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### **Supplementary methods:**

#### **Clinical Data Collection**

 Donor and recipient data were collected at baseline. Donor information included age, race, gender, HLA genotype, cause of death, and graft status (i.e. SCD, ECD, or DCD). Recipient data included age, gender, race, cause of ESRD, HLA genotype, PRA, presence and type of anti-HLA antibodies, cross match status, cold ischemia time (CIT), delayed graft function (DGF), immunosuppression regimen, CMV status, HCV and HBV status, dialysis vintage, dialysis modality, transfusion history, pregnancy history, and previous transplants We have adhered to the STROBE checklist throughout the manuscript. The clinical data from 5 different clinical centers were deposited into a central clinical eRAP database developed at Mount Sinai.

### **Histopathology:**

 2 tissue cores were taken from each of the 3-month and 1 year protocol renal biopsies of the Genomics of Chronic Allograft Rejection (GoCAR) cohort. One core was processed for histology and the other core was processed for mRNA. When only one core could be obtained priority was given to mRNA at 3-months and to histology at 12-months. Renal biopsies were processed and read centrally. Formalin- fixed, paraffin-embedded sections were processed for histologic stains (hematoxylin and eosin, periodic acid Schiff, trichrome and Weigerts elastic stains). Immunohistochemistry for C4d was done on an automated stainer on paraffin sections stained with a rabbit polyclonal antibody (American Research Products, Inc.). All slides were scanned with a whole slide scanner (Aperio CS) and high-resolution digital images and archived in an image database.

 Biopsies were evaluated and scored separately by 2 renal pathologists, without knowledge of the 57 clinical data, using the Revised Banff 2007 Classification for Renal Allograft Pathology<sup>1</sup> (SIS reference). Where diagnoses were discordant, a meeting was held with a third pathologist for a consensus diagnosis.

 Scoring was done on the whole slide images for all cases. Scores were entered into a custom Filemaker Pro database that calculated the Banff categories and Chronic Allograft Damage Index (CADI). The CADI-score is a composite score that includes six histologic components – vascular intimal sclerosis (cv), tubular atrophy (ct), interstitial fibrosis (ci), interstitial inflammation (i), mesangial matrix increase (mm) 63 and glomerusclerosis (g). Each component is scored between 0 & 3, giving a maximum possible score of 18. CADI-scores in protocol biospies has been validated to directly correlate with outcomes by several 65 authors<sup>2-3</sup>.

 Definition of "protocol biopsy" is that the biopsy is performed for the study or as part of a standard protocol at a given site in which a biopsy is performed based on time post-transplant and not based on an increase in creatinine or change in clinical status.

 *Treatment of Censored data:* For analysis for histological outcomes, patients without 12-month biopsies were excluded from analysis. For analysis of functional outcomes or eGFR - we imputed a GFR of 10 ml/min for all death-censored graft losses. For analysis of graft survival via Kaplan-Meier, we censored patients whose follow up data became unavailable at respective time points, whereas patients who had "events" (ie graft-loss) were censored at the time of the event.

### **Microarray experiments**

 The graft biospies from 5 participating centers were sent to Mount Sinai and were stabilized with RNA-later(Qiagen, Inc). Total RNA was extracted from percutaneous graft biopsy samples obtained at 3 month after transplantation using All prep kit (QIAGEN-ALLprep kit, Valencia, CA USA) by one technician at Mount Sinai. RNA quality was assessed using Bioanalyzer 2100 (Agilent Technologies). Samples with an RNA Integrity Number greater than eight were used in subsequent microarray experiments. Affymetrix humanexon 1.0 ST arrays were used following standard protocol provided by 81 the manufacturer (Affymetrix Inc.). In brief, ENCORE amplification and labeling kit (NuGen, San Carlos, CA) was applied to the first batch of samples starting with approximately 100ng of total RNA to generate

 biotin-labeled RNA fragments for hybridization to the chip. For samples with a low RNA concentration, the Nugen Ovation PICO amplification kit (NuGen, San Carlos, CA) was applied. The chips were scanned using GeneChip Scanner 7G (Affymetrix Inc.). The Affymetrix genechip experiments were performed at Mount Sinai Microarray Core.

