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Supplemental Information

**Immunogenomic Landscape Contributes
to Hyperprogressive Disease
after Anti-PD-1 Immunotherapy for Cancer**

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Supplemental Information

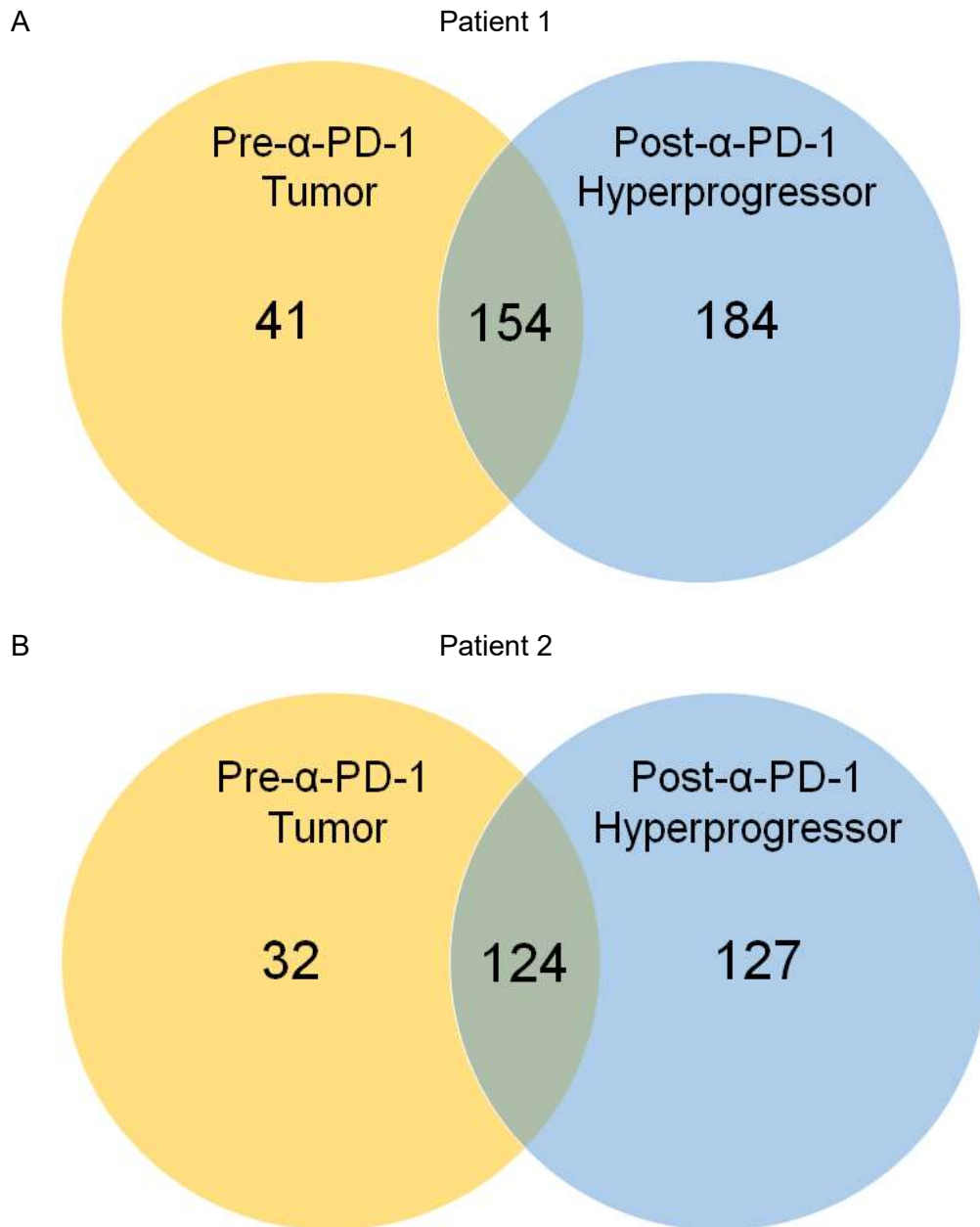


Figure S1. The number of somatic mutations in the pre- and post- anti-PD-1 treatment tumor samples of the two patients. Related to Figure 1 and Figure 2. A) Patient 1; B) Patient 2.

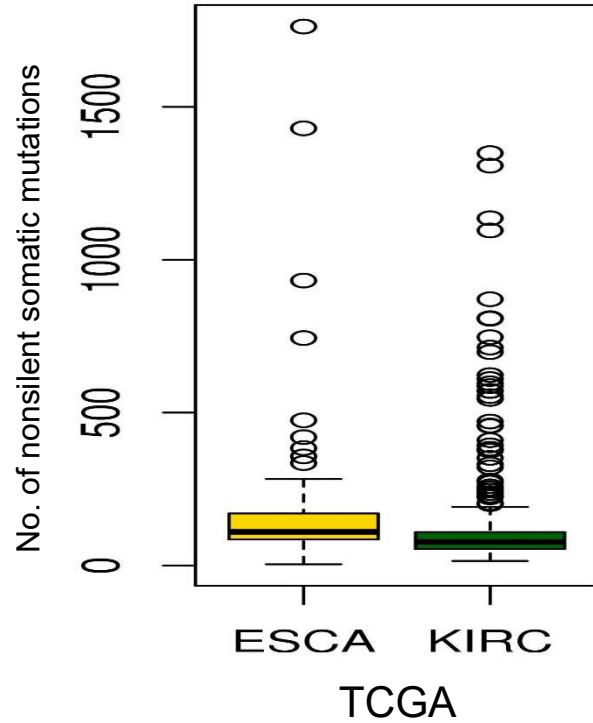


Figure S2. The distribution of nonsilent somatic mutations in the two TCGA cancer types analyzed in the hyperprogressive tumor context in the present study. Related to Figure 1 and Figure 2. The numbers of nonsilent somatic mutations of the esophageal carcinoma (ESCA, n=184) and kidney renal clear cell carcinoma (KIRC, n=384) samples from TCGA.

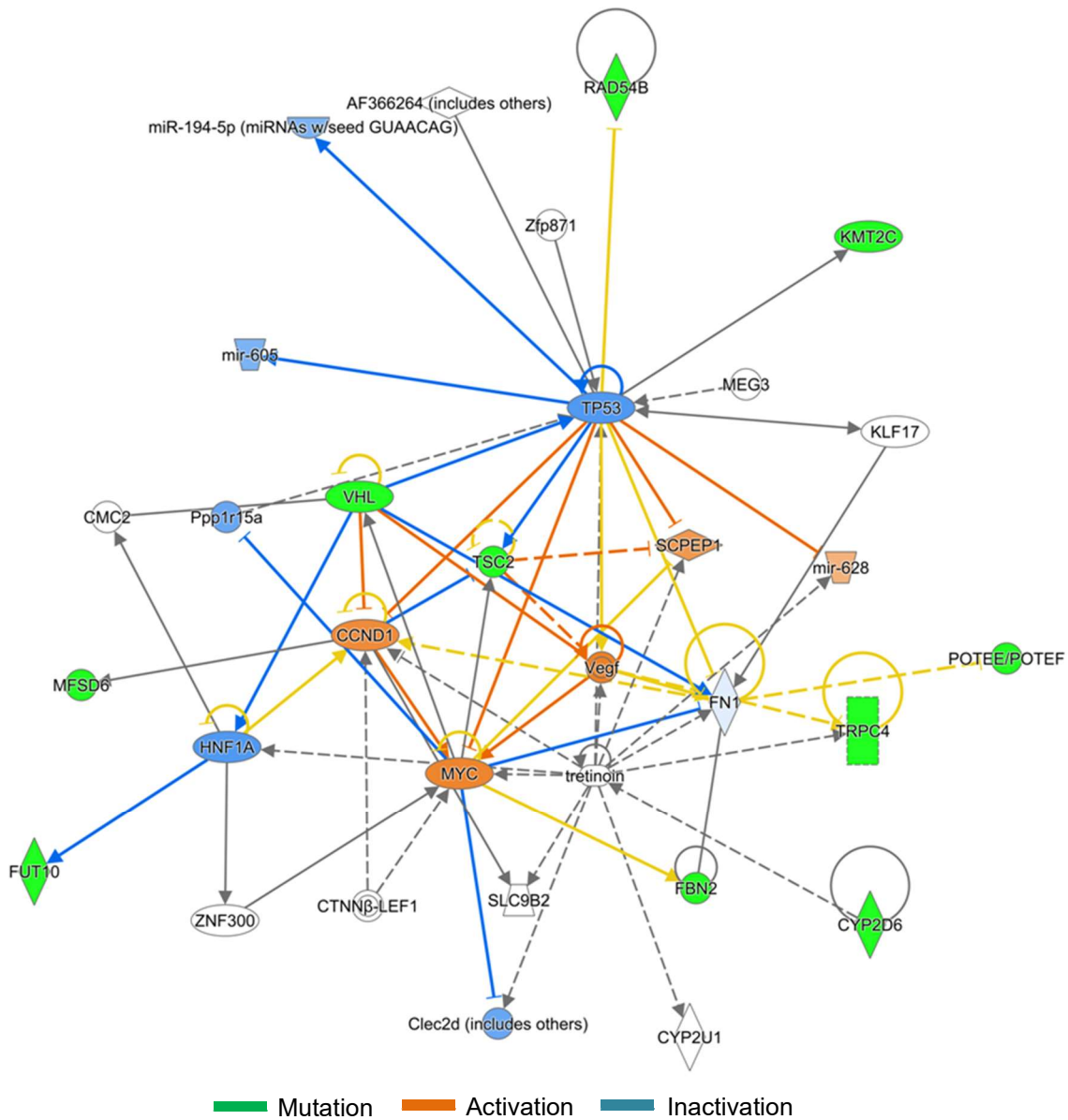


Figure S3. Key mutated cancer genes interacting network. Related to Table 2. Based on the eleven genes with the deleterious somatic mutations, a mechanistic network was built by IPA in which ten genes carrying these mutations resulted in the suppression of TP53 tumor suppressor pathway and activation of MYC, CCND1 and VEGF oncogenic pathways.

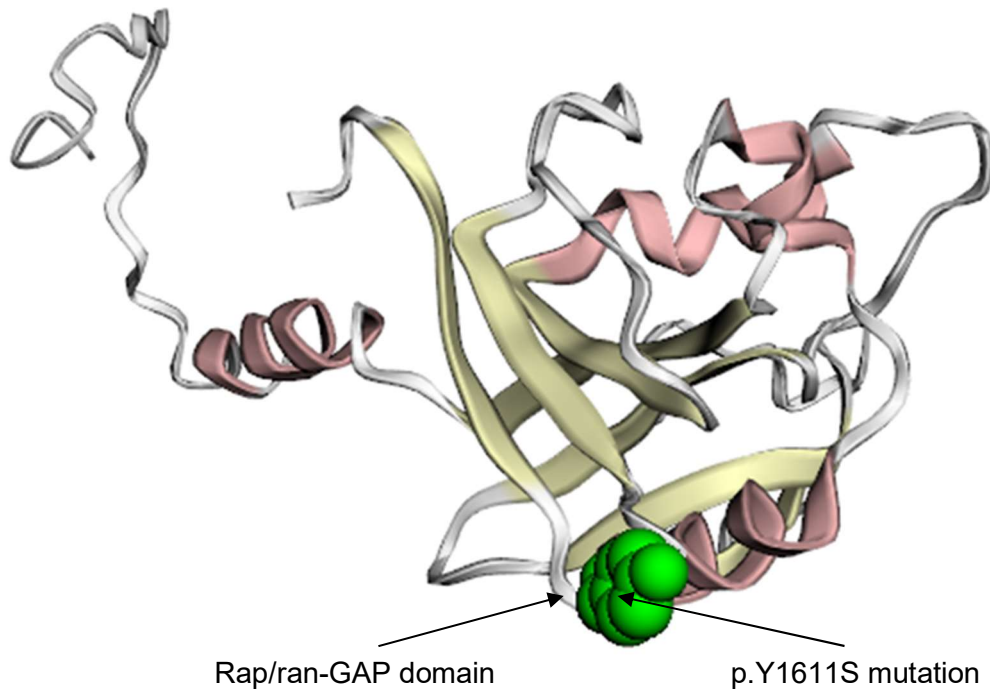


Figure S4. Key mutation in the TSC2 protein. Related to Table 2. The 3D structure of the TSC2 protein and the location of the amino acid residue harboring the p.Y1611S mutation, which is within the Rap/ran-GAP domain of the TSC2 protein critical to its biological function.

