

SUPPLEMENTARY INFORMATION

Metabolic drug survey highlights cancer cell dependencies and vulnerabilities

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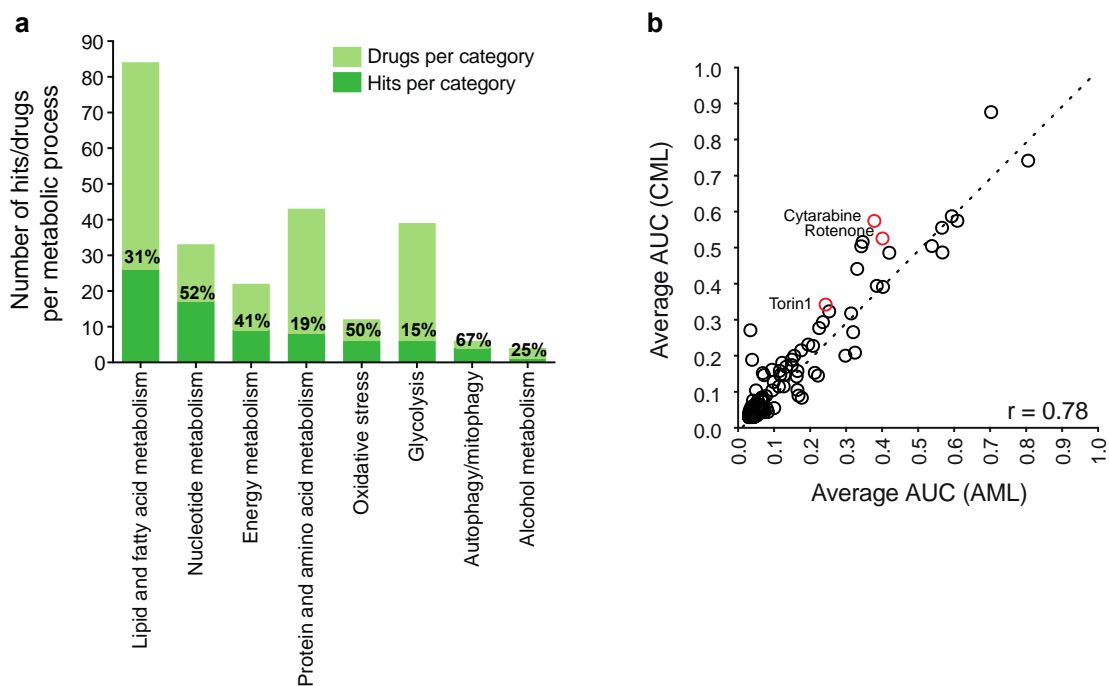
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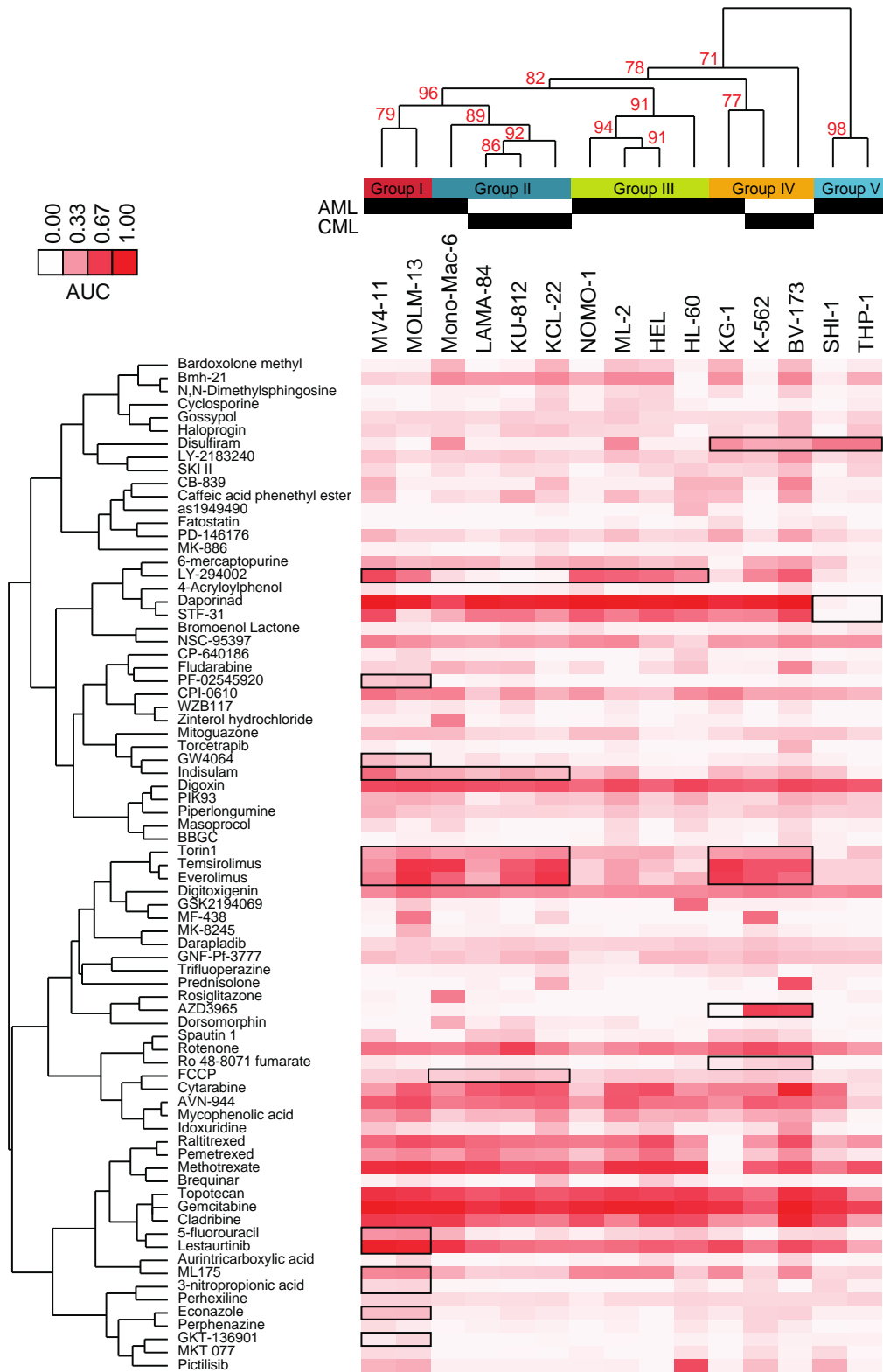
Supplementary Table 1: Patients' characteristics.