### **Microarray data processing**

 The intensity data of microrray experiments at the gene level were extracted and summarized 89 with the RMA algorithm<sup>4</sup>. Data quality was assessed using the Affymetrix Expression Console (Affymetrix Inc). The Affymetrix control probesets and probesets with a low intensity (less than 20% quantile among all the data points) across all samples were excluded from downstream analysis. Batch 92 effects were adjusted using the ComBat R package<sup>5</sup>.

# **Bioinformatic analyses**

 The workflow of bioinformatic analysis is depicted in Suppl. Fig 3. and the analysis was performed with statistical R packages. The goal of analyses was to derive a relatively robust set of genes (~10-20) that predicts the development of chronic graft nephropathy.

 *Identification of the graft transcriptional signature:* Spearman correlation analyses were performed on the 3-month graft gene expression data for 3-month graft CADI score (CADI-3) as well as 12-month CADI score (CADI-12). The correlation coefficient and the p-value for the relationship between the level of expression and CADI score were calculated for each gene. The slope of gene expression against the CADI score was also computed using a linear regression model. Genes with a p value of < 0.05 were selected. Two lists of genes with p<0.05 were generated corresponding to either the 3 month or 12 month CADI scores. Annotated functional and molecular mechanisms of these 2lists of genes were determined by Gene Ontology (GO) enrichment analysis based on Fisher-exact test. To investigate which immune 105 cell type genes are associated with CADI-3 or CADI-12, we downloaded the public expression data of various immune cell types (https://www.immgen.org/) and identified highly expressed genes for each immune cell type by the rank of gene expression across cell types. We then checked which immune cell types are correlated with CADI-3 or CADI-12 based on the enrichment of immune cell type genes.

 Alternatively, the gene expression dataset was analyzed to determine biological functions that are enriched in biopsies with higher CADI scores. To accomplish this, we applied Geneset Enrichment Analysis  $(GSEA)^{6-7}$  to the entire microarray dataset and determined gene functions that are enriched in samples with a high CADI score (CADI≥2) versus those with a low CADI score (CADI<2). Top GO terms associated with both the high and low CADI groups were determined, and compared to the results of GO enrichment analysis derived from the analyses of correlation between gene expression level and CADI score described above.

*Prediction analysis:*

 To derive a more significant and focused geneset from the large list of genes that have statistically significant association with CADI-3 or CADI-12 scores, we filtered the gene list by applying various statistical prediction models. First, the whole cohort of patients was randomly assigned to 2 groups in a 1:1 ratio. Spearman correlation analysis was applied to determine the genes with expressions levels that correlated with the severity of CADI score at 3 and 12 months. The 1:1 randomization was repeated 100 times and correlation analysis of gene expression with CADI score at 3 and 12 month was performed for each of the 100 iterations. We considered genes that occurred more than twice in the 100 iterations of randomization with a correlation at a P<0.05 with CADI in both groups as a focused geneset from which a minimal prediction set was identified for predicting kidney fibrosis. Genes that were exclusive to the CADI-12 focus geneset (i.e. genes not shared with the CADI-3 focus geneset) were derived and further filtered by correction for clinical confounders (donor age, living vs deceased donor, donor gender and race, cold ischemia time(CIT, minutes), induction therapy, anti HLA class I, and II antibodies) using multiple linear regression analysis, as well as exclusion of genes with a low median log2 intensity of less than 5.