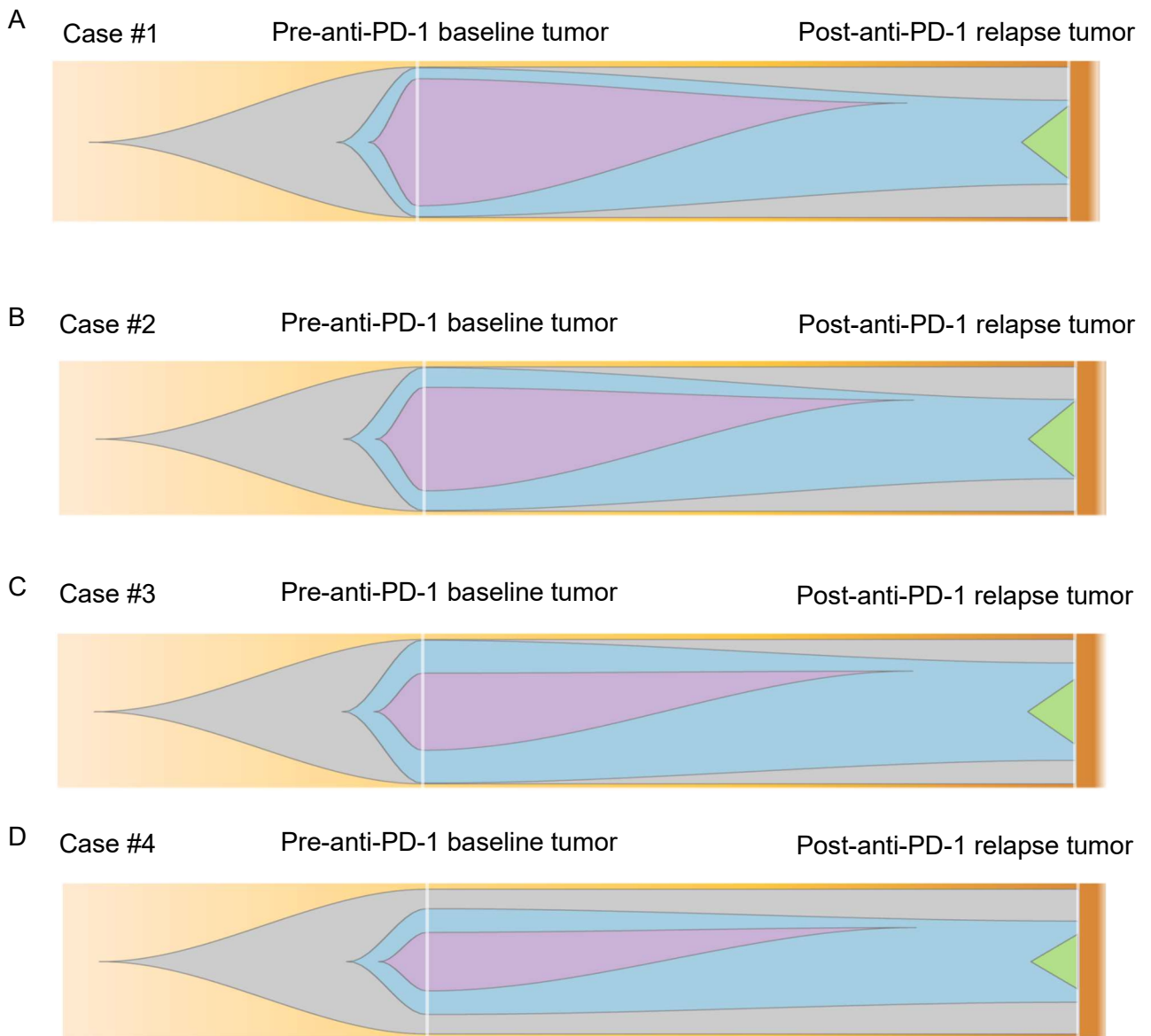


Figure S5. Clonal evolution from the pre-anti-PD1 therapy baseline tumor to post-anti-PD-1 relapsing tumor in the four melanoma patients from a previous study. Related to Figure 4. The graphical representation of clonal evolution in the four melanoma patients: (A) Case #1; (B) Case #2; (C) Case #3; (D) Case #4.

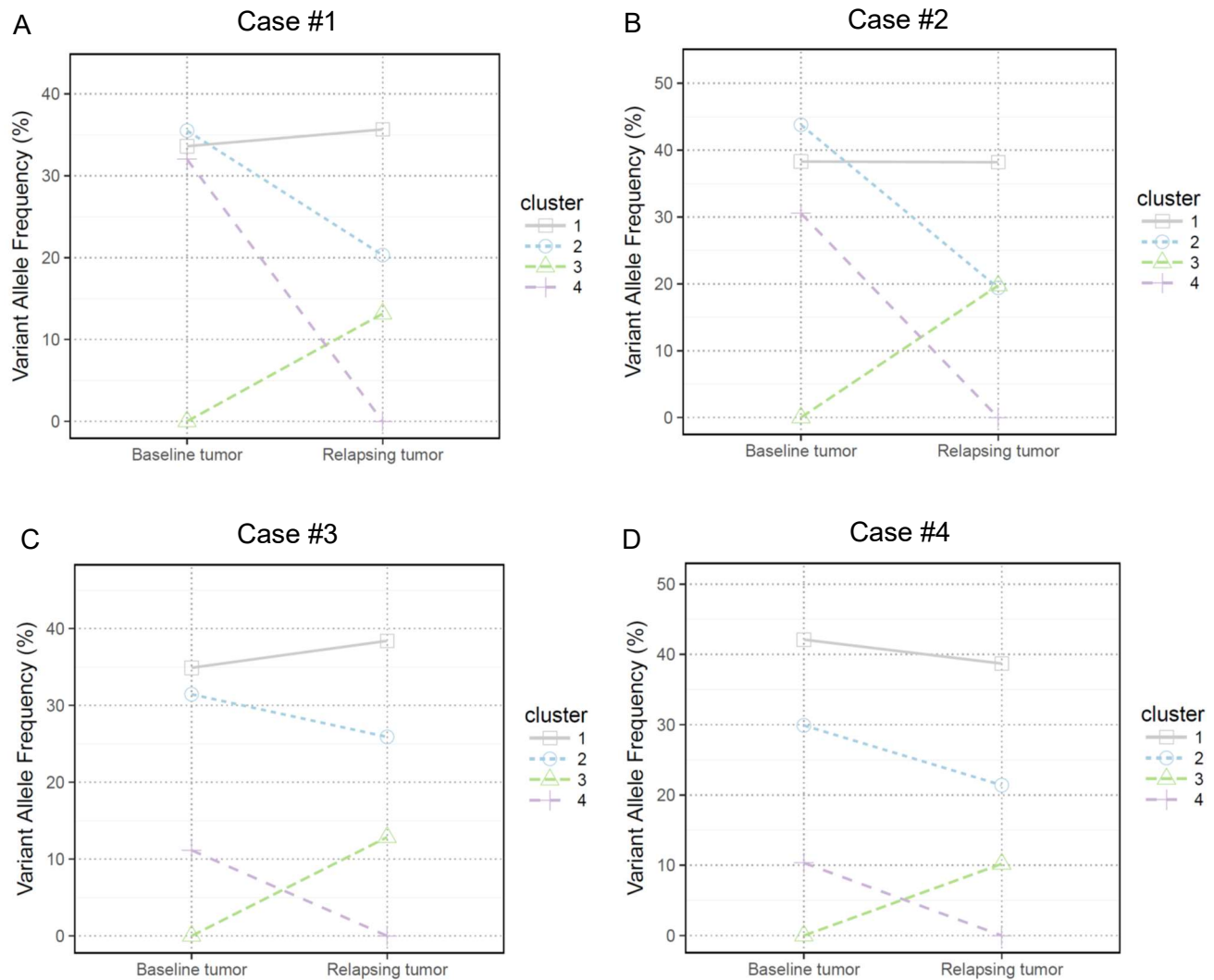
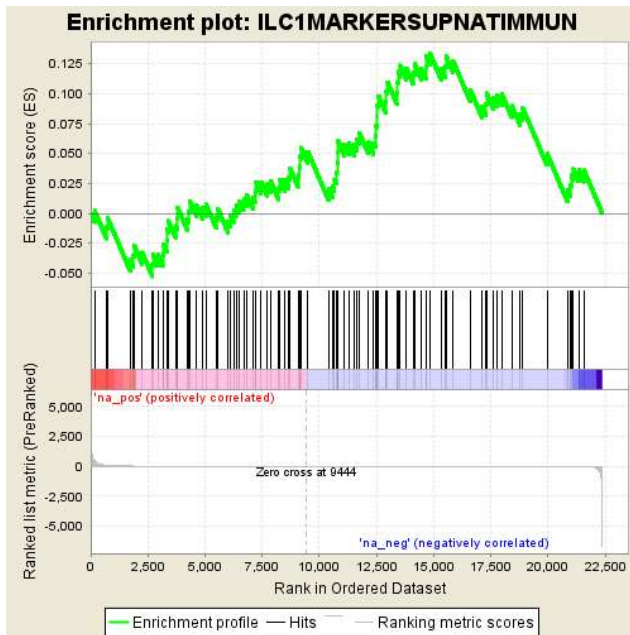


Figure S6. The mutation clusters representing clonal evolution from the pre-anti-PD1 therapy baseline tumor to post-anti-PD-1 relapsing tumor in the four melanoma patients from a previous study. Related to Figure 4. The mutation clusters detected in the pre-anti-PD1 therapy baseline tumor to post-anti-PD-1 relapsing tumor in the patients: (A) Case #1; (B) Case #2; (C) Case #3; (D) Case #4. The relationship between the clusters in the pre-therapy and post-therapy tumors are indicated by lines linking them.