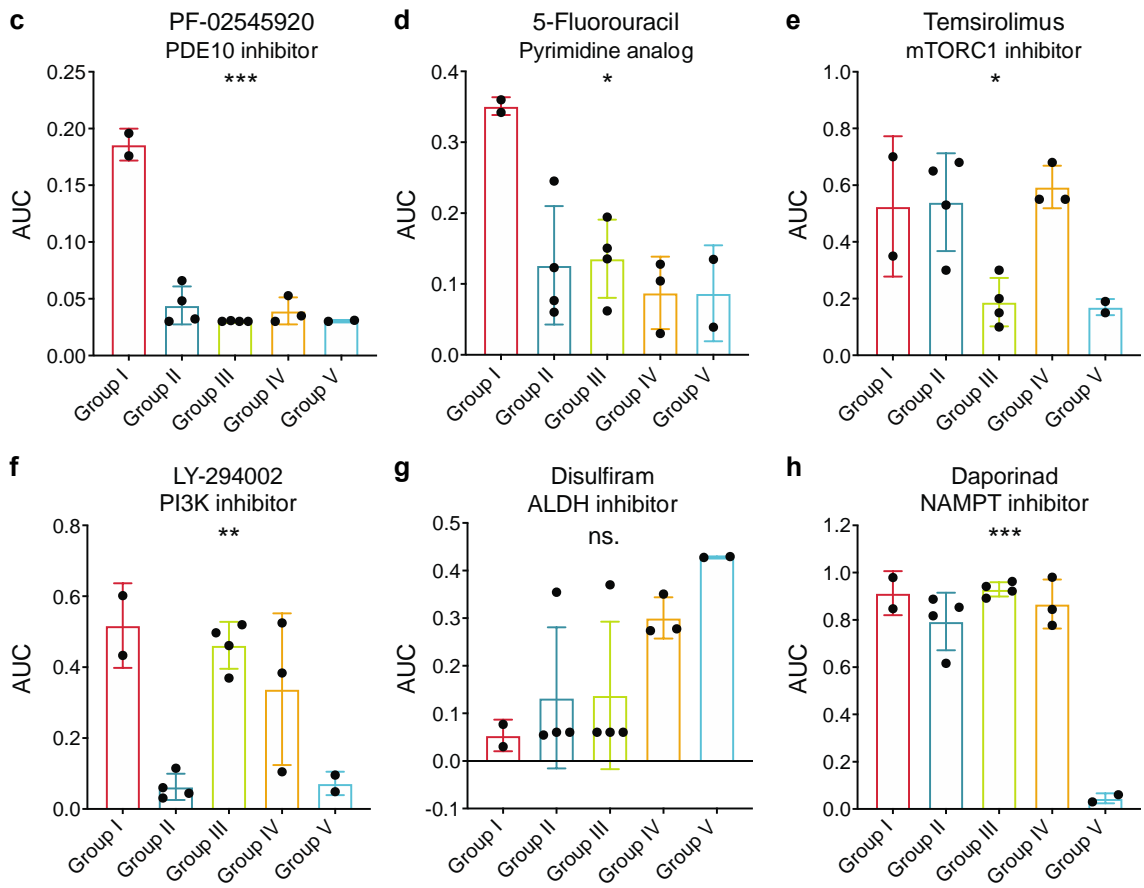
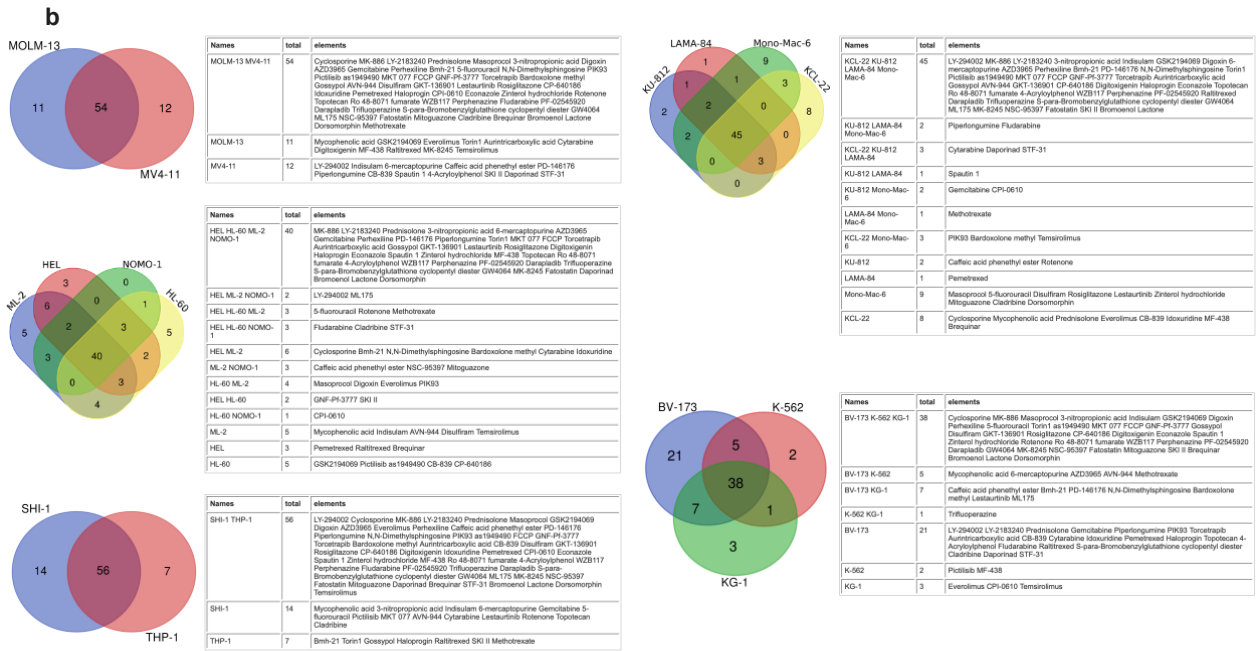
Supplementary References



Supplementary Fig. 1| Distribution of metabolic inhibitors affecting cellular viability per metabolic pathway / process and identification of selectively acting compounds in disease-specific manner. a, Metabolic pathway coverage of compounds that had an effect on cell viability in the tested cell lines highlighting the percentage of hits in relation of all compounds in a given metabolic category. **b,** Correlation of the average metabolic drug sensitivity profile of AML and CML cell lines showing disease specific vulnerabilities.

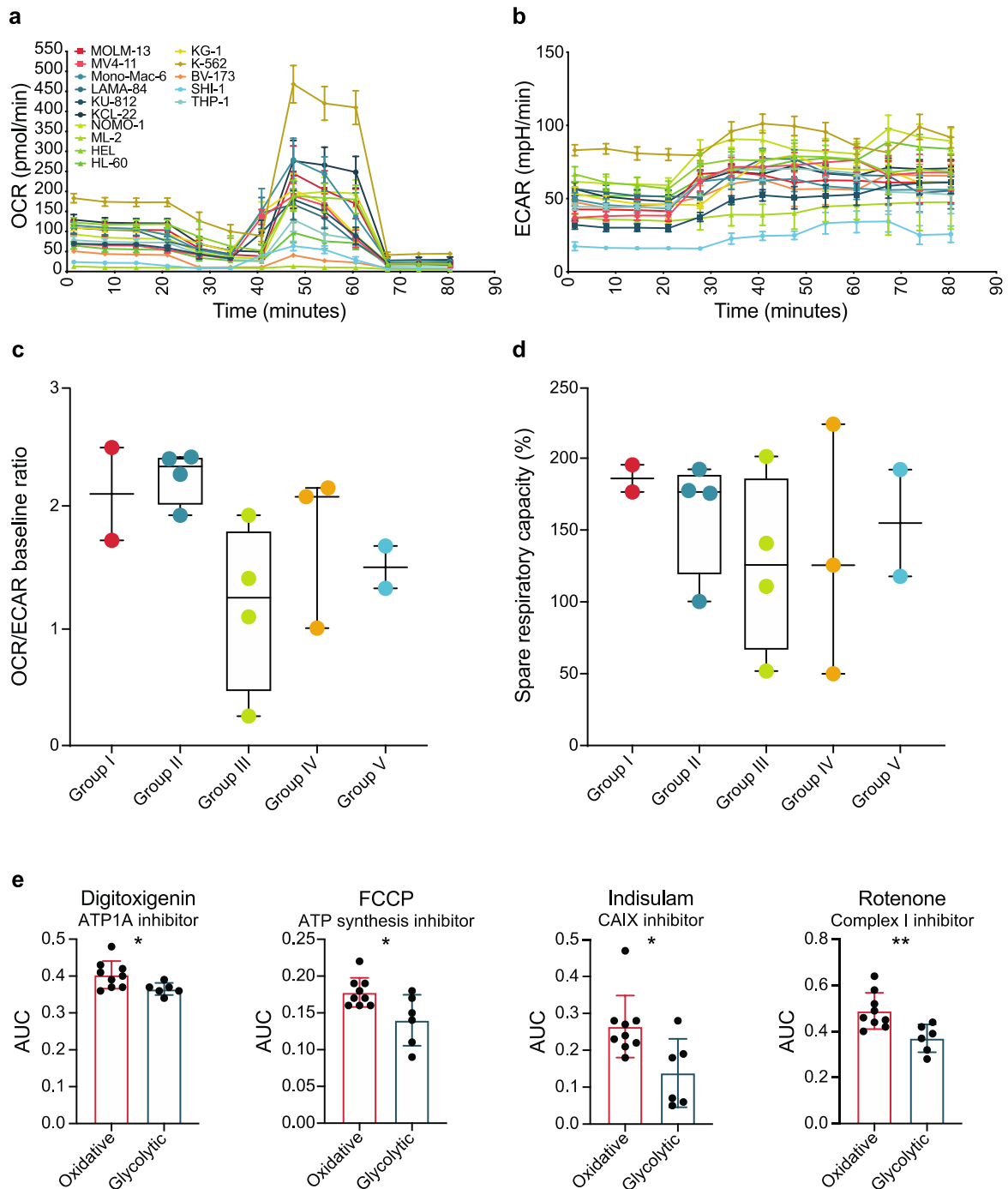
a





Supplementary Fig. 2| Metabolic drug sensitivity testing classifies myeloid leukemia cell lines in 5 functional groups. a, Unsupervised hierarchical clustering of the 77 viability affecting drugs is presented as a heatmap across 15 cell lines.