 Finally, we performed iterative logistic model fitting (5000 iterations) in order to identify an optimal and minimal geneset for prediction of future kidney fibrosis. We started by randomly selecting 20 genes from the filtered CADI-12 focus geneset. The expression data of the 20-gene group was fitted into 134 Firth-type bias-reduced logistic regression model which panelizes the maximum likelihood in logistf 135 R package for prediction of high (CADI-12 > 2) and low (CADI-2) CADI-12. We used a CADI-12 cutoff 136 of  $\geq$  2.0 to derive our prediction geneset. The paper we referenced by Yilmaz<sup>2</sup> also evaluated protocol biopsies at 1 year and divided their biopsies into 3 groups <2, 2-3.9 and >4. Whilst a CADI score >4 had 138 the strongest association with graft loss, those with a CADI score of 2-3.9, were also associated with graft **loss** where as those with a score <2 did not. We selected a CADI-12 $\geq$ 2 based on this prior publication<sup>3</sup>. 140 The genes with significant association with high/low CADI-12 ( $p<0.05$ ) were identified from the regression model for each of the 20-gene group. The steps above were repeated 5000 times. Statistically significant genes (P<0.05) were identified from each iterative operation. The occurrence of significant genes from the 5000 iterations was calculated. Finally, the top 40 genes ranked by the number of occurrences were applied back to the penalized logistic regression model for high vs. low CADI-12 prediction. Statistically significant genes (P<0.05) using this model were considered the final optimal geneset. The AUC score and sensitivity and specificity were calculated from logistic regression model using the final optimal geneset. To investigate the overfitting issues of prediction of training set with the geneset, cross-validated prediction AUC was also calculated using a 3-fold cross-validation method. Briefly, the patients were randomly divided into 3 groups of equal size and equal number of high and low CADI-12 patients and the data for any 2groups were used as the training set with the third as the prediction set. The penalized logistic regression model that was built on the training set was applied on the prediction set to predict the outcome and the true and false positive rates. Prediction accuracy was calculated from the prediction data set and then averaged from three possible permutations. We repeated the steps over 100 times. The overall true or false positive rates and prediction accuracy were computed. The distribution of AUCs on the testing set based on the model derived using the training set for 100 iterations was plotted.

 To assess if the geneset we identified was an optimal geneset for high/low CADI-12 prediction, we compared the original prediction AUC with prediction AUCs from the genesets that were identified from high/low CADI-12 groups after 2000-time random re-shuffling of CADI-12 scores. Briefly, CADI-12 scores were randomly re-assigned to the patients, the prediction geneset from re-shuffled high/low

161 CAD-12 groups was identified in the same approach as for original CADI-12 groups and the AUC was therefore calculated. These steps were repeated 2000 times and the original AUC was compared to the 163 1000 AUCs from randomly-assigned CADI-12 groups.

164 Our geneset identification and prediction approach was further fully cross-validated with leave- one-out cross-validation algorithm. Briefly, we took one patient as validation set and the remaining patients as training set and identified new geneset from training set in the same approach as for original cohort. The logistic model built on training set with new geneset was then applied to the patient that was 168 left out and the prediction probability was calculated. These steps were repeated in all the possible ways 169 of selecting training and testing sets and ROC curve was drawn based on the probabilities of testing sets 170 from all iterations.

171 Prediction of high/low CADI-12 at a different threshold (high CADI-12≥3 or high CADI-12 ≥4) was also performed to assess the robustness of 13 geneset prediction. To check if the inflammation was 173 the driver of the 13 geneset, we evaluated the prediction of Banff criteria (Ci+Ct scores), IFTA and high 174 CADI-12 on the patients without acute rejection. Lastly we investigated if the geneset can predict the 175 kidney function and we calculated prediction AUC of eGFR at 12 month or 24 month with geneset.

 To investigate whether prediction by the geneset is superior to prediction by clinical variables, we performed the multivariate logistic regression for prediction of high/low CADI-12 by including the following demographic/clinical variables: donor age, recipient race and gender, deceased donor status, extended-criteria donor kidney, cold ischemia time (CIT, minutes), induction therapy, presence of Anti-**HLA** antibodies, delayed graft function and HLA mismatch. After step-wise selection, the variables that remained significant were used in final model. The AUC for the ROC curve of the final model was then calculated and compared to CADI-12 prediction with the geneset.

