-	Restriction of reductive glutamine metabolic rate by glutamine uptake rate	
n_{Q,Q_r}	2	-	Hill coefficient	
$M_{Q_r}^0$	150	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Threshold of reductive glutamine metabolism regulation by MYC	
λ_{M,Q_r}	2	-	Fold change of reductive glutamine metabolism regulation by MYC	
n_{M,Q_r}	2	-	Hill coefficient	
$H_{Q_r}^0$	200	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Threshold of reductive glutamine metabolism regulation by HIF-1	
λ_{H,Q_r}	2	-	Fold change of reductive glutamine metabolism regulation by HIF-1	
n_{H,Q_r}	4	-	Hill coefficient	
$A_{Q_r}^0$	200	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Threshold of reductive glutamine metabolism regulation by AMPK	
λ_{A,Q_r}	0.5	-	Fold change of reductive glutamine metabolism regulation by AMPK	
n_{A,Q_r}	2	-	Hill coefficient	
$\underline{A_{Q_2}^0}$	250	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Threshold for AMPK regulation of GSH	
$\underline{\lambda_{A,Q_2}}$	5	-	Fold change of glutathione synthesis regulation by AMPK	
$\underline{n_{A,Q_2}}$	4	-	Hill coefficient	
$\underline{H_{F_r}^0}$	200	$\mu mol \cdot L^{-1} \cdot s^{-1}$	Threshold for HIF-1 regulation of reductive fatty acid metabolism.	

λ_{H,E_r}	2	-	Fold change of reductive fatty acid regulation by HIF-1	
n_{H,E_r}	4	-	Hill coefficient	
	29		ATP production from glucose oxidation	(8)
	2		ATP production from Glycolysis	(9)
	24		ATP production from glutamine oxidation	(10,11)
	106		ATP production from fatty acid oxidation	(12)
	7		ATP consumption in reductive fatty acid metabolism	(12)
	13		ATP consumption in reductive glutamine	(13)
	2		ATP consumption for GSH synthesis	(14)

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204

205 **Supplementary Table 2: Genes selected to evaluate metabolic pathway activity.**
206 List of genes selected in this study for various metabolic pathways. Gene sets were generated
207 using Gene Ontology database AmiGO (AmiGO 2 version: 2.5.17, (15)). Genes present in
208 multiple pathways were excluded according to a priority list based on the order of appearance in
209 the table.
210