A. ILC1 population



B. ILC2 population

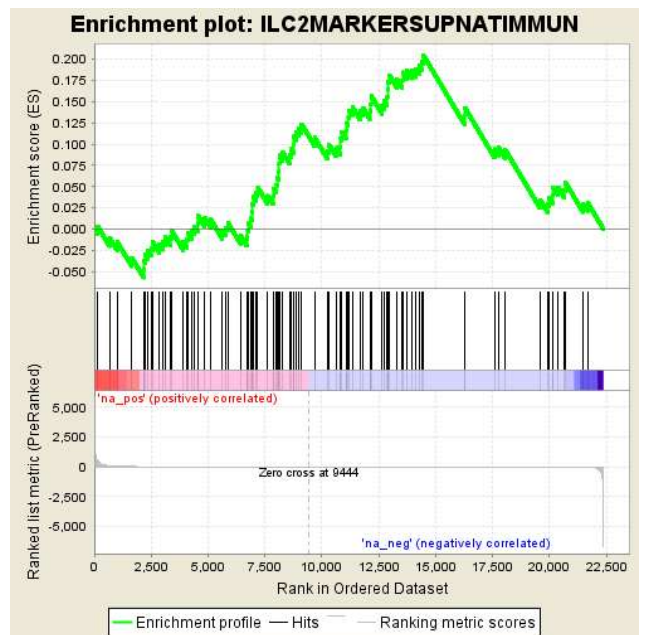


Figure S7. The ILC1 and ILC2 populations activity do not have significant changes in the HPD tumors after anti-PD-1 therapy. Related to Figure 7. (A) The ILC1 and (B) the ILC2 marker genes were not enriched in either the top up- or down-regulated genes in the HPD tumors.

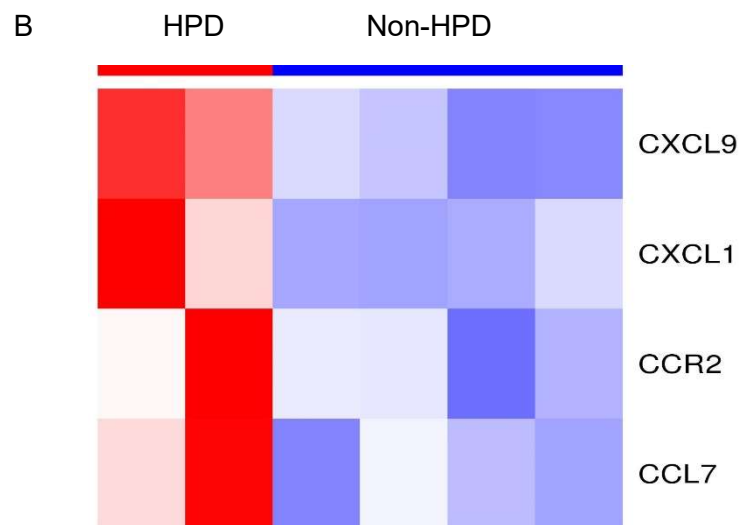
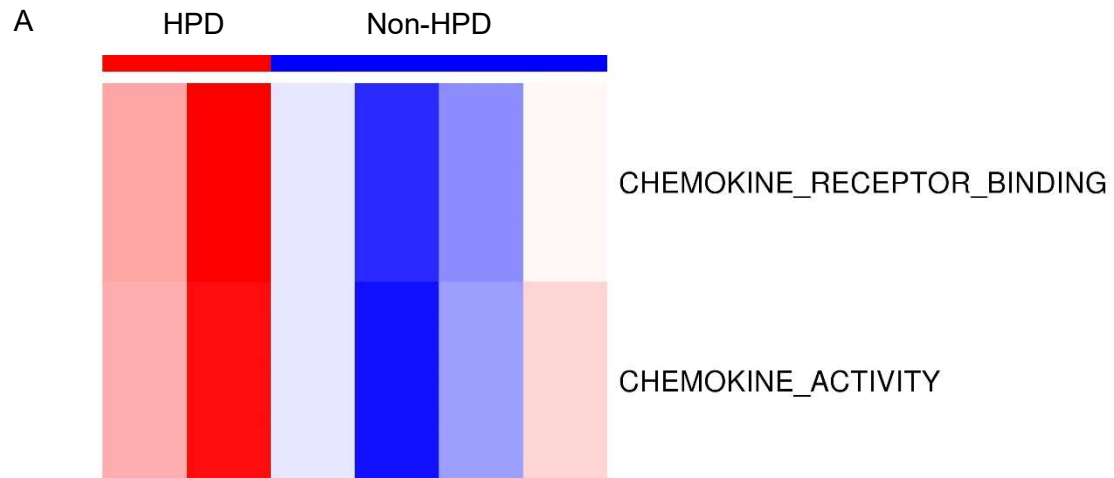
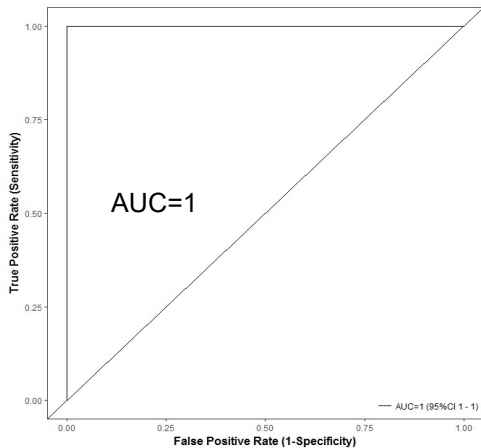


Figure S8. Pre- α -PD-1 therapy tumors of hyperprogressive patients have elevated inflammation pathway activity (mainly chemokine activity) compared to the responsive patients. Related to Figure 8. (A) GSEA identified the activation of two founder data sets of inflammation pathways in the pre-therapy tumors of HPD patients compared to the non-HPD patients; (B) The chemokine encoding genes that were up-regulated in the pre-therapy tumors of HPD patients compared to the non-HPD patients.

Performance of the 121-gene set in the discovery dataset (Dataset_1)



I) Clonal mutated genes:

AFF1, HIVEP1, NOTCH3, SATB1, TSC2, HSPG2, ARID2, SPP1, NFE2L2, CARD8, CYP2D6, VHL, OBSCN

II) Oncogenic pathways of IGF-1, ERK/MAPK, PI3K/AKT, TGF- β :

EP300, SMURF1, TLN1, YWHAQ, LAMTOR3, YWHAQ, PPM1L

III) Immune checkpoint:

TNFRSF25, KDR, CD96, CTLA4

IV) ILC3 population marker genes:

CLSTN3, SLC27A1, TSPAN3, TCF4, CORO1C, CD96, SORT1, TRIO, UBTF, GOLIM4, TLN1, CD63, FUCA2, ZFP36L1, SSBP2, OBFC1, GPR18, YWHAQ, ARMC9

V) Marker genes for other immune populations like monocytes, CD4 T cells and dendritic cells:

HIVEP2, NOTCH3, CD63, CARD8, GPR18, ATP5L, CCNA1, ANXA5, COL4A1, ARL1

VI) Differential expressed genes in post-anti-PD-1 HPD tumors vs pre-anti-PD-1 non-HPD tumors:

DGKD, FAM104B, TRIP12, EP300, CLSTN3, SLC27A1, GBF1, KLHDC8B, CPT1A, SMURF1, CAMSAP1, CSNK1G1, SLC25A34, GALNT10, TNKS2, PTPN3, ADAR

Figure S9. Results of the 121-gene expression signature in the discovery data set

(Dataset_1). Related to Figure 9. ROC curves was shown for separating HPD patients from non-HPD patients in the discovery data set (4 HPD vs 16 non-HPD patients, AUC=1). The majority of these genes (70 of 121) belonged to the gene sets that we identified as significant to different aspects of the HPD tumors in our samples. Specifically, these genes were classified into the following six categories.

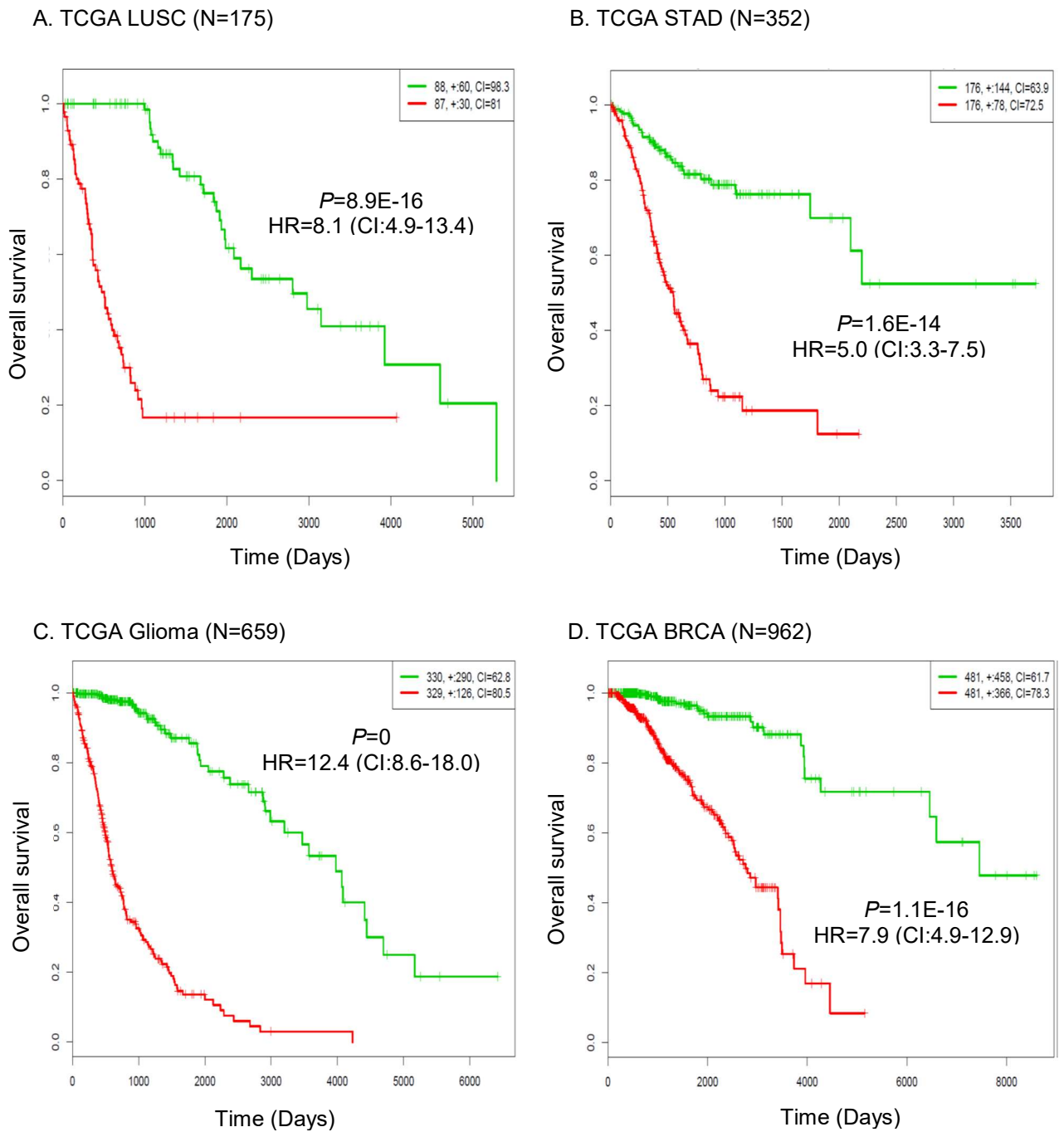
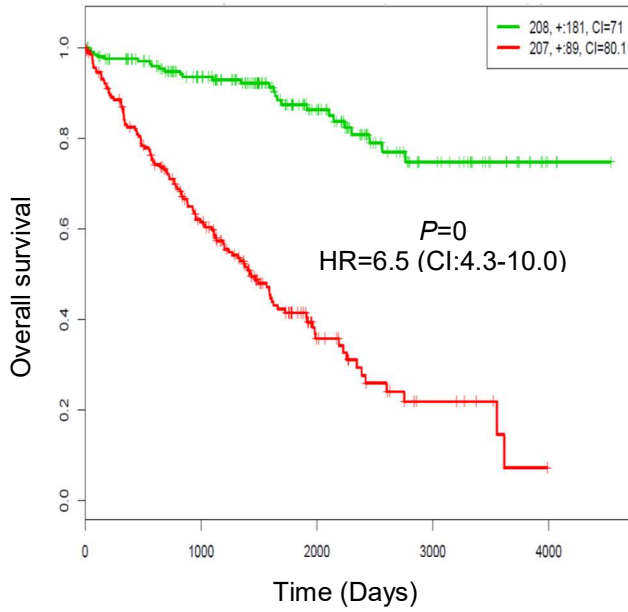
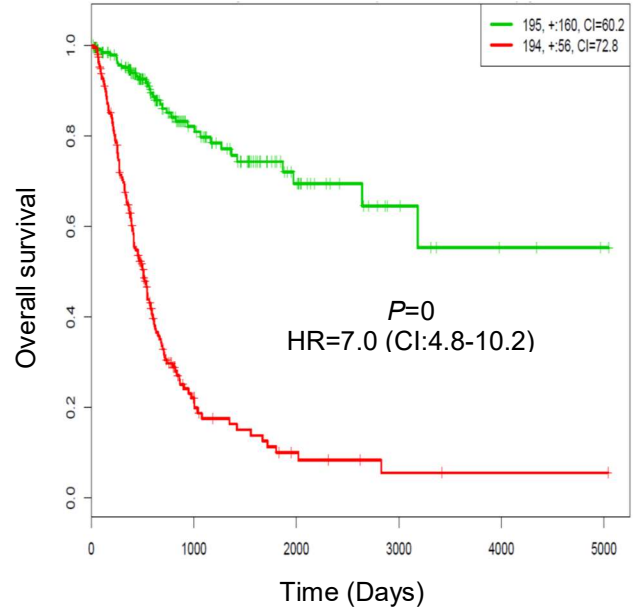