 We also applied our optimal geneset to predict the progressors and non-progressors using the same approach described above. Patients who had CADI-3≤3 and demonstrated a ∆CADI≥2 by 12 month were considered as progressors, and those who had ∆CADI ≤1 were considered non-progressors. A

 similar assessments were done for those with CADI score at 24 months and also for the patients with CADI-3≤2.

 To test if our geneset could predict early graft loss post-transplant for the original 159 patients, we applied logistic regression prediction model with our geneset among only those patients who either had graft loss within 3yr or had been followed-up for at least three years without graft loss and calculated the AUC. Secondly, survival analysis on all 159 patients was performed to examine if our geneset was associated with graft loss: to assess the association of the whole geneset with clinical outcome, the major principle components of the expression data of the geneset rather than individual genes can be used to fit an association statistic model along with clinical parameters, especially in the case where the geneset 195 contains many genes<sup>10-11</sup>. In this study, we initially performed Principle Components Analysis (PCA) on expression data for the 13 genes and the top 10 principle components (PC) were applied to Cox proportional hazard model of time to graft loss. The principle components (PC) that were significantly 198 associated with graft loss were selected  $(p<0.05)$  and the linear combination of eigenvalues of significant components multiplied by the coefficiencies of corresponding PCs from Cox model was used as the geneset risk score (GR-score). The patients were then stratified into 2populations based on geneset risk score (GR-score) for Kaplan-Meier survival analysis. Finally the time-dependent ROC for graft loss prediction within 2 or 3 yrs post-transplant was plotted and the AUCs calculated. The demographic and clinical variables, including 3-month estimated glomerular filtration rate (m3\_eGFR), acute cellular rejection at- or before 3-months (pre\_or\_m3\_ACR), CADI-3, cold ischemia time (CIT, minutes), deceased donor status, the presence of Anti-HLA antibodies, induction therapy, recipient race,donor age, 206 delayed graft function and HLA mismatch were also fitted in Cox proportional hazard model of time to graft loss to investigate if the demographic or clinical variables were associated with graft loss.

#### **Validation of Geneset:**

 We also validated our final optimal geneset on 2independent public datasets. Both public datasets 211 were on the Affymetrix GeneChip platform HU430plus2 (GSE21374<sup>12</sup>, GSE25902<sup>13</sup>). The raw data of 212 these public datasets were processed separately in Affymetrix Expression Console using the RMA normalization approach. The expression data for each of the genes in our final optimal geneset was extracted and a prediction model with the geneset was built on each individual dataset. Predictions of clinical data (graft loss post biopsy at any time for GSE21374, and progressor/non-progressor based on CADI score for GSE25902) was performed using the penalized logistic regression model. AUC scores for each of these 2 datasets were calculated from the ROC curves for prediction specificity over sensitivity. 218 We also performed time to graft loss analysis on dataset1 (GSE21374) using the same approach as that 219 for GOCAR dataset.

## **qPCR experiments**

222 Total RNA was extracted from graft biopsy samples of 45 independent GOCAR patients (N=18: 223 CADI-12  $\geq$ 2, and N=27:CADI-12 <2) using Allprep kit (QIAGEN-ALLprep kit, Valencia, CA USA). cDNA was synthesized using AffinityScript RT kit with oligo DT primers (Agilent Inc. Santa Clara, CA). TaqMan qPCR assays for the 13 geneset, 2 house-keeping genes (ACTB, GAPDH) and 18s were purchased from ABI Life Technology (Grand Island, NY). qPCR experiments were performed on cDNA using TAQMAN universal mix and PCR reaction was monitored and acquired using an ABI7900HT system. Samples were measured in triplicates. Cycle Times (CT)values for the prediction geneset as well as the 3 housing genes were generated. The ∆CT value of each gene was calculated by subtracting the average CT value for the house-keeping genes from the CT value of each gene and penalized logistic regression fitting model was then applied on ∆CT values for prediction of the high and low CADI-12 in 232 45 patients and AUC score was then calculated as described above.