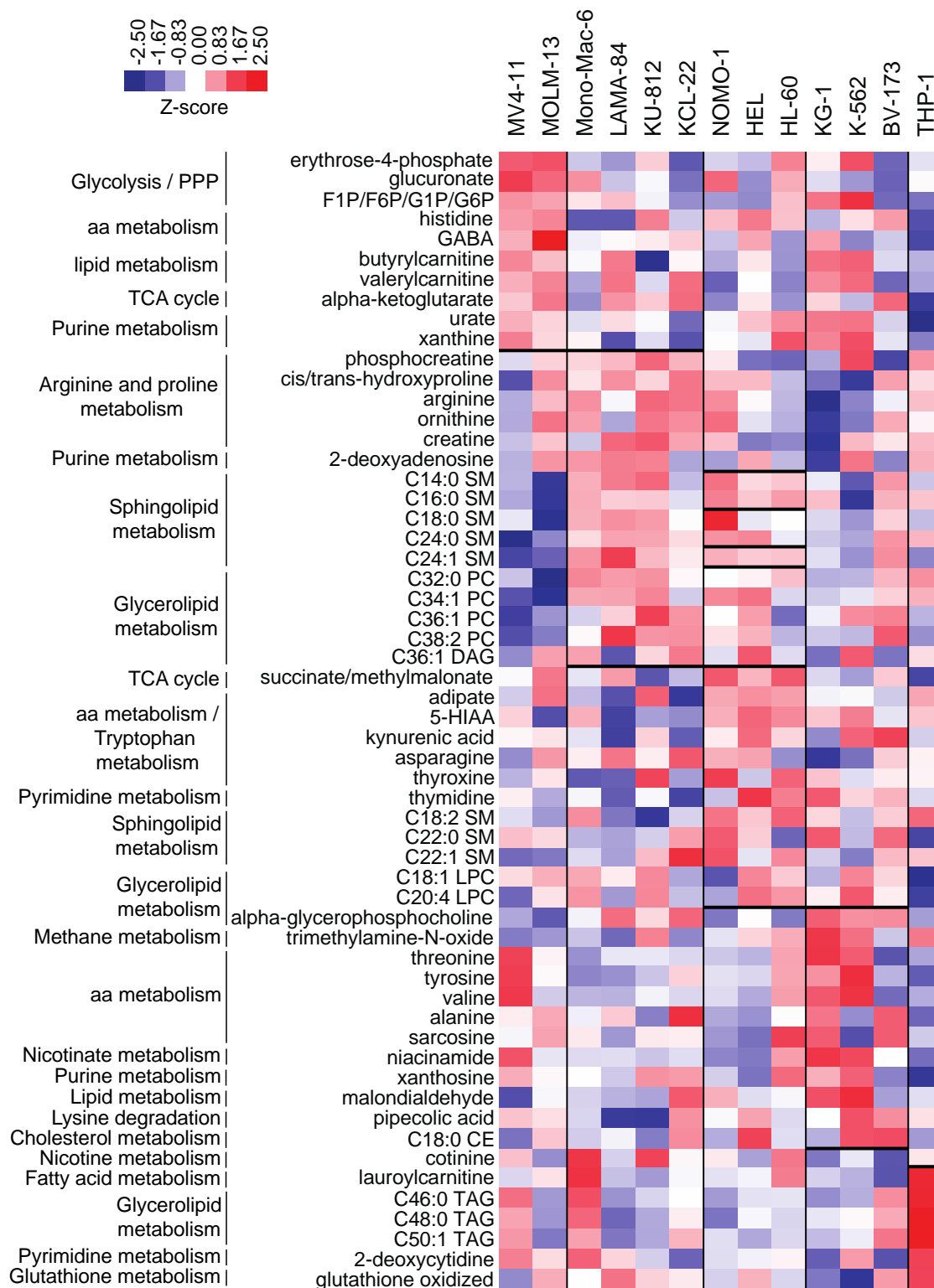
Clustering was performed using the complete linkage clustering method and Euclidian and Spearman distance measures of the AUC values of cell lines and drugs, respectively. The response profiles of several compounds and compounds classes display differential effects across the cell lines tested and are outlined with black boxes. The reproducibility of the clusters was evaluated by randomly resampling 10,000 bootstrap samples of the original dataset and calculating the frequency at which each cluster appears in the hierarchical clustering of the bootstrap replicates. The numbers in the dendrogram tree of the cell lines indicate the approximately unbiased (AU) empirical frequencies (0-100%) from the multiscale bootstrap resampling implemented in the Pvcust R-package. **b**, Venn diagrams depicting concordant and discordant drug responses within the functional taxonomic clusters defined in Fig. 2c. **c-h**, Bar graphs depicting the distribution of AUC values for selected compounds significantly contributing to the grouping of cell lines (Group I, n=2; Group II, n=4; Group III, n=4; Group IV, n=3; and Group V, n=2) shown in **Fig. 2** (an ordinary one-way ANOVA analysis; FDR of 10% was deemed significant; * $P_{adj} \leq 0.1$; ** $P_{adj} \leq 0.05$; *** $P_{adj} \leq 0.01$; ns not significant). Error bars indicate mean \pm SD.



Supplementary Fig. 3| Metabolic phenotypes of the myeloid leukemia cell lines.

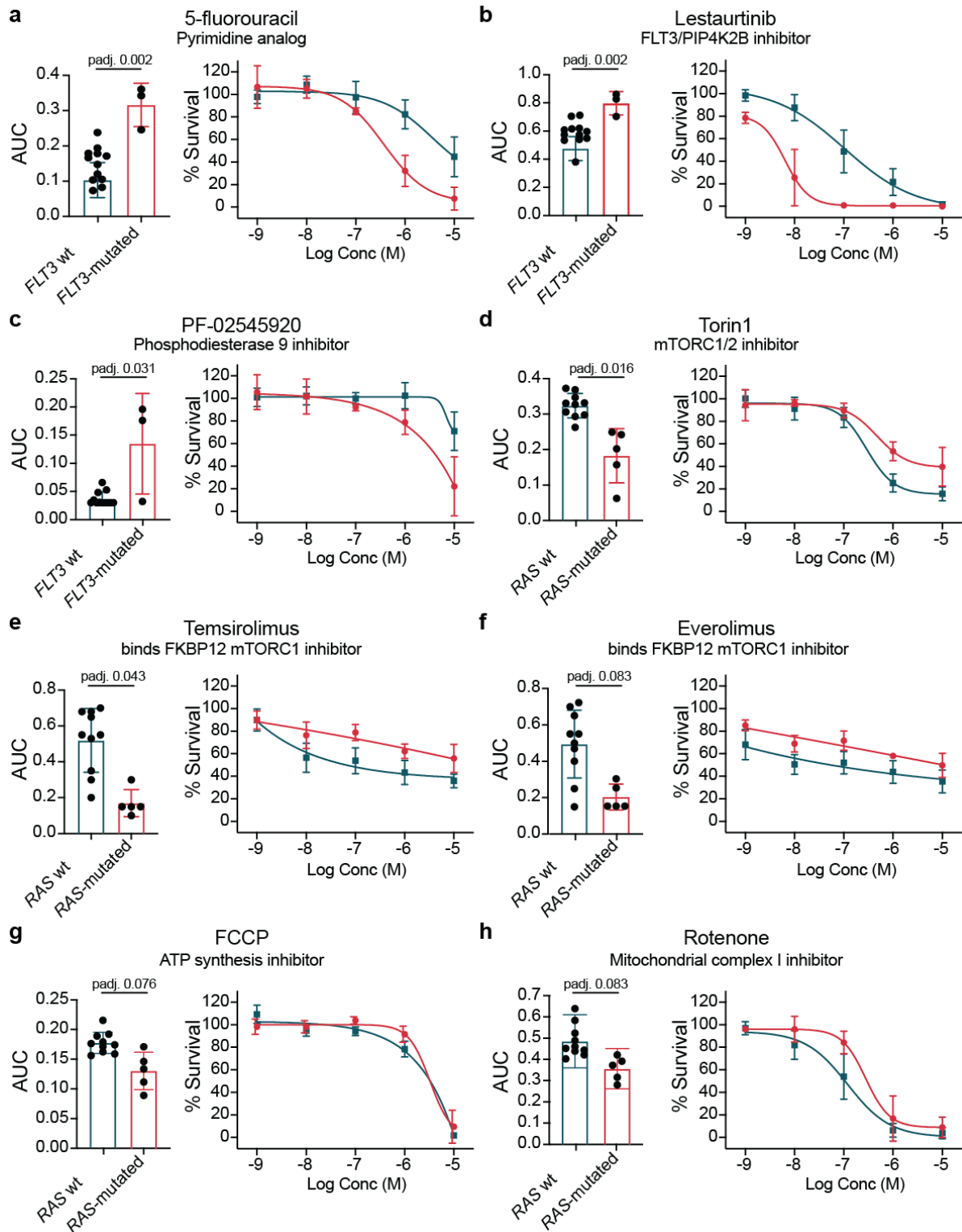
a-b, Measurement of oxygen consumption rate (OCR) and extracellular acidification rate (ECAR) with the Seahorse analyzer XF96 at basal level and after consecutive injections of oligomycin (1 μ M), FCCP (1 μ M), and antimycin A (1 μ M) / rotenone (1 μ M) (n = 8 technical replicates; error bars mean \pm SD). **c-d**, Box and whiskers (min to max) plot showing the basal bioenergetics state (the mean OCR at baseline (n = 8 technical