Figure S10. Kaplan–Meier analysis showed that the 121-gene set classifier can separate significantly low- and high-risk groups in the 13 major TCGA cancers. Related to Figure 9. The Kaplan–Meier curves of the TCGA cancer types of (A) LUSC, (B) STAD, (C) glioma, (D) BRCA were shown in this figure.

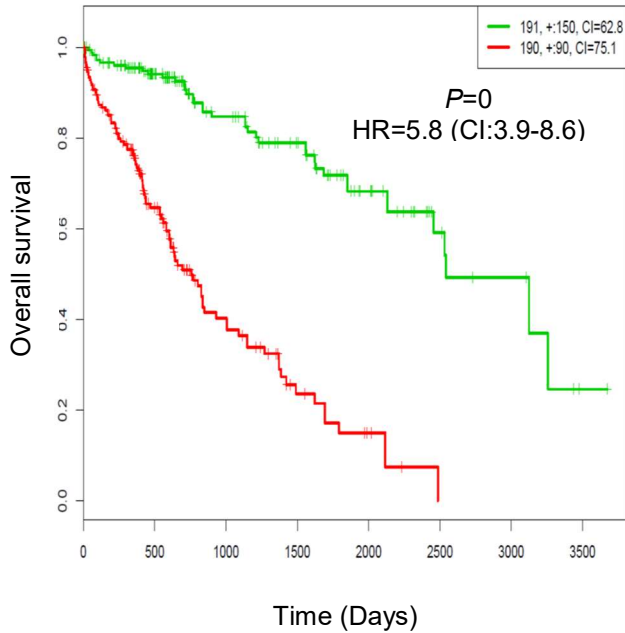
A. TCGA KIRC (N=415)



B. TCGA BLCA (N=389)



C. TCGA LIHC (N=381)



D. TCGA LUAD (N=475)

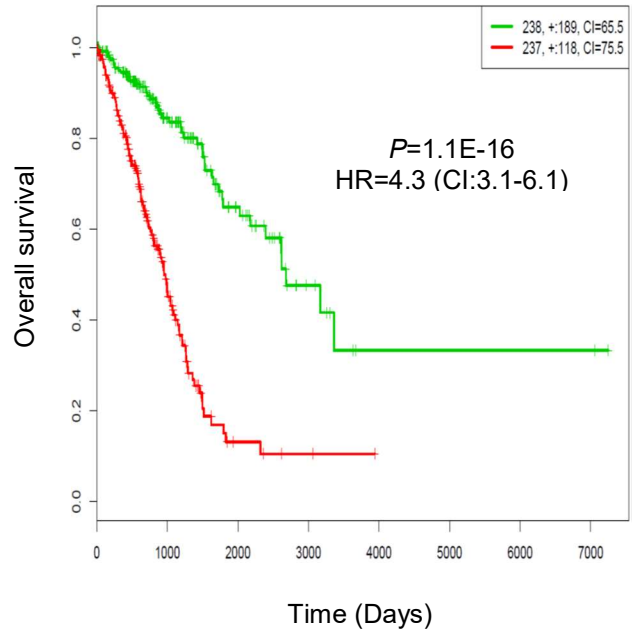
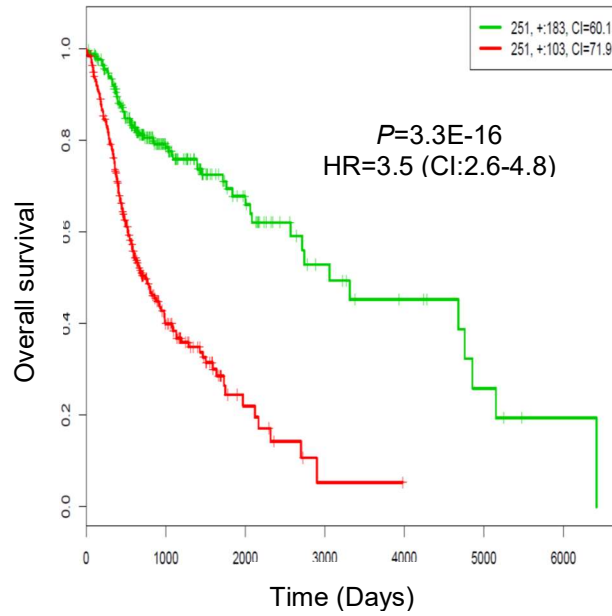


Figure S11. Kaplan–Meier analysis showed that the 121-gene set classifier can separate significantly low- and high-risk groups in the 13 major TCGA cancers. Related to Figure 9. The Kaplan–Meier curves of the TCGA cancer types of (A) KIRC, (B) BLCA, (C) LIHC, (D) LUAD were shown in this figure.

A. TCGA HNSC (N=502)



B. TCGA SKCM (N=335)

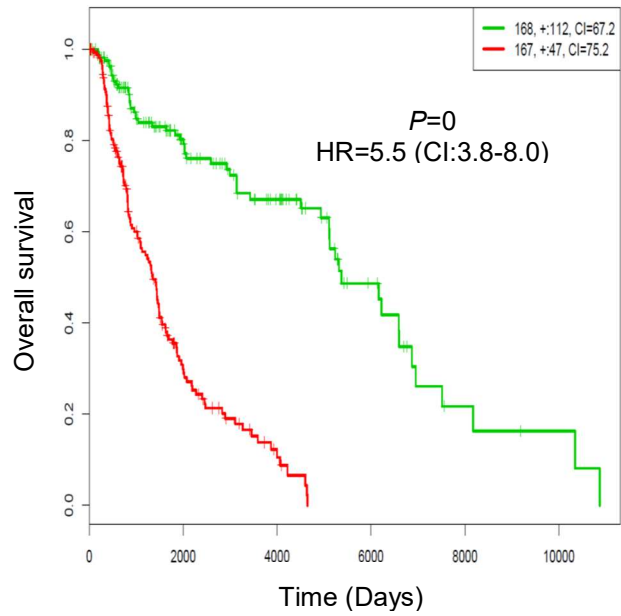


Figure S12. Kaplan–Meier analysis showed that the 121-gene set classifier can separate significantly low- and high-risk groups in the 13 major TCGA cancers. Related to Figure 9. The Kaplan–Meier curves of the TCGA cancer types of (A) HNSC, (B) SKCM were shown in this figure.

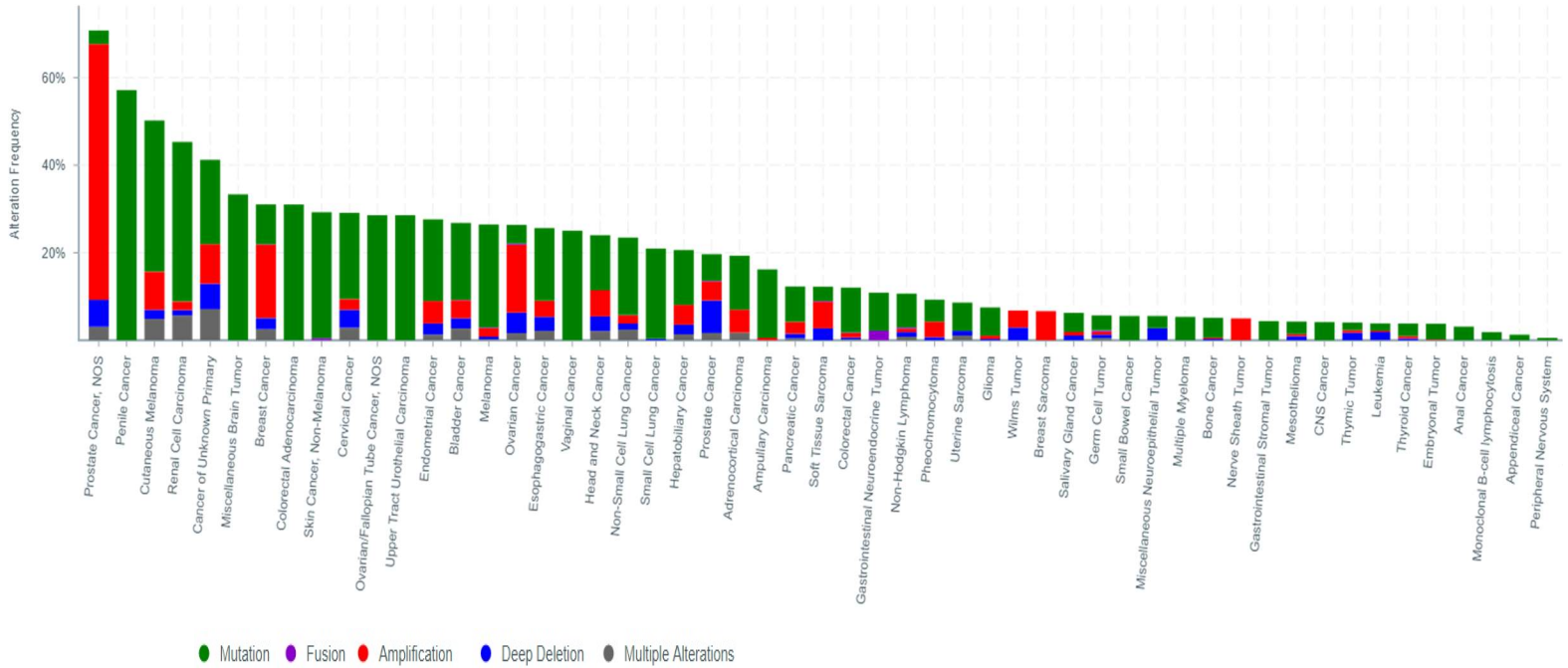


Figure S13. The mutation analysis highlighted eleven genes with deleterious mutations in the HPD tumors after anti-PD-1 therapy. Related to Table 2. Most of these genes have not been adequately studied in the cancer context before. Querying the HPD tumors associated 11-mutated-gene set in the cBioPortal website (<http://www.cbioportal.org/>) showed that this gene set had somatic mutations or copy number aberrations (CNAs) in 8887 (22%) of 41320 sequenced patients. The frequencies of tumor samples having somatic alterations in at least one of the eleven genes among each type of cancers archived in cBioPortal were shown in the figure.