## 235 **Supplementary results**

#### 236 **Intragraft molecular phenotype is time dependent.**

237 Gene expression profiles from m3 biopsies were analyzed by correlation analysis and Geneset 238 Enrichment Analysis (GSEA) to understand molecular mechanisms of IF/TA (Figure S2) (n=159). We 239 identified 1127 genes significantly correlated with CADI-3 (716 positively and 411 negatively) and 1,143 240 genes with CADI-12 (914 positively and 229 negatively) at a cutoff unadjusted  $p \le 0.05$ , (Figure S3a, S3b) 241 and S3c). Only 230 genes (20.4%) correlated with both CADI-3 and CADI-12 (Figure S3a). Gene 242 Ontology enrichment indicated that the transcripts specifically associated with CADI-3 alone were related 243 to alloimmunity, including T-cell activation; while genes involved in programmed cell death/apoptosis 244 and cell adhesion were associated with CADI-12 alone (Figure S4a). By enrichment analysis of immune 245 cell type genes, we observed that dendritic cell genes were specifically associated with CADI-3; however 246 stromal cell genes (mostly fibroblast cells) were the most significantly associated with CADI-12 in 247 addition to macrophage, dentritic and CD4 T cell related genes (Figure S4b). Biological functions were 248 further confirmed by GSEA method in which gene expression data in GO categories were compared 249 between patients with high  $(\geq 2)$  and low  $(\leq 2)$  CADI at 3- or 12-months (Figure S5).

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Figure S1









# Figure S3b







# Figure s4b















a)

Figure S6





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False Positive Rate





c)





Figure S9

a) b)









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Figure S10





# Figure S11





**Table S1** : Baseline clinical and demographic characteristics for GoCAR patient cohorts.

\*P-value by Unpaired T-test (or non-parametric) and, Chi-square/Fisher's exact test. \*\* 97/101 & 38/45 patients had HLA antibodies measured.