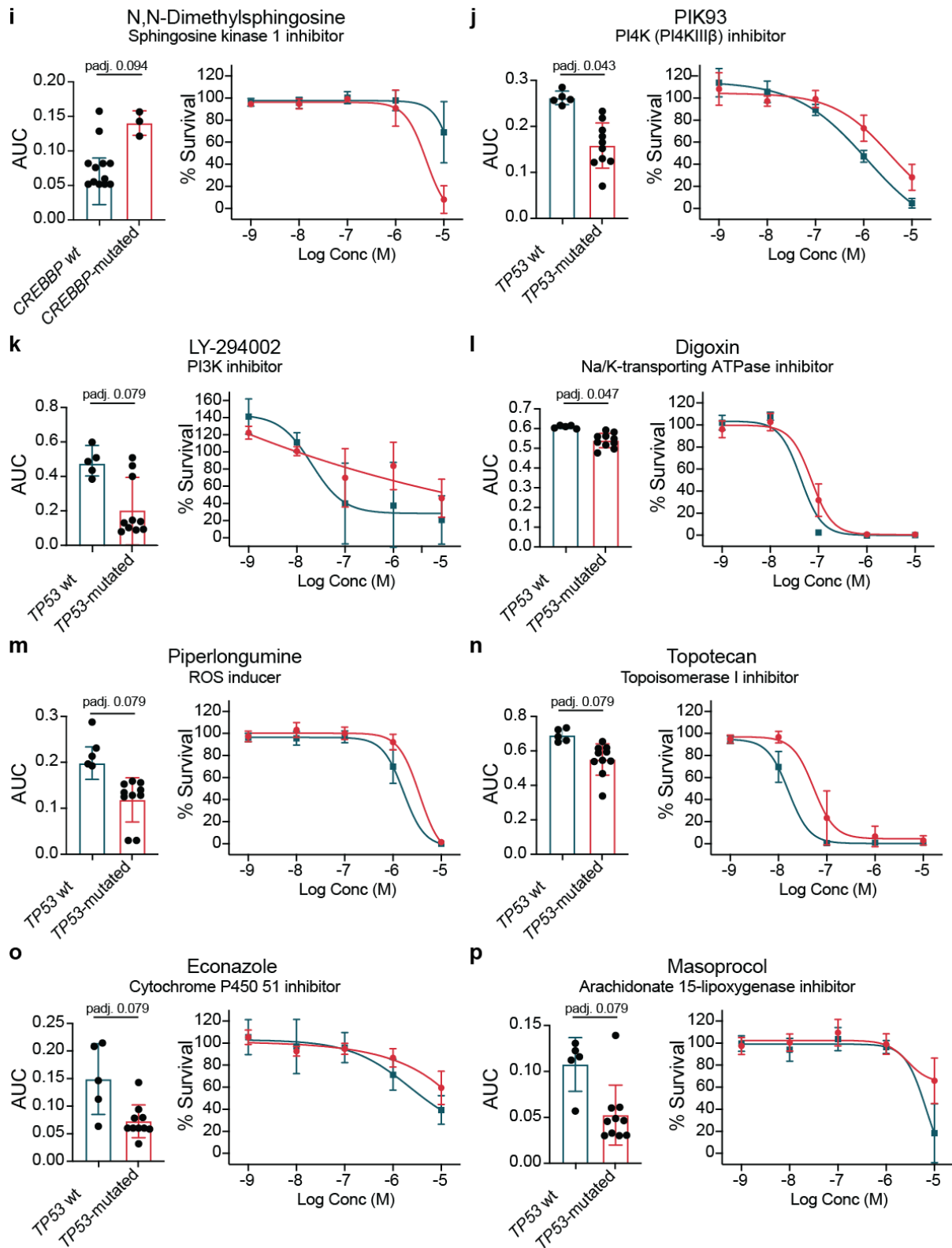
replicates) divided by the mean ECAR at baseline ($n = 8$ technical replicates) for each individual cell line ($n=15$) from the second baseline timepoint at approximately 8 minutes after assay start) and percentage spare respiratory capacity of the myeloid cell lines. The black line in the middle of the box depicts the median and the box extends from the 25th to 75th percentiles. **e**, Bar graph illustrating a significant difference in sensitivity to inhibitors targeting energy metabolism between more oxidative cell lines (ones falling in Group I, II and IV; $n=9$) and the more glycolytic cell lines (ones in Group III and V; $n=6$). Data is presented as mean \pm SD; Unpaired two-tailed T-test; * $P < 0.05$, ** $P < 0.01$ (digitoxigenin $P = 0.0358$; FCCP $P = 0.0182$; indisulam $P = 0.0272$; rotenone $P = 0.0081$).



Supplementary Fig. 4| Analysis of publicly available targeted metabolomics data from the CCLE Resource¹. The levels of 57 metabolites, represented as Z-scores and visualized with a heatmap, were significantly different between at least two of the drug sensitivity pre-defined groups with a two-way ANOVA analysis (FDR of 10% was

deemed significant). For analysis the clean imputed Log2 transformed values provided in the original publication were used.



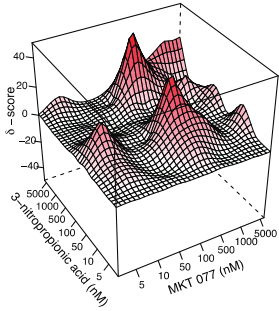


Supplementary Fig. 5 | Significant genotype to phenotype associations. a-p, Box-plots and mean dose response curves depicting sensitivity of several metabolic modifiers that have significantly higher or lower sensitivity in *FLT3-ITD* (a-c), *RAS* (d-

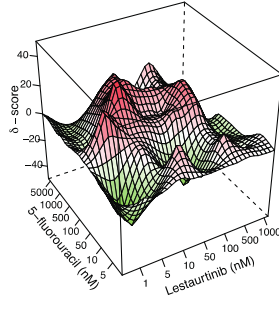
h), *CREBBP* (**i**), and *TP53* (**j-p**) mutant versus wild-type cell lines as depicted in **Fig. 3a**. Error bars signify mean \pm SD and the difference in response was assessed with a two-tailed unpaired *T*-test after multiple testing correction (FDR of 10% was deemed significant; * $P_{adj} \leq 0.1$; ** $P_{adj} < 0.05$; *** $P_{adj} < 0.01$).

HL-60

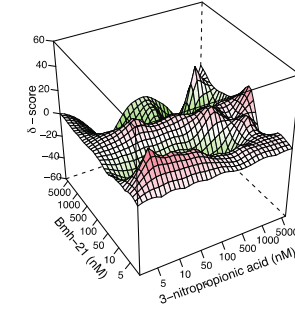
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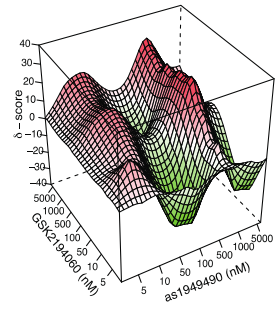
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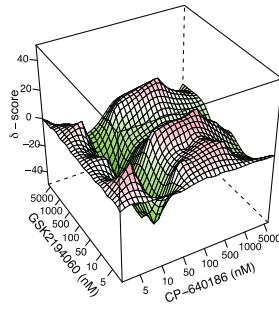
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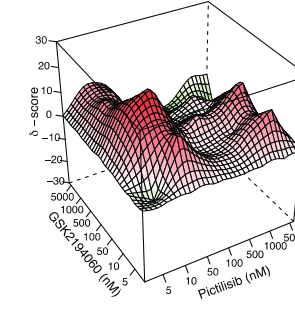
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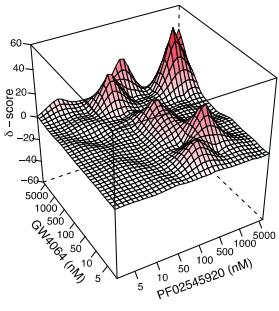
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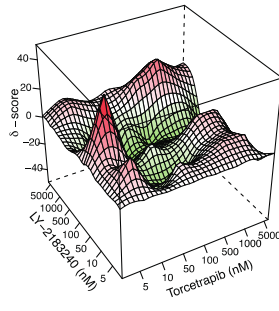
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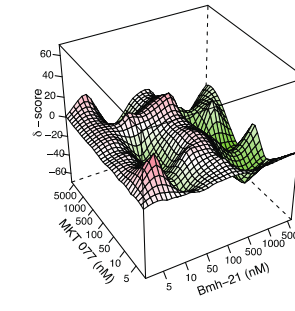
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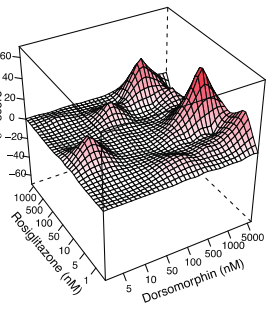
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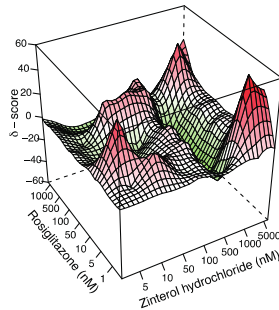
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Bliss synergy score: 5.782
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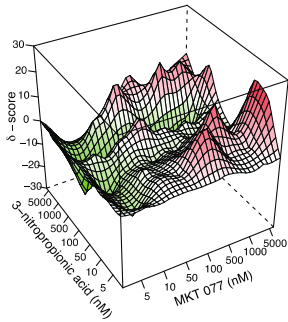