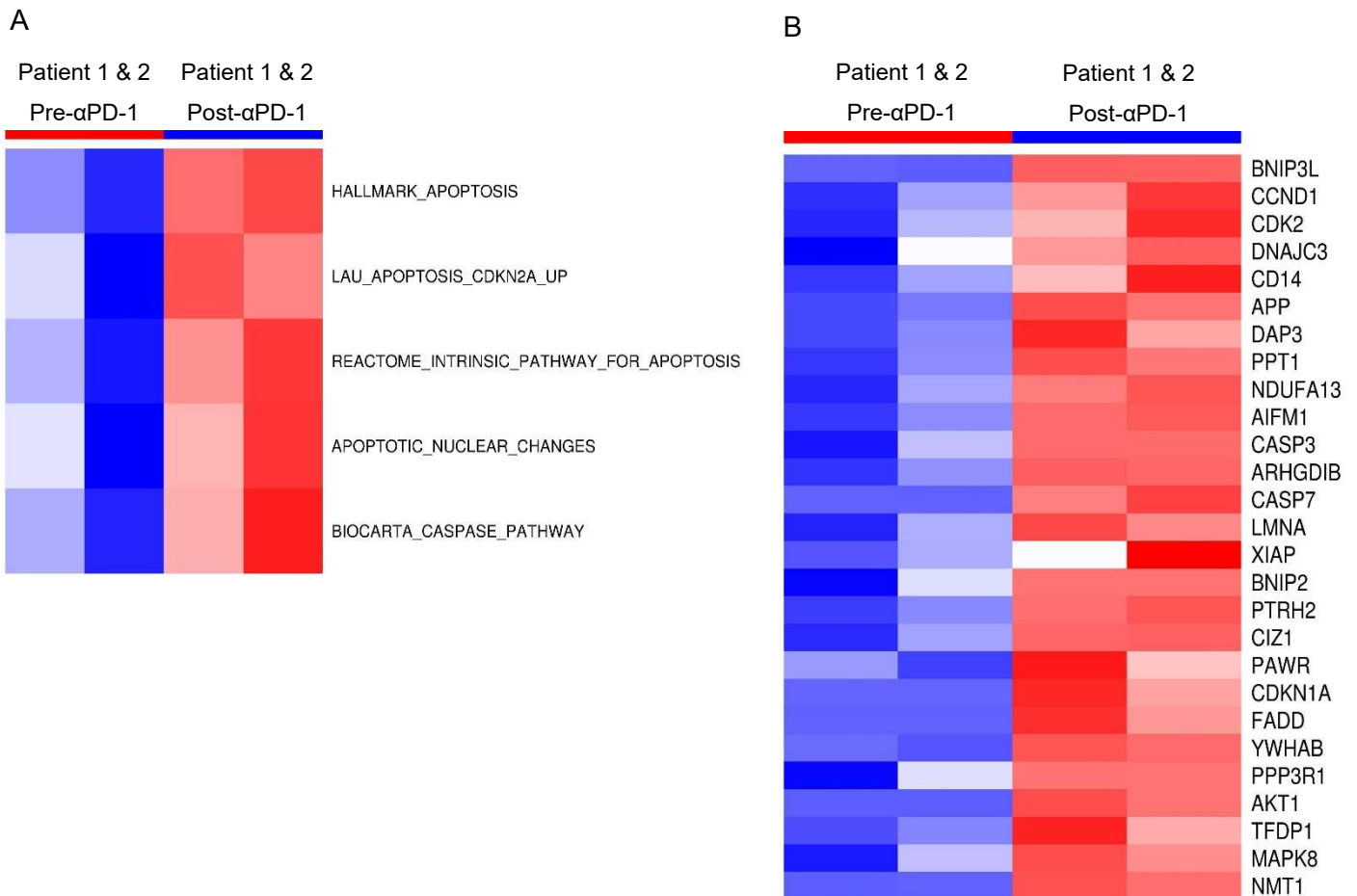


Figure S14. Changes of the apoptosis pathway activity in the after anti-PD-1 immunotherapy tumors of the HPD patients. Related to Figure 5 and Figure 6. (A) Five apoptosis gene sets were activated in the two patients after anti-PD-1 immunotherapy; (B) 27 apoptotic genes of these five apoptosis gene sets including marker genes in caspase/bcl2 pathways (CASP3, CASP7, BNIP2, BNIP3L) were significantly up-regulated.

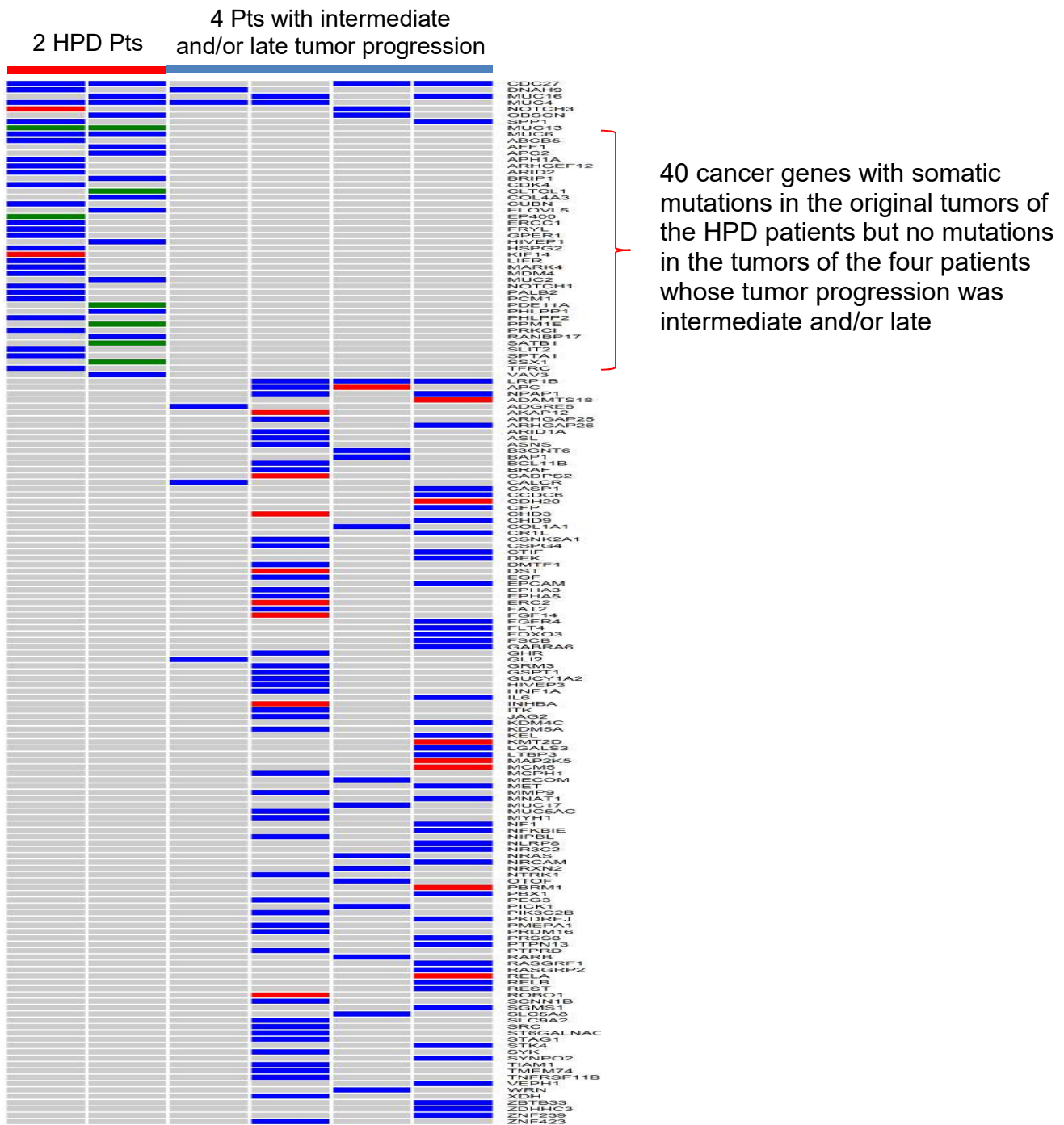


Figure S15. Comparison of the somatic mutation profiles of pretreatment tumor samples between HPD patients and a subset of non-HPD patients. Related to Figure 9. Mutation analysis showed that 40 cancer genes had somatic mutations in the original tumors of the HPD patients but no mutations in the tumors of the patients whose tumor progression was intermediate and/or late.