**Table S2:** The 84 focus geneset

ProbelD		<b>Gene Symbc Gene Description</b>		Cytoband mRNA Accessic CADI Corr Pvalue		
3040518 MACC1		metastasis associated in colon cancer 1	7p21.1	NM_182762	0.411	1.95E-05
	3954887 CHCHD10	coiled-coil-helix-coiled-coil-helix domain containing 10	22q11.23	NM 213720	0.404	2.85E-05
3464860 DUSP6		dual specificity phosphatase 6		12q22-q23 NM_001946	0.391	5.20E-05
2761842 PROM1		prominin 1	4p15.32	NM_001145841	0.380	9.03E-05
	2721959 SLC34A2	solute carrier family 34 (sodium phosphate), member 2		4p15.3-p15NM 001177999	0.375	1.11E-04
3596147 GCNT3		glucosaminyl (N-acetyl) transferase 3, mucin type	15q21.3	NM_004751	0.373	1.22E-04
3796620 DLGAP1		discs, large (Drosophila) homolog-associated protein 1	18p11.3	NM_004746	0.369	1.44E-04
4019160 KLHL13		kelch-like 13 (Drosophila)	Xq23-q24	NM 001168302	0.369	1.49E-04
3326826 FJX1		four jointed box 1 (Drosophila)	11p13	NM_014344	0.367	1.60E-04
2868265 LIX1		Lix1 homolog (chicken)	5q15	NM 153234	0.359	2.29E-04
3020192 TES		testis derived transcript (3 LIM domains)	7q31.2	NM_015641	0.357	2.51E-04
3020343 MET		met proto-oncogene (hepatocyte growth factor receptor)	7q31	NM_001127500	0.352	3.01E-04
2583465 ITGB6		integrin, beta 6	2q24.2	NM 000888	0.352	3.09E-04
3129065 CLU		clusterin	8p21-p12	NM_001831	0.349	3.46E-04
2344888 CYR61		cysteine-rich, angiogenic inducer, 61	1p31-p22	NM_001554	0.342	4.60E-04
	3167110 ANXA2P2	annexin A2 pseudogene 2	9p13	NR_003573	0.340	5.02E-04
2602770 DNER		delta/notch-like EGF repeat containing	2q36.3	NM_139072	0.340	5.02E-04
2825629 TNFAIP8		tumor necrosis factor, alpha-induced protein 8	5q23.1	NM 014350	0.338	5.45E-04
2974413 MOXD1		monooxygenase, DBH-like 1		6q23.1-q23NM_015529	0.328	8.11E-04
2864449 SERINC5		serine incorporator 5	5q14.1	NM_001174072	0.318	0.0012
	3108489 LAPTM4B	lysosomal protein transmembrane 4 beta	8q22.1	NM_018407	0.318	0.0012
3024025 MEST		mesoderm specific transcript homolog (mouse)	7q32	NM_002402	0.304	0.0020
	3662041 OGFOD1	2-oxoglutarate and iron-dependent oxygenase domain containing 1 16q12.2		NM_018233	0.303	0.0021
	3605395 ADAMTSL3	ADAMTS-like 3	15q25.2	NM 207517	0.300	0.0023
2876361 PITX1		paired-like homeodomain 1	5q31	NM 002653	0.294	0.0028
3224087 TTLL11		tubulin tyrosine ligase-like family, member 11	9q33.2	NM_001139442	0.287	0.0036
3872335 ZNF416		zinc finger protein 416	19q13.4	NM_017879	0.287	0.0037
	3332913 TMEM216	transmembrane protein 216	11q13.1	NM_016499	0.286	0.0037
3888383 SLC9A8		solute carrier family 9 (sodium/hydrogen exchanger), member 8	20q13.13	NM 015266	0.286	0.0037
2669979 CX3CR1		chemokine (C-X3-C motif) receptor 1		3p21 3p21 NM_001171171	0.284	0.0040
	2486927 ARHGAP25	Rho GTPase activating protein 25	2p13.3	NM_014882	0.284	0.0040
2435218 TDRKH		tudor and KH domain containing	1q21	NM 00108396!	0.283	0.0041







Table S3a: Multivariate analysis of high CADI-12 prediction with clinical/pathological variables only

\*N=83 patients have complete demographic, clinical and pathological data

Table S3b: Multivariate analysis of high CADI-12 prediction with clinical/ pathological variables and the geneset



\*N=83 patients have complete demographic, clinical and pathological data

	3-month			12-month			
Parameter	Progressors	Non-Progressors	*p-value	Progressors	Non-Progressors	*p-value	
	Mean±SD	Mean±SD		Mean±SD	Mean±SD		
<b>CADI</b>	$1.36 \pm 1.28$	$1.07 \pm 1.06$	0.45	$5.50 \pm 2.56$	$1.25 \pm 1.17$	< 0.0001	
ct-score	$0.38 \pm 0.50$	$0.46 \pm 0.50$	0.75	$1.71 \pm 0.91$	$0.56 \pm 0.50$	< 0.0001	
cv-score	$0.22 \pm 0.67$	$0.22 \pm 0.59$	0.95	$0.91 \pm 1.09$	$0.19 \pm 0.55$	0.0025	
ci-score	$0.15 \pm 0.38$	$0.15 \pm 0.41$	0.99	$1.93 \pm 1.07$	$0.21 \pm 0.45$	< 0.0001	
i-score	$0.07 \pm 0.27$	$0.02 \pm 0.14$	0.36	$0.35 \pm 0.74$	$0.07 \pm 0.43$	0.0439	
mm-score	$0.0 + 0.0$	$0.02 \pm 0.1$	0.99	$0.14 \pm 0.53$	$0.04 \pm 0.28$	0.39	
g-score	$0.45 \pm 0.82$	$0.17 \pm 0.61$	0.09	$0.35 \pm 0.74$	$0.08 \pm 0.44$	0.0478	