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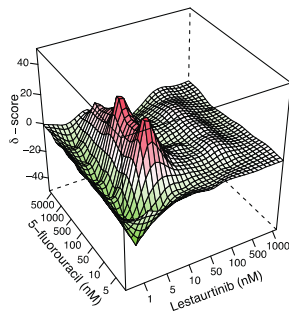


Mono-Mac-6

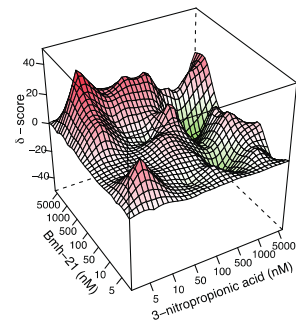
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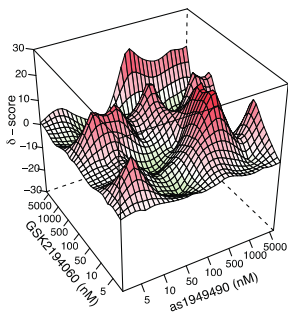
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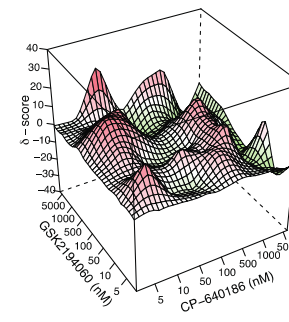
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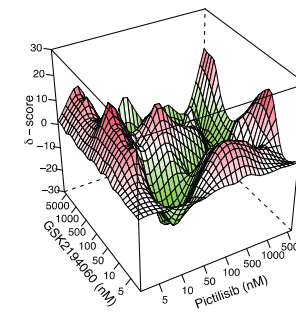
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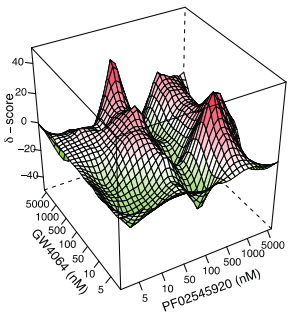
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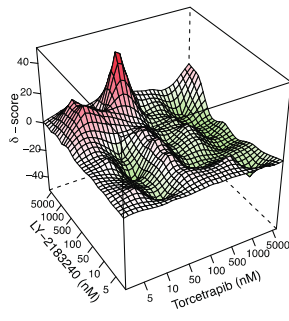
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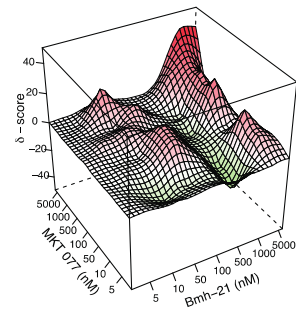
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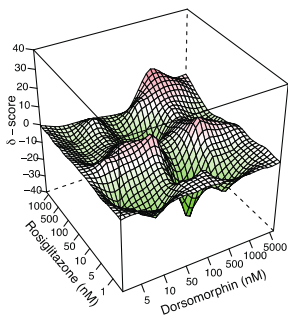
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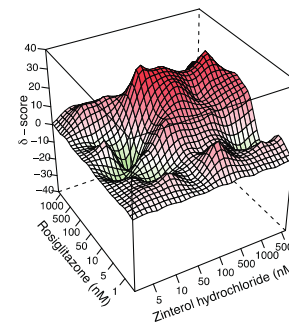
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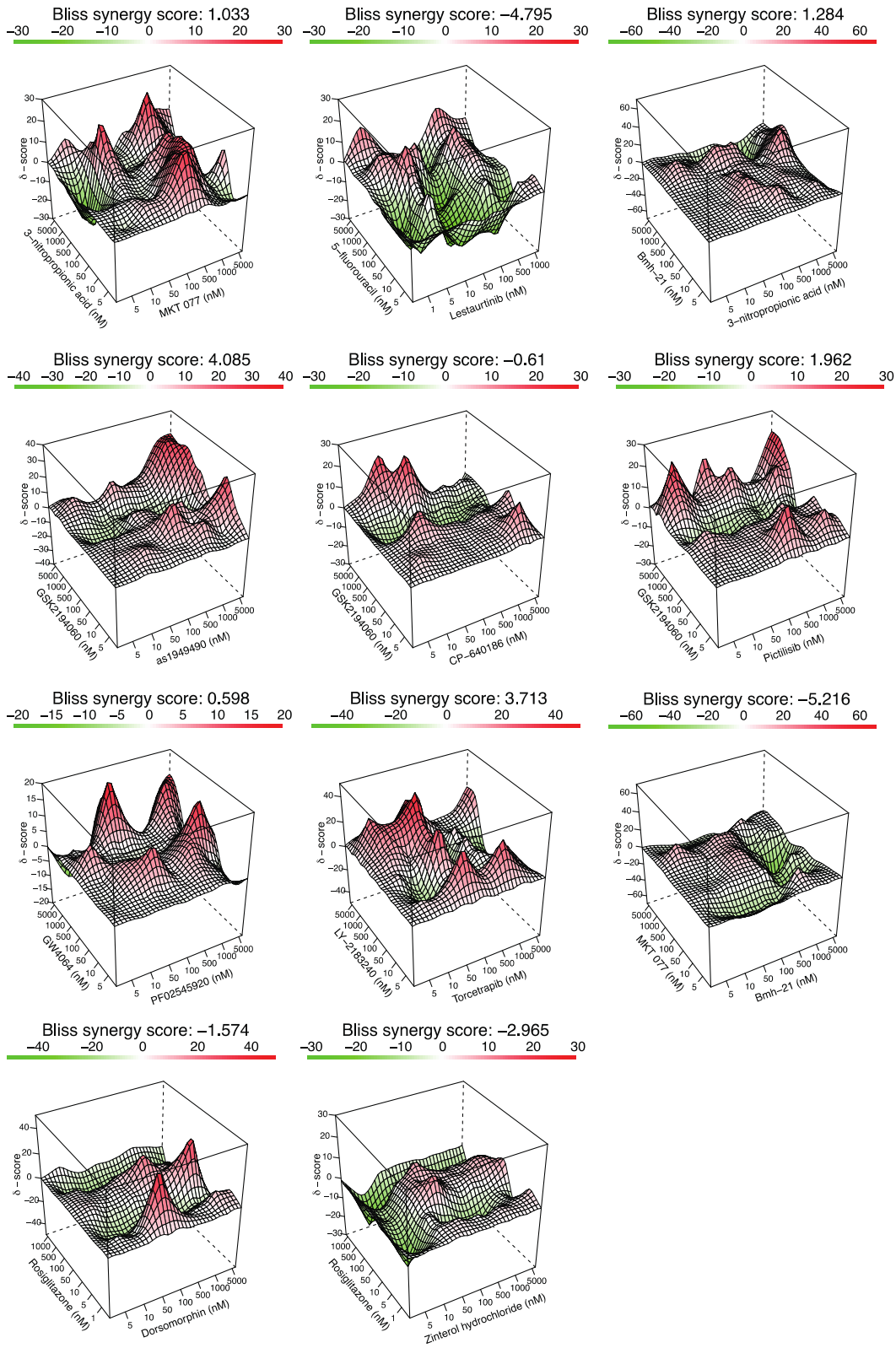
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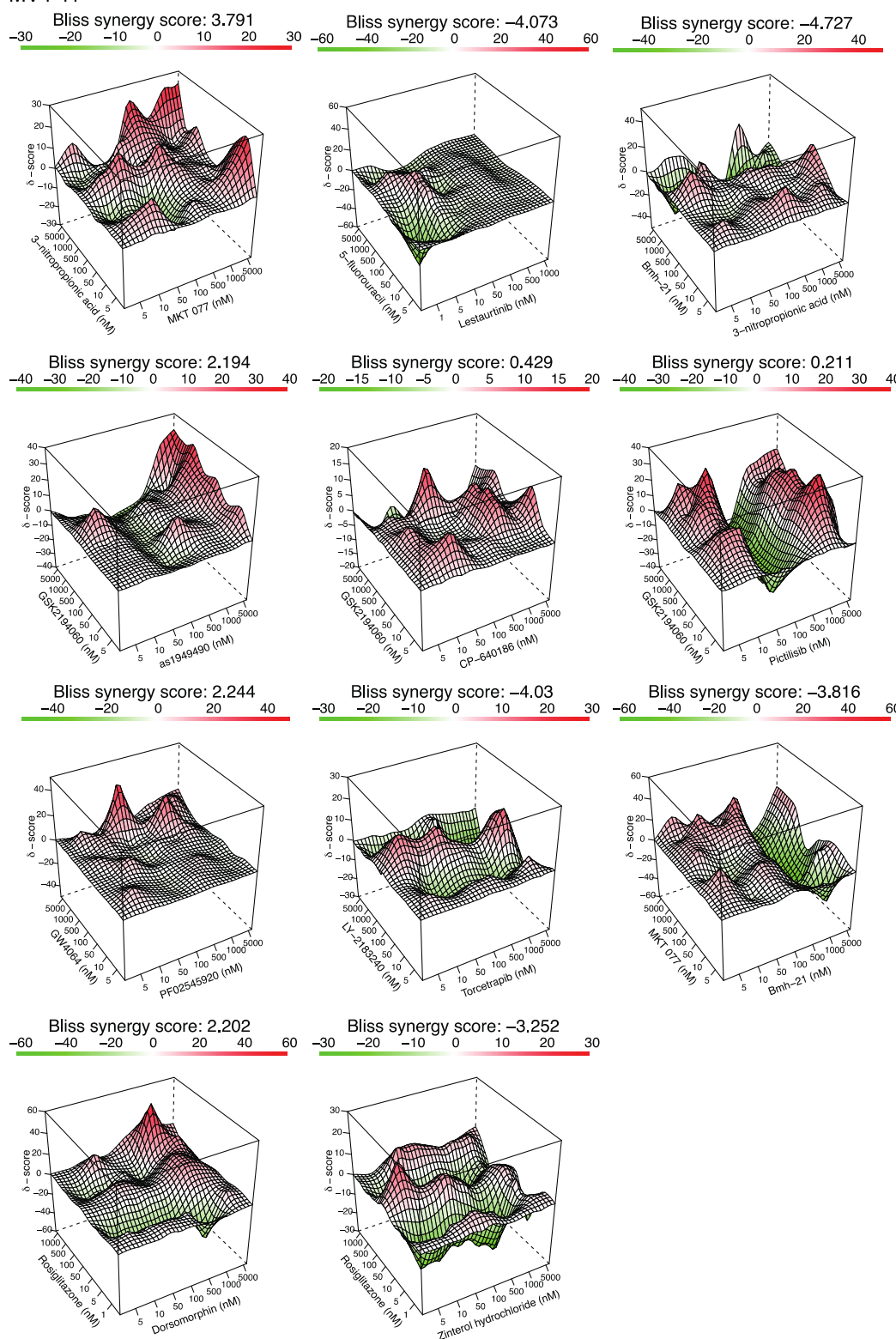
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BV-173