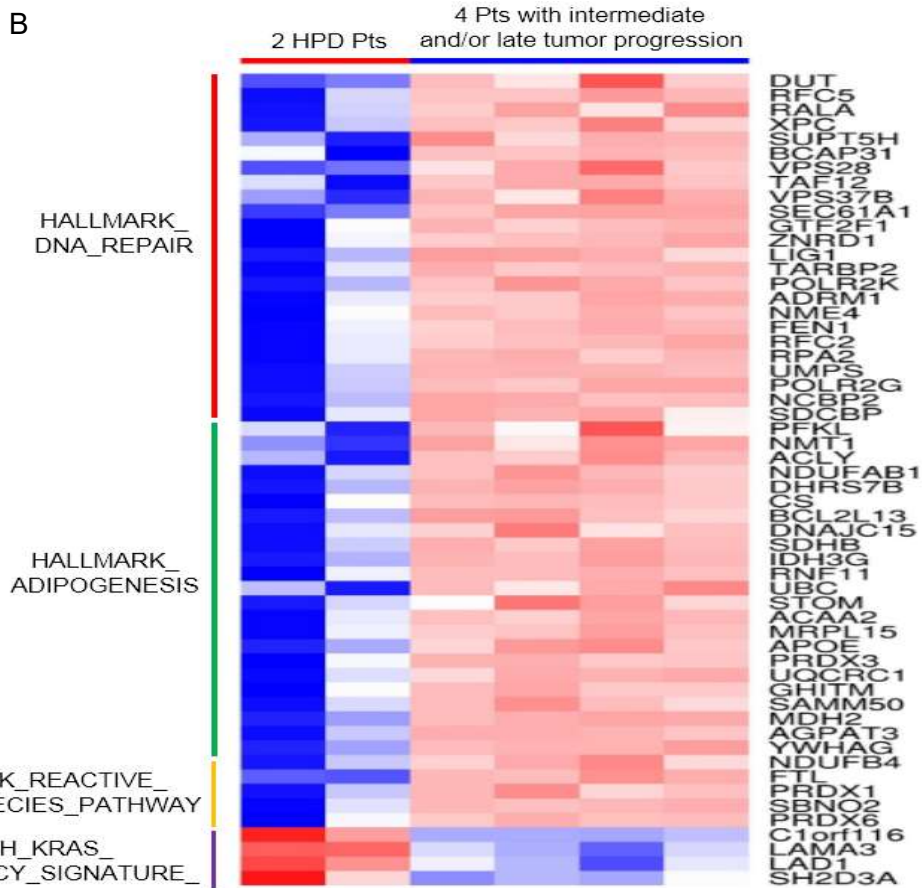
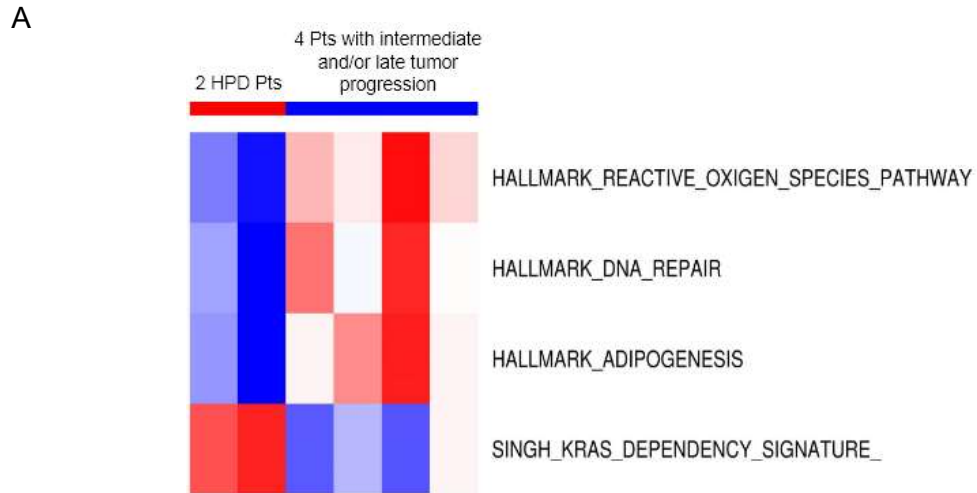


Figure S16. GSEA analysis of the transcriptional profiles of pretreatment tumor samples between HPD patients and a subset of non-HPD patients. Related to Figure 9. (A) Four gene sets were significantly altered in the tumors of HPD patients compared to the patients with intermediate and/or late tumor progression; (B) The corresponding gene expression changes of the above significantly altered pathways were also shown.

Table S1, Table S2, Table S3 were the supplemental Excel files.

Table S4. The clinical information of the eighteen follicular lymphoma patients from the GSE52562 study, among whom two patients had PFS less than two months together with advanced tumor progression phenotypes after anti-PD-1 treatment. Related to Figure 9.

ExpId	SampleID	gender	age	pfs.censorship	pfs.time.month	treatment	tissue	HPDstatus
GSM1269893	SAMPLE.25	F	67	1	1.8	pre-pidilizumab	tumor biopsy	HPD
GSM1269873	SAMPLE.5	F	79	1	2.0	pre-pidilizumab	tumor biopsy	HPD
GSM1269883	SAMPLE.15	M	46	1	3.7	pre-pidilizumab	tumor biopsy	nonHPD
GSM1269886	SAMPLE.18	M	69	0	4.1	pre-pidilizumab	tumor biopsy	nonHPD
GSM1269877	SAMPLE.9	F	58	1	6.5	pre-pidilizumab	tumor biopsy	nonHPD
GSM1269888	SAMPLE.20	F	56	0	7.1	pre-pidilizumab	tumor biopsy	nonHPD
GSM1269875	SAMPLE.7	M	60	1	10.1	pre-pidilizumab	tumor biopsy	nonHPD
GSM1269889	SAMPLE.21	F	62	1	12.7	pre-pidilizumab	tumor biopsy	nonHPD
GSM1269871	SAMPLE.3	M	51	1	13.5	pre-pidilizumab	tumor biopsy	nonHPD
GSM1269894	SAMPLE.26	M	58	1	15.3	pre-pidilizumab	tumor biopsy	nonHPD
GSM1269890	SAMPLE.22	M	70	1	18.6	pre-pidilizumab	tumor biopsy	nonHPD
GSM1269892	SAMPLE.24	M	63	0	18.8	pre-pidilizumab	tumor biopsy	nonHPD
GSM1269879	SAMPLE.11	M	67	1	19.6	pre-pidilizumab	tumor biopsy	nonHPD
GSM1269869	SAMPLE.1	F	61	1	21.6	pre-pidilizumab	tumor biopsy	nonHPD
GSM1269891	SAMPLE.23	F	37	0	26.5	pre-pidilizumab	tumor biopsy	nonHPD
GSM1269887	SAMPLE.19	F	41	0	30.4	pre-pidilizumab	tumor biopsy	nonHPD
GSM1269881	SAMPLE.13	M	58	0	30.8	pre-pidilizumab	tumor biopsy	nonHPD
GSM1269885	SAMPLE.17	F	45	0	35.0	pre-pidilizumab	tumor biopsy	nonHPD

Table S5. The information of the 121 genes in the expression signature of pre-anti-PD-1 treatment tumors that may be predictive of HPD (hyperprogressive disease) patients after anti-PD-1 immunotherapy. Related to Figure 9.

Gene Symbol	Entrez Gene Name	Location	Type(s)
AAK1	AP2 associated kinase 1	Cytoplasm	kinase
ACOT1	acyl-CoA thioesterase 1	Cytoplasm	enzyme
ACOT2	acyl-CoA thioesterase 2	Cytoplasm	enzyme
ADAR	adenosine deaminase, RNA specific	Nucleus	enzyme
AFF1	AF4/FMR2 family member 1	Nucleus	transcription regulator
ANKS6	ankyrin repeat and sterile alpha motif domain containing 6	Cytoplasm	other
ANXA5	annexin A5	Plasma Membrane	transporter
ARID2	AT-rich interaction domain 2	Nucleus	transcription regulator

ARL1	ADP ribosylation factor like GTPase 1	Cytoplasm	enzyme
ARMC9	armadillo repeat containing 9	Cytoplasm	other
ATF7IP	activating transcription factor 7 interacting protein	Nucleus	transcription regulator
ATP11C	ATPase phospholipid transporting 11C	Plasma Membrane	transporter
ATP5L	ATP synthase membrane subunit g	Cytoplasm	enzyme
BAZ1B	bromodomain adjacent to zinc finger domain 1B	Nucleus	transcription regulator
BAZ2A	bromodomain adjacent to zinc finger domain 2A	Nucleus	transcription regulator
C17orf97	chromosome 17 open reading frame 97	Other	other
CAMSAP1	calmodulin regulated spectrin associated protein 1	Cytoplasm	other
CARD8	caspase recruitment domain family member 8	Nucleus	other
CCNA1	cyclin A1	Nucleus	other
CCNT1	cyclin T1	Nucleus	transcription regulator
CD63	CD63 molecule	Plasma Membrane	other
CD96	CD96 molecule	Plasma Membrane	other
CHD4	chromodomain helicase DNA binding protein 4	Nucleus	enzyme
CLSTN3	calsyntenin 3	Plasma Membrane	other
COL4A1	collagen type IV alpha 1 chain	Extracellular Space	other
COL4A2	collagen type IV alpha 2 chain	Extracellular Space	other
COMMD9	COMM domain containing 9	Cytoplasm	other
CORO1C	coronin 1C	Cytoplasm	other
CPT1A	carnitine palmitoyltransferase 1A	Cytoplasm	enzyme
CREBZF	CREB/ATF bZIP transcription factor	Nucleus	transcription regulator
CSNK1G1	casein kinase 1 gamma 1	Cytoplasm	kinase
CTLA4	cytotoxic T-lymphocyte associated protein 4	Plasma Membrane	transmembrane receptor
CYP2D6	cytochrome P450 family 2 subfamily D member 6	Cytoplasm	enzyme
DGKD	diacylglycerol kinase delta	Cytoplasm	kinase
DIAPH1	diaphanous related formin 1	Plasma Membrane	other
EID2	EP300 interacting inhibitor of differentiation 2	Nucleus	other
ELK4	ELK4, ETS transcription factor	Nucleus	transcription regulator
EP300	E1A binding protein p300	Nucleus	transcription regulator
ERN1	endoplasmic reticulum to nucleus signaling 1	Cytoplasm	kinase
FAHD1	fumarylacetoacetate hydrolase domain containing 1	Cytoplasm	enzyme
FAM104B	family with sequence similarity 104 member B	Other	other
FBXL17	F-box and leucine rich repeat protein 17	Other	other

FPGT	fucose-1-phosphate guanylyltransferase	Cytoplasm	enzyme
FUBP3	far upstream element binding protein 3	Nucleus	transcription regulator
FUCA2	alpha-L-fucosidase 2	Extracellular Space	enzyme
GALNT10	polypeptide N-acetylgalactosaminyltransferase 10	Cytoplasm	enzyme
GALNT2	polypeptide N-acetylgalactosaminyltransferase 2	Cytoplasm	enzyme
GAPVD1	GTPase activating protein and VPS9 domains 1	Cytoplasm	other
GATAD2B	GATA zinc finger domain containing 2B	Nucleus	transcription regulator
GBF1	golgi brefeldin A resistant guanine nucleotide exchange factor 1	Cytoplasm	other
GOLIM4	golgi integral membrane protein 4	Cytoplasm	other
GPR18	G protein-coupled receptor 18	Plasma Membrane	G-protein coupled receptor
HADH	hydroxyacyl-CoA dehydrogenase	Cytoplasm	enzyme
HHLA3	HERV-H LTR-associating 3	Other	other
HIVEP1	human immunodeficiency virus type I enhancer binding protein 1	Nucleus	transcription regulator
HIVEP2	human immunodeficiency virus type I enhancer binding protein 2	Nucleus	transcription regulator
HMBS	hydroxymethylbilane synthase	Cytoplasm	enzyme
HPGDS	hematopoietic prostaglandin D synthase	Cytoplasm	enzyme
HSPG2	heparan sulfate proteoglycan 2	Extracellular Space	enzyme
KDM6B	lysine demethylase 6B	Extracellular Space	enzyme
KDR	kinase insert domain receptor	Plasma Membrane	kinase
KLHDC8B	kelch domain containing 8B	Cytoplasm	other
LAMTOR3	late endosomal/lysosomal adaptor, MAPK and MTOR activator 3	Cytoplasm	other
LGALS12	galectin 12	Extracellular Space	other
LNPEP	leucyl and cystinyl aminopeptidase	Cytoplasm	peptidase
LRP6	LDL receptor related protein 6	Plasma Membrane	transmembrane receptor
MAGEH1	MAGE family member H1	Cytoplasm	other
MEF2D	myocyte enhancer factor 2D	Nucleus	transcription regulator
MTIF3	mitochondrial translational initiation factor 3	Cytoplasm	translation regulator
NFE2L2	nuclear factor, erythroid 2 like 2	Nucleus	transcription regulator
NOTCH3	notch 3	Plasma Membrane	transcription regulator
NPLOC4	NPL4 homolog, ubiquitin recognition factor	Nucleus	other
NSD1	nuclear receptor binding SET domain protein 1	Nucleus	transcription regulator
NUP188	nucleoporin 188	Nucleus	other
OBSCN	obscurin, cytoskeletal calmodulin and titin-interacting RhoGEF	Cytoplasm	kinase
OTUD7B	OTU deubiquitinase 7B	Cytoplasm	peptidase