**Table S4:** CADI subscore comparisons between 12-month progressors/non-progressors

\*Mann-Whitney test

Terms	<b>OR</b>		lower	upper	pvalue
Donor_Age		1.020	$-0.025$	0.073	0.3869
Race:Caucasian vs Non-					
Caucasian		2.686	$-0.698$	2.860	0.2477
Gender		0.421	$-2.607$	0.708	0.2797
Deceased_donor		4.036	$-0.609$	3.910	0.1791
ECD_kidney		0.188	$-5.168$	1.446	0.2938
$CIT$ <sub>_</sub> min		1.001	$-0.001$	0.004	0.3131
Induction_Therapy		0.983	$-1.658$	1.761	0.9833
Anti HLA Ab		0.245	$-3.581$	0.358	0.1227
Delayed_Graft_Function		0.217	$-4.557$	0.878	0.2236
HLA Mismatch		0.992	$-0.508$	0.463	0.9731
m3_eGFR		0.951	$-0.116$	$-0.002$	0.0425
pre_or_m3_ACR		5.795	0.118	3.691	0.0353
m <sub>3_CADI</sub>		0.626	$-1.346$	0.244	0.2040

**Table S5a: Multivariate analysis of m12 progressor prediction with clinical parameters and geneset**

\*N=63 patients have complete demographic, clinical and pathological data

# **Table S5b: Multivariate analysis of m12 progressor prediction with clinical parameters and geneset**



\*N=63 patients have complete demographic, clinical and pathological data

<b>Terms</b>	<b>OR</b>	lower	upper	pvalue
Donor_Age		0.993 $-0.057$	0.042	0.7850
Race:Caucasian vs Non-				
Caucasian		0.525 $-2.106$	0.740	0.3601
Gender		1.315 $-1.050$	1.642	0.6826
Deceased_donor		0.606 $-3.013$	1.872	0.6784
ECD_kidney		0.649 $-4.509$	2.914	0.8043
$CIT$ <sub>_</sub> min		1.000 $-0.002$	0.003	0.6818
Induction_Therapy		$-2.256$ 0.441	0.541	0.2389
Anti HLA Ab		1.186 $-1.493$	1.783	0.8340
Delayed_Graft_Function		$-1.780$ 2.057	3.125	0.5504
HLA Mismatch		$-0.304$ 1.086	0.498	0.6746
m3_eGFR		0.980 $-0.068$	0.021	0.3413
pre_or_m3_ACR		2.062 $-0.795$	2.260	0.3428
m3_CADI		1.058 $-1.033$	1.146	0.9179

**Table S5c: Multivariate analysis of m24 progressor prediction with clinical parameters and geneset**

\*N=50 patients have complete demographic, clinical and pathological data





\*N=50 patients have complete demographic, clinical and pathological data

	coef	$exp($ coef $)$	se(coef)	z	р	
PC <sub>1</sub>	$-5.592$	3.73E-03	29.95	$-0.1867$	0.8500	
PC <sub>2</sub>	$-7.413$	6.03E-04	6.37	$-1.1642$	0.2400	
PC <sub>3</sub>	$-2.874$	5.65E-02	8.23	$-0.3494$	0.7300	
PC4	$-14.75$	3.93E-07	5	$-2.9512$	0.0032	$\ast$
PC <sub>5</sub>	0.783	2.19E+00	4.02	0.1948	0.8500	
PC <sub>6</sub>	13.701	8.92E+05	5.45	2.5141	0.0120	$\ast$
PC <sub>7</sub>	6.738	8.44E+02	4.11	1.6389	0.1000	
PC <sub>8</sub>	0.224	$1.25E + 00$	3.72	0.0601	0.9500	
PC <sub>9</sub>	$-0.749$	4.73E-01	4.95	$-0.1513$	0.8800	
<b>PC10</b>	4.418	8.29E+01	4.07	1.0853	0.2800	