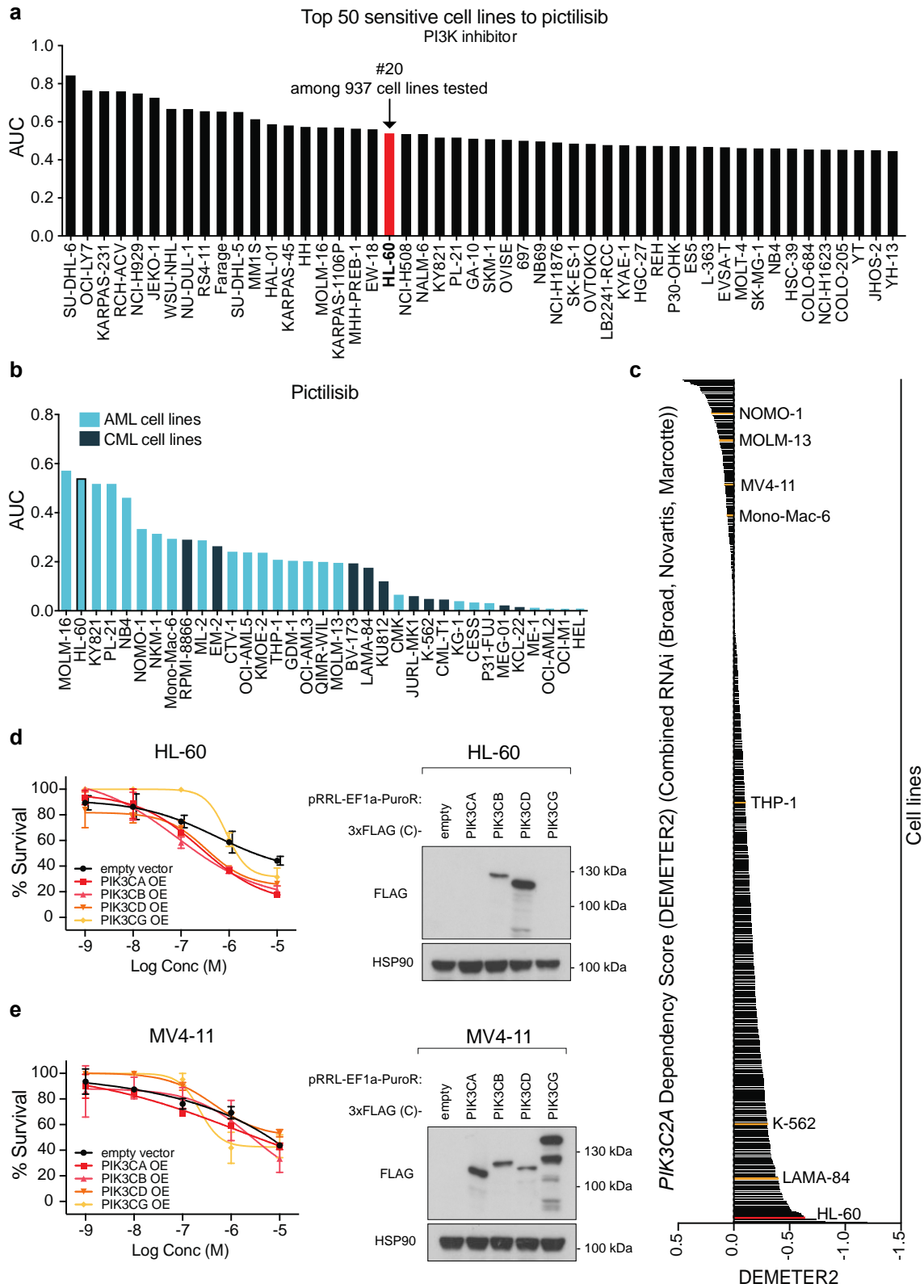


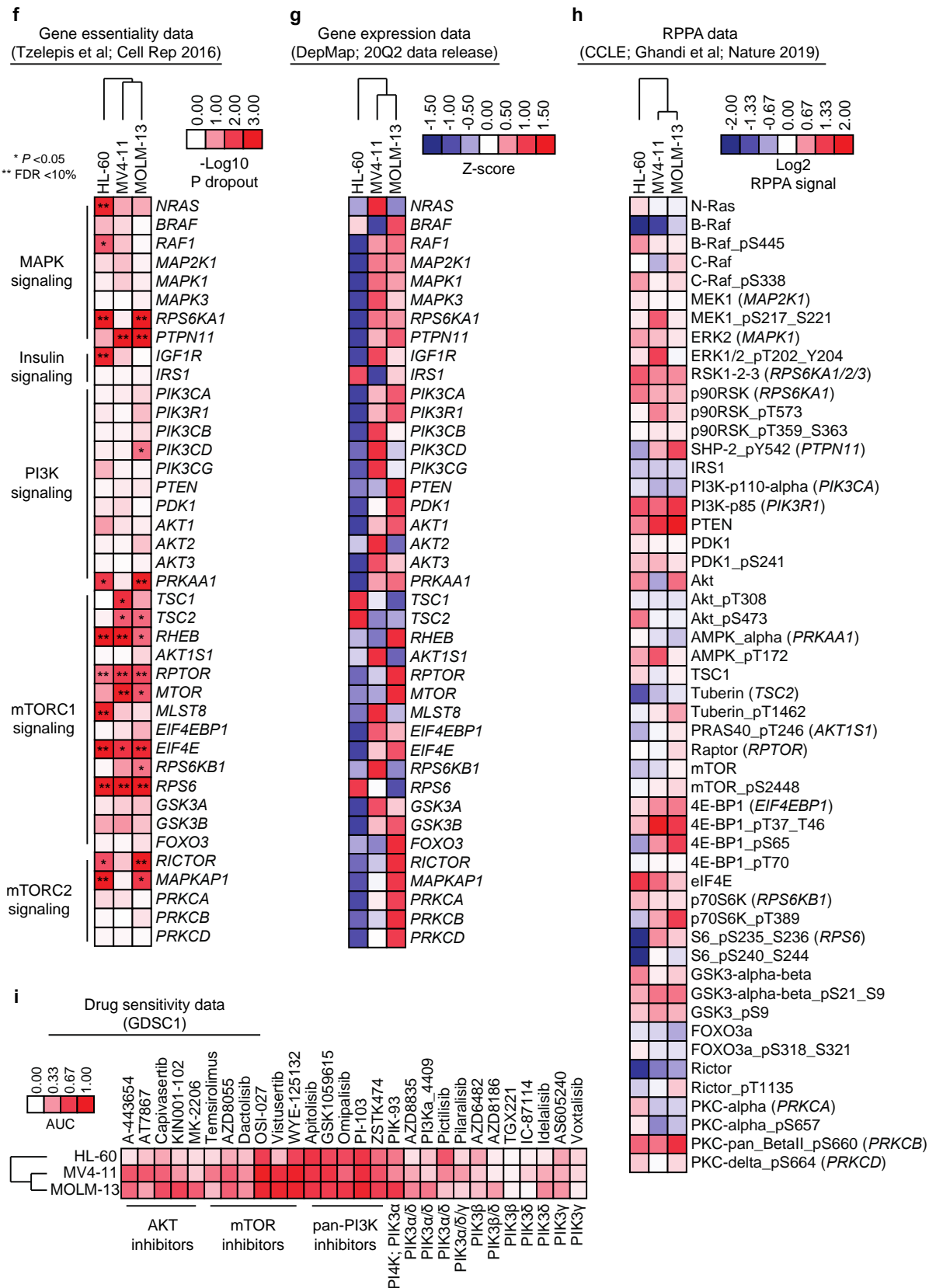
MV4-11



Supplementary Fig. 6| 3D drug synergy visualizations for 11 different drug-drug interactions in HL-60, Mono-Mac-6, BV-173, and MV4-11 cells. Data was generated in 8x8 drug synergy matrices and analyzed using the SynergyFinder tool

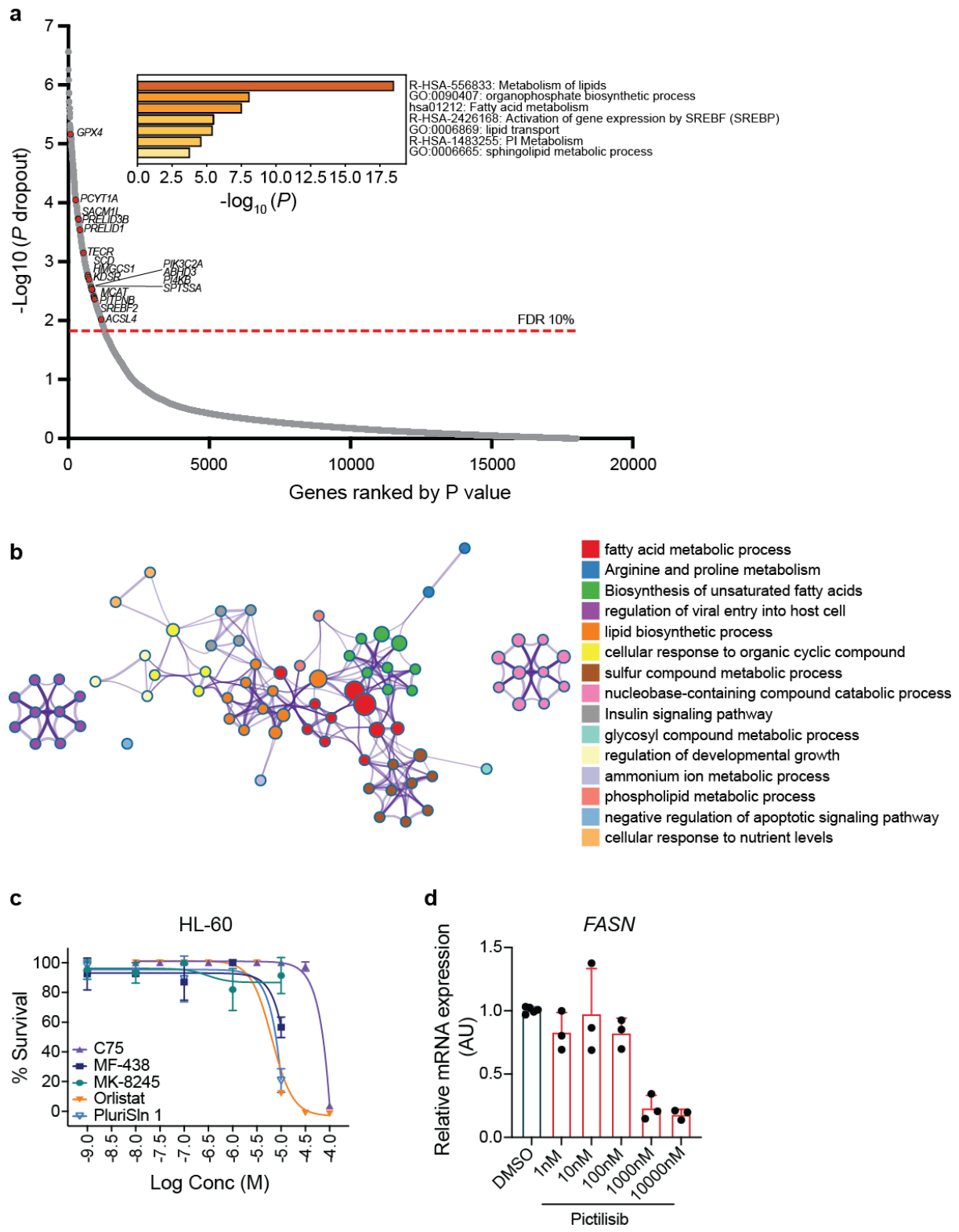
using the Bliss independence model with % survival values at each tested concentration relative to DMSO (negative