PAK2	p21 (RAC1) activated kinase 2	Cytoplasm	kinase
PCDHGB7	protocadherin gamma subfamily B, 7	Other	other
PHF8	PHD finger protein 8	Nucleus	enzyme
PPM1L	protein phosphatase, Mg ²⁺ /Mn ²⁺ dependent 1L	Cytoplasm	phosphatase
PPP2R3C	protein phosphatase 2 regulatory subunit B"gamma	Cytoplasm	other
PTPN3	protein tyrosine phosphatase, non-receptor type 3	Cytoplasm	phosphatase
PTS	6-pyruvoyltetrahydropterin synthase	Cytoplasm	enzyme
RANGAP1	Ran GTPase activating protein 1	Nucleus	other
SATB1	SATB homeobox 1	Nucleus	transcription regulator
SERPINF1	serpin family F member 1	Extracellular Space	other
SETX	senataxin	Nucleus	enzyme
SLC25A34	solute carrier family 25 member 34	Cytoplasm	other
SLC27A1	solute carrier family 27 member 1	Plasma Membrane	transporter
SLC38A6	solute carrier family 38 member 6	Plasma Membrane	transporter
SLC6A6	solute carrier family 6 member 6	Plasma Membrane	transporter
SMURF1	SMAD specific E3 ubiquitin protein ligase 1	Cytoplasm	enzyme
SNAPC4	small nuclear RNA activating complex polypeptide 4	Nucleus	transcription regulator
SORT1	sortilin 1	Plasma Membrane	G-protein coupled receptor
SPEN	spen family transcriptional repressor	Nucleus	transcription regulator
SPIN2A	spindlin family member 2A	Other	other
SPP1	secreted phosphoprotein 1	Extracellular Space	cytokine
SSBP2	single stranded DNA binding protein 2	Nucleus	transcription regulator
OBFC1	STN1, CST complex subunit	Nucleus	other
SYTL4	synaptotagmin like 4	Cytoplasm	transporter
TCF4	transcription factor 4	Nucleus	transcription regulator
TEX261	testis expressed 261	Extracellular Space	other
TGOLN2	trans-golgi network protein 2	Cytoplasm	other
TIMM8B	translocase of inner mitochondrial membrane 8 homolog B	Cytoplasm	transporter
TLN1	talin 1	Plasma Membrane	other
TMEM99	transmembrane protein 99	Other	other
TNFRSF25	TNF receptor superfamily member 25	Plasma Membrane	transmembrane receptor
TNKS2	tankyrase 2	Nucleus	enzyme
TRIO	trio Rho guanine nucleotide exchange factor	Cytoplasm	kinase
TRIP12	thyroid hormone receptor interactor 12	Cytoplasm	enzyme
TSC2	TSC complex subunit 2	Cytoplasm	other
TSPAN3	tetraspanin 3	Plasma Membrane	other

UBTF	upstream binding transcription factor, RNA polymerase I	Nucleus	transcription regulator
KIAA2018	upstream transcription factor family member 3	Other	other
VHL	von Hippel-Lindau tumor suppressor	Nucleus	transcription regulator
WDR44	WD repeat domain 44	Cytoplasm	other
YWHAE	tyrosine 3-monooxygenase/tryptophan 5-monooxygenase activation protein epsilon	Cytoplasm	other
YWHAQ	tyrosine 3-monooxygenase/tryptophan 5-monooxygenase activation protein theta	Cytoplasm	other
ZFP36L1	ZFP36 ring finger protein like 1	Nucleus	transcription regulator
ZNF609	zinc finger protein 609	Nucleus	other
ZNF878	zinc finger protein 878	Other	other

Table S6. The clinical information of the 51 melanoma patients subjected to nivolumab immunotherapy from the CA209-038 study, among whom 21 patients had PFS less than two months together with post-therapy tumor progression phenotypes. Related to Figure 9.

PatientID	Sample	SampleType	PFS Censorship	Clinical Phenotype	PFS (days)	HPD status
Pt103	Pt103_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	50	HPD
Pt106	Pt106_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	56	HPD
Pt11	Pt11_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	59	HPD
Pt17	Pt17_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	48	HPD
Pt1	Pt1_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	54	HPD
Pt24	Pt24_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	50	HPD
Pt27	Pt27_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	50	HPD
Pt29	Pt29_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	50	HPD
Pt31	Pt31_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	50	HPD
Pt39	Pt39_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	57	HPD
Pt46	Pt46_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	51	HPD
Pt47	Pt47_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	57	HPD
Pt52	Pt52_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	57	HPD
Pt5	Pt5_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	56	HPD
Pt62	Pt62_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	56	HPD
Pt66	Pt66_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	59	HPD
Pt78	Pt78_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	50	HPD
Pt84	Pt84_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	50	HPD
Pt85	Pt85_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	49	HPD
Pt8	Pt8_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	52	HPD
Pt90	Pt90_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	44	HPD
Pt101	Pt101_Pre	Pre-anti-PD-1 tumor	0	PARTIAL RESPONSE	612	nonHPD
Pt10	Pt10_Pre	Pre-anti-PD-1 tumor	0	STABLE DISEASE	119	nonHPD
Pt18	Pt18_Pre	Pre-anti-PD-1 tumor	0	NA	519	nonHPD
Pt23	Pt23_Pre	Pre-anti-PD-1 tumor	0	DEATH PRIOR TO DISEASE ASSESSMENT	52	nonHPD
Pt26	Pt26_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	294	nonHPD
Pt28	Pt28_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	61	nonHPD
Pt2	Pt2_Pre	Pre-anti-PD-1 tumor	1	STABLE DISEASE	115	nonHPD
Pt30	Pt30_Pre	Pre-anti-PD-1 tumor	0	PARTIAL RESPONSE	603	nonHPD
Pt34	Pt34_Pre	Pre-anti-PD-1 tumor	1	NA	834	nonHPD
Pt36	Pt36_Pre	Pre-anti-PD-1 tumor	1	NA	737	nonHPD
Pt37	Pt37_Pre	Pre-anti-PD-1 tumor	0	STABLE DISEASE	176	nonHPD
Pt38	Pt38_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	167	nonHPD
Pt3	Pt3_Pre	Pre-anti-PD-1 tumor	0	PARTIAL RESPONSE	583	nonHPD
Pt44	Pt44_Pre	Pre-anti-PD-1 tumor	0	PARTIAL RESPONSE	560	nonHPD
Pt48	Pt48_Pre	Pre-anti-PD-1 tumor	1	NA	1046	nonHPD
Pt49	Pt49_Pre	Pre-anti-PD-1 tumor	1	PARTIAL RESPONSE	827	nonHPD
Pt4	Pt4_Pre	Pre-anti-PD-1 tumor	0	STABLE DISEASE	175	nonHPD
Pt59	Pt59_Pre	Pre-anti-PD-1 tumor	0	STABLE DISEASE	111	nonHPD
Pt65	Pt65_Pre	Pre-anti-PD-1 tumor	1	STABLE DISEASE	280	nonHPD
Pt67	Pt67_Pre	Pre-anti-PD-1 tumor	0	STABLE DISEASE	281	nonHPD
Pt72	Pt72_Pre	Pre-anti-PD-1 tumor	0	PARTIAL RESPONSE	333	nonHPD
Pt76	Pt76_Pre	Pre-anti-PD-1 tumor	0	NA	10	nonHPD

Pt77	Pt77_Pre	Pre-anti-PD-1 tumor	0	STABLE DISEASE	163	nonHPD
Pt79	Pt79_Pre	Pre-anti-PD-1 tumor	0	STABLE DISEASE	171	nonHPD
Pt82	Pt82_Pre	Pre-anti-PD-1 tumor	0	STABLE DISEASE	220	nonHPD
Pt89	Pt89_Pre	Pre-anti-PD-1 tumor	0	STABLE DISEASE	219	nonHPD
Pt92	Pt92_Pre	Pre-anti-PD-1 tumor	0	STABLE DISEASE	190	nonHPD
Pt94	Pt94_Pre	Pre-anti-PD-1 tumor	1	COMPLETE RESPONSE	729	nonHPD
Pt98	Pt98_Pre	Pre-anti-PD-1 tumor	0	STABLE DISEASE	408	nonHPD
Pt9	Pt9_Pre	Pre-anti-PD-1 tumor	0	PROGRESSION	66	nonHPD

Table S7. The information of the 40 HPD associated cancer genes having nonsilent somatic mutations in the original tumors of the HPD patients but no mutations in the tumors of the patients whose tumor progression was intermediate and/or late. Related to Figure 9.

Symbol	Entrez Gene Name	Location	Type(s)
ABCB5	ATP binding cassette subfamily B member 5	Plasma Membrane	transporter
AFF1	AF4/FMR2 family member 1	Nucleus	transcription regulator
APC2	APC2, WNT signaling pathway regulator	Cytoplasm	enzyme
APH1A	aph-1 homolog A, gamma-secretase subunit	Cytoplasm	peptidase
ARHGEF12	Rho guanine nucleotide exchange factor 12	Cytoplasm	other
ARID2	AT-rich interaction domain 2	Nucleus	transcription regulator
BRIP1	BRCA1 interacting protein C-terminal helicase 1	Nucleus	enzyme
CDK4	cyclin dependent kinase 4	Nucleus	kinase
CLTCL1	clathrin heavy chain like 1	Plasma Membrane	other
COL4A3	collagen type IV alpha 3 chain	Extracellular Space	other
CUBN	cubilin	Plasma Membrane	transmembrane receptor
ELOVL5	ELOVL fatty acid elongase 5	Cytoplasm	enzyme
EP400	E1A binding protein p400	Nucleus	other
ERCC1	ERCC excision repair 1, endonuclease non-catalytic subunit	Nucleus	enzyme
FRYL	FRY like transcription coactivator	Other	other
GPER1	G protein-coupled estrogen receptor 1	Plasma Membrane	G-protein coupled receptor
HIVEP1	human immunodeficiency virus type 1 enhancer binding protein 1	Nucleus	transcription regulator
HSPG2	heparan sulfate proteoglycan 2	Extracellular Space	enzyme
KIF14	kinesin family member 14	Cytoplasm	enzyme
LIFR	LIF receptor alpha	Plasma Membrane	transmembrane receptor
MARK4	microtubule affinity regulating kinase 4	Cytoplasm	kinase
MDM4	MDM4, p53 regulator	Nucleus	enzyme
MUC13	mucin 13, cell surface associated	Extracellular Space	other
MUC2	mucin 2, oligomeric mucus/gel-forming	Extracellular Space	other
MUC6	mucin 6, oligomeric mucus/gel-forming	Extracellular Space	other
NOTCH1	notch 1	Plasma Membrane	transcription regulator
PALB2	partner and localizer of BRCA2	Nucleus	other
PCM1	pericentriolar material 1	Cytoplasm	other
PDE11A	phosphodiesterase 11A	Cytoplasm	enzyme
PHLPP1	PH domain and leucine rich repeat protein phosphatase 1	Cytoplasm	enzyme
PHLPP2	PH domain and leucine rich repeat protein phosphatase 2	Cytoplasm	enzyme
PPM1E	protein phosphatase, Mg ²⁺ /Mn ²⁺ dependent 1E	Nucleus	phosphatase
PRKCI	protein kinase C iota	Cytoplasm	kinase
RANBP17	RAN binding protein 17	Nucleus	transporter
SATB1	SATB homeobox 1	Nucleus	transcription regulator
SLIT2	slit guidance ligand 2	Extracellular Space	other
SPTA1	spectrin alpha, erythrocytic 1	Cytoplasm	other
SSX1	SSX family member 1	Nucleus	transcription regulator
TFRC	transferrin receptor	Plasma Membrane	transporter
VAV3	vav guanine nucleotide exchange factor 3	Extracellular Space	cytokine