**Table S6:** Association of 10 principle components of 13 geneset with graft loss in Cox proportional hazard model

Likelihood ratio test=20.1 on 10 df, p=0.0287 n= 159, number of events= 11



Table S7: Association of demographic or clinical variables with graft loss in Cox proportional hazard mode

Anti\_HLA\_Ab : Yes (donor specific antigen or non dsa antibody), No : no antibody

Induction type: Yes (Lymphocyte Depletion or Lymphocyte Non-Depletion); No; Induction

Likelihood ratio test=11.5 on 11 df,  $p=0.4010$  n= 120, number of events= 7



**Table S8:** Validation of the GoCAR gene set in other kidney transplant cohorts.

### **Reference**

1. Solez K, Colvin RB, Racusen LC, Haas M, Sis B, Mengel M, et al. Banff 07 classification of renal allograft pathology: updates and future directions. Am J Transplant. 2008 Apr;8(4):753-60.

2. Yilmaz S, Tomlanovich S, Mathew T, Taskinen E, Paavonen T, Navarro M, et al. Protocol core needle biopsy and histologic Chronic Allograft Damage Index (CADI) as surrogate end point for longterm graft survival in multicenter studies. J Am Soc Nephrol. 2003 Mar;14(3):773-9.

3. Yilmaz S, McLaughlin K, Paavonen T, Taskinen E, Monroy M, Aavik E, et al. Clinical predictors of renal allograft histopathology: a comparative study of single-lesion histology versus a composite, quantitative scoring system. Transplantation. 2007 Mar 27;83(6):671-6.

4. Irizarry RA, Bolstad BM, Collin F, Cope LM, Hobbs B, Speed TP. Summaries of Affymetrix GeneChip probe level data. Nucleic Acids Res. 2003 Feb 15;31(4):e15.

5. Johnson WE, Li C, Rabinovic A. Adjusting batch effects in microarray expression data using empirical Bayes methods. Biostatistics. 2007 Jan;8(1):118-27.

6. Mootha VK, Lindgren CM, Eriksson KF, Subramanian A, Sihag S, Lehar J, et al. PGC-1alpharesponsive genes involved in oxidative phosphorylation are coordinately downregulated in human diabetes. Nat Genet. 2003 Jul;34(3):267-73.

7. Subramanian A, Tamayo P, Mootha VK, Mukherjee S, Ebert BL, Gillette MA, et al. Gene set enrichment analysis: a knowledge-based approach for interpreting genome-wide expression profiles. Proc Natl Acad Sci U S A. 2005 Oct 25;102(43):15545-50.

8. Firth D. Bias Reduction of Maximum Likelihood Estimates. Biometrika. 1993;80(1):12.

9. Heinze G, Ploner M. Fixing the nonconvergence bug in logistic regression with SPLUS and SAS. Comput Methods Programs Biomed. 2003 Jun;71(2):181-7.

10. Bair E, Tibshirani R. Semi-supervised methods to predict patient survival from gene expression data. PLoS Biol. 2004 Apr;2(4):E108.

11. Zhang B, Gaiteri C, Bodea LG, Wang Z, McElwee J, Podtelezhnikov AA, et al. Integrated systems approach identifies genetic nodes and networks in late-onset Alzheimer's disease. Cell. 2013 Apr 25;153(3):707-20.

12. Einecke G, Reeve J, Sis B, Mengel M, Hidalgo L, Famulski KS, et al. A molecular classifier for predicting future graft loss in late kidney transplant biopsies. J Clin Invest. 2010 Jun;120(6):1862-72.

13. Naesens M, Khatri P, Li L, Sigdel TK, Vitalone MJ, Chen R, et al. Progressive histological damage in renal allografts is associated with expression of innate and adaptive immunity genes. Kidney Int. 2011 Dec;80(12):1364-76.