Pathway		Genes used for the scoring metric
Catabolic	AMPK (5)	ACADL, ACADM, ACOX1, ACOX3, ACSL1, ACSL3, ACSL4, ACSL5, ANGPTL4, APOC3, APOE, ATF4, ATF5, BAX, BCL2L11, BTG2, CAT, CCND1, CCND2, CLU, CPT1A, CPT1B, CPT2, CREM, CYP27A1, CYP4A11, CYP7A1, DDB1, DGAT1, DNMT1, EGR1, EHHADH, ELN, FADS2, FASLG, FOS, FOSB, FOSL1, FOXA2, G6PC, G6PC2, G6PC3, GADD45A, GADD45B, GADD45G, GK, HES1, HNF4A, HSPD1, ID1, ID3, JUNB, JUND, KLF5, LPL, MAFA, MAPK9, MECR, MMP9, NCOA2, NR1H3, NR4A1, NR4A2, NUP155, NUP88, NUP98, OLR1, ONECUT1, ONECUT2, PCK1, PCK2, PDK4, PDX1, PRMT1, PRMT3, RUVBL1, SCD, SLC2A4, SOD2, SORBS1, SP1, STAT5A, TOB1, TXNIP.
	FAO (F1) (16)	CD36, ACSL1, SLC25A20, CPT1, CPT2, ACADVL, ACADL, ACADM, ACADS, ACADSB, ACAD8, ACAD9, ACAD10, ECHS1, HADH, ACAA1, ACAA2
	Reductive glutamine (Qre)	GLUD2, QARS1, GCLC, CPS1, GCLM, EPRS1, CAD, GLUL, ABAT, GAD2, GAD1, PPAT, ASNS, GFPT1
	Glucose Oxidation (G1) (16)	PDHA1, ACO2, IDH1, OGDH, SDHA, SDHC, FH, MDH1, CS, PC
	Mitochondrial ROS (Rm)	NDUFS1, CYTB, SDHA, MAOB, CYCS, VDAC, UCP2, SOD2, CAT, GPX1
	Glutamine oxidation (Q1)	GLS, GLS2, GOT1, GOT2, GLUD1, GPT2
Anabolic	HIF-1 (5)	ADM, ALDH4A1, ALDOA, ALDOC, ARHGEF1, ASPH, BHLHE40, BNIP3, BTAF1, CA9, CCNB1, CITED2, CP, DDIT4, EDN1, EGLN1, EGLN3, ENO1, EPRS, ETS1, FN1, GLCCI1, GRK6, HACD3, HSP90B1, IVNS1ABP, KDM3A, MECOM, MET, MXD1, MYLK, NAMPT, NDRG1, NOS2, NOS3, P4HA1, P4HA2, P4HTM, PDGFA, PFKL, PGAM1, PGK1, PLOD1, RARA, RBPJ, RNF165, RRAGD, RSBN1, SERPINE1, SLC31A1, SLC7A6, SOX6, SSRP1, STC2, TFRC, TGFB3, TMEFF1, TMEM45A, VEGFA.
	GSH synthesis (QSH)	GGT1, GGT7, GGT5, GSS, OPLAH, CNDP2, GGCT, GGT6
	Reductive glucose (Gre)	G6PC2, G6PC3, G6PC1, PCK2, PCK1, PC, GPI, TPI1, FBP1, FBP2
	Glycolysis (G2) (16)	HK1, GPI, PFKM, ALDOA, TPI1, GAPDH, PGK1, PGAM2, ENO1, PKM
	Reductive Fatty acids (Fre)	PCCB, DEGS1, MECR, SCD, PLA2G1B, ABHD3, ACACB, ACSF3, PRKAA2, PTGS2, PTGES, FA2H, FAAH, GSTM4, CYP1A1, MGLL, HTD2, HSD17B8, AKR1C3, FASN, LIPE, ABCD1, PRKAG2, CBR4, ELOVL6, ACACA, MCAT, DECR2, PEER, HPGDS, FADS1, PRKAB2, CBR1, PRXL2B, ACLY, NDUFAB1, PLA2G10, OLAH, ALOX12B, FADS2, ALOX5, LTC4S, ALOX12, ELOVL2, ALOX15B, ELOVL7, PTGDS, PLA2G4A, ALOXE3, ALOX15, TBXAS1, SCD5, PTGS1
	NADPH oxidase-derived ROS (Rn)	CYBB, CYBA, NCF1, NCF2, NCF4, NOX1, NOX3, NOX4, NOX5
Uptake	Glucose Uptake (G0)	SLC5A1, SLC5A3, SLC2A7, SLC2A10, SLC2A14, SLC2A6, SLC2A9, SLC2A4, SLC2A8, SLC2A3, SLC2A2, SLC2A1, SLC5A2, SLC2A5
	Fatty Acid Uptake (F0)	SLC27A5, SLC27A1, SLC27A6, SLC27A4, SLC27A2, CD36, FABP3, ABCD1, ABCD2, ABCD3, ABCD4, APOA1, APOA4, APOA5, PLTP, CETP, MTTP, SCARB1, SPNS1, MFSD2A, PITPNB, PITPNM3, PLSCR1, GLTPD2, GLTP
	Glutamine Uptake (Q0)	SLC25A22, SLC38A5, SLC6A19, SLC7A5, SLC38A2, SLC38A1, SLC25A13, SLC1A5, SLC38A3, SLC38A8, SLC7A7, SLC7A6, SLC6A14, SLC7A11, SLC38A7
Oncogene	MYC	MTDH, ACTL6A, ENO1, BAX, BCAT1, COMMD3-BMI1, POLR3D, CAD, CDC25A, CDK4, CCNB1, CCND2, DDX18, DKC1, E2F3, EIF2S1, EIF4A1, EIF4E, EIF4G1, FOSL1, GAPDH, KAT2A, SLC2A1, GPAM, HUWE1, HMGA1, HSPD1, HSPA4, HSP90AA1, ID2, IREB2, CDCA7, KIR3DL1, LDHA, LIN28B, MAX, NDUFAF2, RIOX2, MMP9, MTA1, MYC, MYCT1, NBN, NME1, NME1-NME2, PMAIP1, NPM1, NCL, ODC1, TP53, PDCD10, PEG10, PFKM, PIM1, PRDX3, PTMA, RCC1, RPL11, SERPINI1, SHMT1, SMAD3, SMAD4, SNAI1, SUPT3H, SUPT7L, BIRC5, TAF10, TAF12, TAF4B, TAF9, TERT, TFRC, RUVBL1, RUVBL2, KAT5, TK1, TRRAP, UBTf

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