control) and 10 μ M bortezomib (positive control). The synergy score for a drug combination is averaged over all the dose combination measurements. The 2D and 3D synergy maps highlight synergistic and antagonistic dose regions in red and green, respectively.





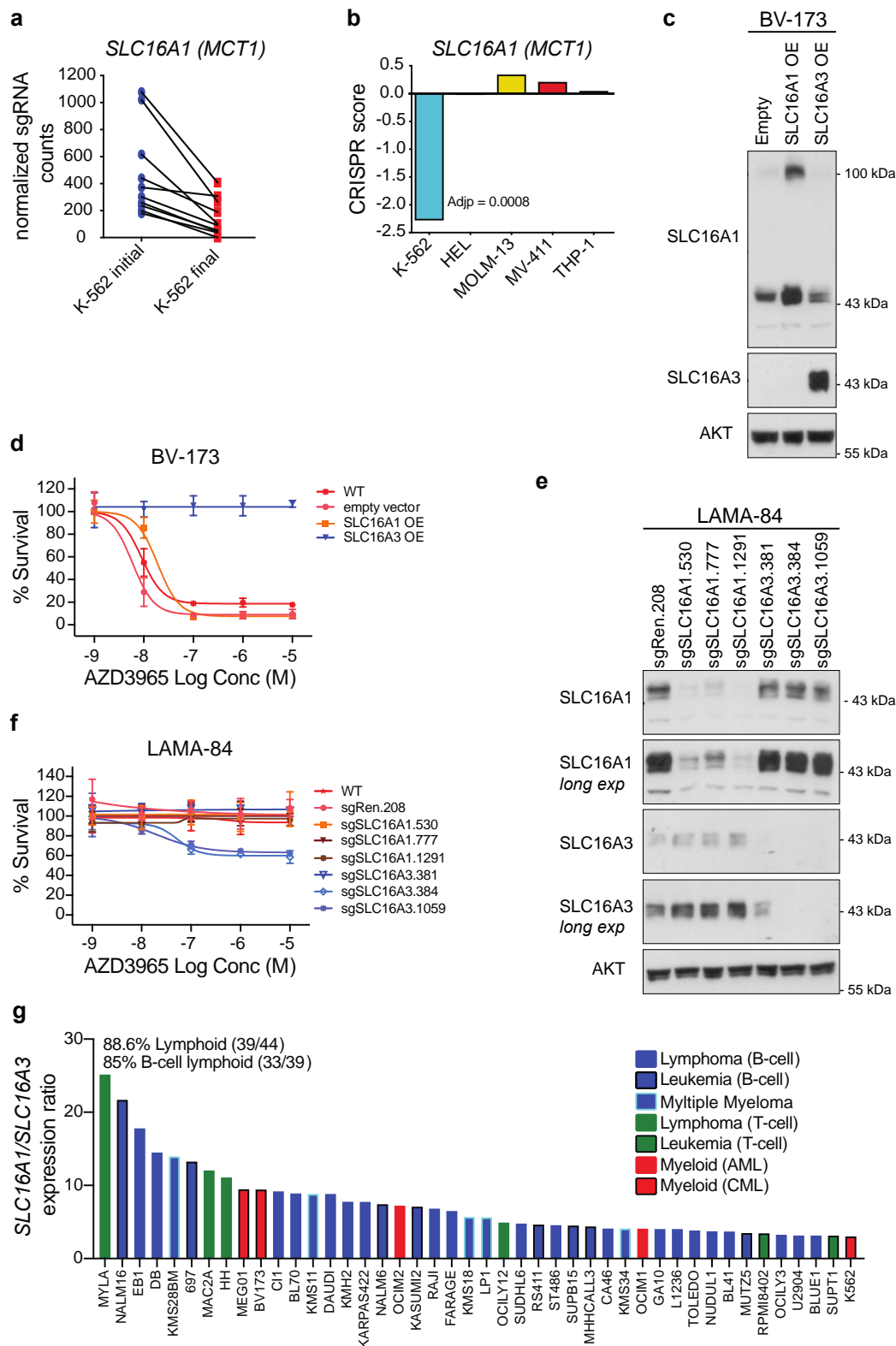
Supplementary Fig. 7 | HL-60 cells are vulnerable to PI3K inhibition. a, Distribution of *in vitro* sensitivity (expressed as AUC) to pictilisib among 937 cancer cell lines tested