Transparent Methods:

Whole-exome sequencing (WES) and RNA-seq experimentation and data analyses

For each set of paired tumor samples, a section of formalin-fixed tissue was examined with hematoxylin and eosin (H&E) staining to confirm the presence of tumor and determine the relative tumor burden. At least five 10-mm FFPE slides were used for each tumor specimen, from which DNA and RNA were purified by a commercial vendor (Omega Bio-tek, Inc., Norcross, GA 30071) and subjected to WES and RNA-seq after library purification. The Illumina Nextera Rapid Capture Exome kit was used for the preparation of exome libraries, which were sequenced to the average depth of 150 X coverage in the paired end 150 bp (PE150) mode with a HiSeq 4000 system. The Illumina TruSeq RNA Access kit was used for the preparation of total RNA libraries that were sequenced to the average depth of 75 million reads in the paired end 100 bp (PE100) mode using the HiSeq 2500 system.

The WES short reads were aligned to a reference genome (NCBI human genome assembly hg19) using the BWA (Burrows-Wheeler Aligner) program (Li and Durbin, 2009). Each alignment was assigned a mapping quality score by BWA (Li and Durbin, 2009), which generated a Phred-scaled probability that the alignment is correct. Reads with low mapping quality scores (< 5) were removed to reduce the false positive rate. The PCR duplicates were detected and removed using Picard software. Local realignment of the BWA-aligned reads was performed using the Genome Analysis Toolkit (GATK) (McKenna et al., 2010). VarScan 2 (Koboldt et al., 2012) was used to identify somatic variants based on the local realignment results comparing each tumor with the two reference blood samples. Default parameters in VarScan 2 were used. The lists of shared SNVs/indels were then annotated using ANNOVAR (Wang et al., 2010). Single nucleotide polymorphisms (SNPs) were filtered against dbSNP version 142 (dbSNP 142). Plots of mutations were generated using the “oncoPrint” function provided by the R package – ComplexHeatmap (Gu et al., 2016). To identify somatic mutations with the most significant functional consequences, we predicted the impact of the mutations on

HPD tumors using the bioinformatics programs SIFT, PolyPhen-2, and FATHMM according to our previous approaches (Xiong et al., 2015). Network analysis of the eleven genes having deleterious mutations in HPD tumors was performed and graphically depicted using Ingenuity Pathway Analysis software (IPA, QIAGEN Inc., <https://www.qiagenbioinformatics.com/products/ingenuitypathway-analysis>). Mapping of the p.Y1611S mutation to the 3D structure of the TSC2 protein was performed using MuPIT software (Niknafs et al., 2013). The bioinformatics tools SciClone (Miller et al., 2014) and Clonevol (Dang et al., 2017) were used to identify the clonal structures of the paired tumors of the two HPD patients. Plots of the clonal mutation clusters were generated using the fishplot software feature (Miller et al., 2016).

RNA-seq sample quality was analyzed using the FastQC program (<http://www.bioinformatics.babraham.ac.uk/projects/fastqc/>). Raw sequence data reads in fasta format were first processed through Perl scripts (Haas et al., 2013). Data were then refined by removing reads containing adapter, poly-N, or low-quality reads (Pei et al., 2016; Wang et al., 2015). All downstream analyses were based on refined data. The “rsem prepare reference” script of the RSEM package was used to generate reference transcript sequences by using the gene annotation file (GTF) format and the full genome sequence (FASTA) format of human GRCh37 assembly. All of the quality reads of different samples were mapped to generated reference transcript sequences using the Bowtie-2 program (Langmead et al., 2009) to determine the identity between cDNA sequences and corresponding genomic exons in regions of exact matches. The “rsem calculate expression” script of RSEM was used to analyze both the alignment of reads against reference transcript sequences and the calculation of relative abundances. Normalized gene expression values in TPM (Transcripts Per Kilobase Million) were used as input of the AltAnalyze software (Olsson et al., 2016) for differential gene expression analysis. FDR (False discovery rate) corrected *P*-values of less than 0.05 were used as criteria for significantly regulated genes.

To perform oncogenic pathway or network analysis, the list of differentially expressed genes between paired pre- and post-anti-PD-1 therapy tumors of the two patients was analyzed through the use of IPA. The GSVA (Gene Set Variation Analysis) (Hanzelmann et al., 2013) and GSEA (Gene Set Enrichment Analysis) (Subramanian et al., 2005) approaches were used to analyze the activity and enrichment of immune cell populations, respectively. GSEA analysis was performed for pre-ranked differentially expressed genes using the option 'GseaPreranked'. One thousand permutations were used to calculate significance. A gene set was considered to be significantly enriched in one of the two groups when the *P* value was lower than 0.05 and the FDR was lower than 0.25 for the corresponding gene set. For inflammatory pathway analysis, we performed a focused gene expression study by analyzing the changes of the inflammatory related genes included in the Hallmark gene set for inflammatory response named "HALLMARK_INFLAMMATORY_RESPONSE" downloaded from the MSigDB database (Liberzon et al., 2015; Liberzon et al., 2011). The GSVA approach (Hanzelmann et al., 2013) was used to characterize the activity of inflammation pathways in the post-anti-PD-1 treatment HPD tumors vs pre-treatment tumors. All heatmaps of gene expression were generated using the R package – heatmap3 (<https://cran.r-project.org/web/packages/heatmap3/>).

Tumor immunogenicity analysis

Immunogenicity of the pre-anti-PD-1 treatment tumors and post-treatment HPD tumors was analyzed using published criteria (Charoentong et al., 2017; Hakimi et al., 2016). The immunophenoscore (IPS) was calculated on an arbitrary 0–10 scale based on the sum of the weighted averaged Z score of the four categories shown in Figure 5 in accordance to the previous methods (Charoentong et al., 2017; Tappeiner et al., 2017). Briefly, the four categories include 20 single factors such as the presence of specific immune cell types along with the abundance of MHC molecules, or molecules known to act as immunoinhibitors or immunostimulators. For each determinant, a sample-wise Z score from gene expression data

was calculated. For the six cell types, an average Z score from the corresponding metagenes was calculated. The metagenes were defined previously as non-overlapping sets of genes that are representative for specific immune cell subpopulations and are not expressed in normal tissue (Charoentong et al., 2017). The detailed list of genes included in the metagenes were available from the same literature (Charoentong et al., 2017). The determinants were then divided into four categories—effector cells (activated CD4+ or CD8+ T cells and effector memory CD4+ T cells or CD8+ T cells), and suppressive cells (Tregs and MDSCs [myeloid-derived suppressor cells]), MHC-related molecules, and checkpoints or immunomodulators are color-coded in the outer part of the wheel (red: positive Z score, blue: negative Z score).

Development and validation of an HPD classifier based on gene expression data

Previously, no gene expression signature had been identified to predict which patients might develop HPD after receiving anti-PD-1 immunotherapy. To identify such predictors, we analyzed the publicly available gene expression data sets of the anti-PD-1 immunotherapy studies that may contain subsets of patients that acquired HPD. Similar to previous studies (Champiat et al., 2017; Kato et al., 2017; Saada-Bouزيد et al., 2017), we defined HPD as (1) progression at first restaging on therapy, (2) increase in tumor size > 50%, and (3) >2-fold increase in tumor growth rate (TGR). Based on these criteria, we identified two cohorts in these datasets that received anti-PD-1 treatment and contained patients that developed putative HPD. The first study (Accession # “GSE52562” in the GEO database) performed gene expression profiling of tumor biopsies before and after pidilizumab (a humanized anti-PD-1 monoclonal antibody, also called “CT-011”) therapy in patients with relapsed follicular lymphoma (Westin et al., 2014). Previously, it was suggested that binding to PD-1 was the main driver for pidilizumab’s activity. Recent analyses show that pidilizumab binds to a hypoglycosylated /nonglycosylated form of PD-1 that is present on a distinct subpopulation of exhausted T cells (Fried et al., 2018). Nevertheless, multiple studies have shown that pidilizumab can affect PD-1 function either through binding or

other mechanisms, so pidilizumab treatment is still considered as anti-PD-1 therapy (Abdin et al., 2018; Benson et al., 2010; Jelinek and Hajek, 2016; Mkrtychyan et al., 2011; Rosenblatt et al., 2011; Westin et al., 2014). Two of eighteen follicular lymphoma patients from this study had PFS less than two months after anti-PD-1 treatment. These two patients were classified as HPD patients, while the other sixteen were non-HPD patients (Table S4). To develop an HPD-associated gene expression signature, the pre-therapy tumor expression data of our two HPD patients were combined with the pre-treatment tumor expression data of the two HPD patients and sixteen non-HPD patients from the GSE52562 study. This was used as the HPD signature discovery dataset (called "Dataset_1"). Another study (quoted as "CA209-038") assessed transcriptome changes in tumors from the patients with advanced melanoma before and after nivolumab immunotherapy (Riaz et al., 2017). This CA209-038 study had 21 advanced melanoma patients having PFS < 2 months after anti-PD-1 immunotherapy. Therefore, these 21 patients were classified as the HPD patients while the other 31 patients were classified as non-HPD patients (Table S6). These 51 patients had pre-therapy gene expression data available, and this dataset was used as the validation dataset (called "Dataset_2").

Based on the genome-wide expression data of Dataset_1 and Dataset_2, we developed and validated a 121-gene classifier using the *cancerclass* R package (Budczies et al., 2014). The performance of the 121-gene set as a classifier was evaluated with the use of receiver-operating-characteristic curves, calculation of AUC (Hanley and McNeil, 1982), and estimates of sensitivity and specificity implemented in the *cancerclass* R package (Jan et al., 2014). This classification protocol starts with a feature selection step and continues with nearest-centroid classification. Fisher's exact test was used for categorical variables. All confidence intervals are reported as two-sided binomial 95% confidence intervals. Statistical analysis was performed with R software, version 3.2.3 (R Project for Statistical Computing). We also tested the prognostic performance of the 121-gene signature using gene expression data from the TCGA tumor samples in conjunction with the online biomarker validation tool and database –

SurvExpress (Aguirre-Gamboa et al., 2013). Specifically, Kaplan-Meier survival analyses were implemented to estimate the survival functions after the samples were classified into two risk groups according to their risk scores based on the 121-gene set. Differences in survival risk between the two risk groups were assessed using the Mantel-Haenszel log-rank test.

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