in the Genomics of Drug Sensitivity in Cancer project (GDSC1)². Data is shown from the top 50 most sensitive lines irrespective of tissue origin or lineage. **b**, Distribution of sensitivity to pictilisib in AML and CML cell lines only. **c**, Cancer cell line genetic dependency to *PIK3C2A* estimated using the DEMETER2 model³ across 648 cancer cell lines (data retrieved from Cancer Dependency Map portal). The cell lines from this study for which genetic vulnerability data was available are marked. **d-e**, Average response to pictilisib in HL-60 and MV4-11 empty vector, and *PIK3CA*, *PIK3CB*, *PIK3CD* or *PIK3CG* overexpressing cells. Error bars indicate standard deviation of the mean of technical triplicates. Data is representative of two independent experiments. Moreover, immunoblot analysis of *PIK3CA*, *PIK3CB*, *PIK3CD*, and *PIK3CG* expression in HL-60 and MV4-11 cells lentivirally transduced with empty vector, *PIK3CA*, *PIK3CB*, *PIK3CD* or *PIK3CG*-cDNA is shown. Data is representative of two independent experiments. **f-i**, Gene essentiality⁴, gene expression⁵, reverse phase protein array (RPPA)⁶, and drug sensitivity data², respectively, related to the PI3K/AKT/mTOR signaling in HL-60, MV4-11, and MOLM-13 cells.



Supplementary Fig. 8 | HL-60 cells are dependent on *de novo* FA synthesis. a, Results of genome-wide CRISPR library dropout screen in HL-60 cells. Data obtained from the Yusa lab⁴. Genes involved in lipid metabolism are highlighted in red and gene

enrichment analysis performed with Metascape⁷. **b**, A network layout for enriched ontology clusters of downregulated genes in HL-60 cells generated with Metascape. The network is visualized with Cytoscape (v3.1.2) with “force-directed” layout and with edge bundled for clarity. **c**, Dose response of C75 and orlistat (described to target FASN; technical quadruplicate) as well as 3 stearyl-CoA desaturase 1 (SCD1; technical duplicate data from original screen) inhibitors in HL-60 cells. Error bars indicate mean \pm SD. **d**, *FASN* transcript expression measured by RT-qPCR in response to increasing concentrations of pictilisib treatment. Error bars indicate mean \pm SD; (n = 3). Data is representative of two independent experiments



Supplementary Fig. 9 | *SLC16A1* essentiality and determinants of sensitivity to the *SLC16A1* inhibitor AZD3965. a, Depletion of normalized sgRNA (n = 10) counts for *SLC16A1* in K-562 cells from a CRISPR dropout screen⁸, showing that K-562 cells

are dependent on *SLC16A1*. **b**, Comparison of the CRISPR score (a metric to evaluate CRISPR dropout screens and genetic dependencies developed in the Sabatini lab) for the *SLC16A1* in K-562, HEL, MOLM-13, MV4-11, and THP-1 cells. **c**, Immunoblot analysis of *SLC16A1* and *SLC16A3* expression in BV-173 cells lentivirally transduced with empty vector, *SLC16A1* or *SLC16A3*-cDNA. **d**, Average response to AZD3965 in BV-173 wild type, empty vector, and *SLC16A1* or *SLC16A3* overexpressing cells. **e**, Expression of *SLC16A1* and *SLC16A3* in LAMA-84 CML cells transduced with the indicated sgRNAs. Error bars indicate standard deviation of the mean of technical triplicates. Data is representative of two independent experiments. **f**, Average response to AZD3965 in LAMA-84 wild type, sgRen, and *SLC16A1* or *SLC16A3* deficient cells. Error bars indicate standard deviation of the mean of technical triplicates. Data is representative of two independent experiments. **g**, Distribution of the *SLC16A1/SLC16A3* expression ratio across the 44 hematological cancer cell lines predicted to exhibit sensitivity to AZD3965. Bars are colored based on lineage and broad disease subtype. Gene expression data was accessed from the DepMap portal (Expression Public 20Q2)⁵.

Supplementary Table 1. Patients' characteristics

Sample ID	Age	Sample type	Diagnosis	Genetics	Status at sampling	Treatment before sampling
Pat.1	> 65	BM	AML with MDS-related changes	No mutations detected	Diagnostic	
Pat.2	< 65	BM	CML, chronic phase	BCR-ABL	Diagnostic	
Pat.3	< 65	PB	CML, blast crisis	BCR-ABL	Refractory disease	dasatinib imatinib nilotinib bosutinib FLAG ponatinib
Pat.4	> 65	PB	AML NOS	<i>NRAS</i> G12D	Refractory disease	3+5+7 (daunorubicin, cytarabine, etoposide) followed by mitoxantrone, cytarabine
Pat.5	> 65	PB	sAML post PV	<i>FLT3</i> -ITD <i>JAK2</i> V617F	Diagnostic	
Pat.6	< 65	PB	AML with mutant <i>NPM1</i>	<i>NPM1</i> -B <i>TP53</i> polymorphism R72P	Relapse	high dose cytarabine
Pat.7	< 65	BM	CML, blast crisis	BCR-ABL_T315I	Relapse	imatinib nilotinib dasatinib
Pat.8	> 65	BM	AML with mutant <i>NPM1</i>	<i>NPM1</i> -A	Diagnostic	
Pat.9	< 65	PB	AML with mutant <i>NPM1</i>	<i>NPM1</i> -D <i>FLT3</i> -ITD	Relapse	fludarabine cyclophosphamide allogeneic cord blood transplant

Pat.10	> 65	PB	sAML post MPN	<i>CALR</i> L367fs*46	Relapse	azacytidine venetoclax
Pat.11	< 65	PB	AML with MDS-related changes	<i>TP53</i> R282W heterozygous <i>TP53</i> R72P	Relapse	allogeneous stem cell transplant cyclophosphamide methotrexate total body irradiation
Pat.12	< 65	PB	AML	N/A	Relapse	azacytidine
Pat.13	> 65	PB	sAML post MDS	<i>DEK-NUP214</i> <i>FLT3-ITD</i>	Relapse	azacytidine hydroxyurea
Pat.14	> 65	PB	AML with MDS-related changes	<i>IDH1</i> R132C <i>RUNX1</i> F40Wfs*14 <i>RUNX1</i> R162K <i>CBL</i> C404Y	Relapse	azacytidine
Pat.15	> 65	BM	sAML post MDS/MPN unclassifiable	<i>ASXL1</i> Q512* <i>FLT3-ITD</i> <i>PTPN11</i> S506T <i>SETBP1</i> G870S <i>SRSF2</i> P95R	Relapse	venetoclax decitabine

MDS-myelodysplastic syndrome; FLAG-fludarabine, arabinofuranosyl cytidine, and granulocyte colony-stimulating factor; NOS-not otherwise specified; sAML-secondary AML; PV-polycythemia vera; MPN-myeloproliferative neoplasm; N/A-not available.

Supplementary References

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