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## Holistic Characterization of Tumor Monocyte-to-Macrophage Differentiation Integrates Distinct Immune Phenotypes in Kidney Cancer

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### Abstract

The tumor immune microenvironment (TIME) is commonly infiltrated by diverse collections of myeloid cells. Yet, the complexity of myeloid-cell identity and plasticity has challenged efforts to define *bona fide* populations and determine their connections to T-cell function and their

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#### Author Contributions

A.M.M., A.J.C., M.B., and M.F.K. designed experiments. A.M.M., A.J.C., and M.B. performed experiments unless specified. A.R.R. and J.L.P. participated in the processing and analysis of scRNA-seq. B.S. participated in the analysis of TCGA samples. J.T., A.B., R.J.A., M.K.R., and K.C.B. participated in experimental data collection and flow cytometry analysis. V.C. managed the acquisition of human tumors samples. A.M.M., A.J.C., and M.F.K. wrote the manuscript. A.M.M., A.J.C., M.B., A.B., and R.J.A. edited the manuscript.

#### Declaration of Interests

M.F.K. is a founder and shareholder in Pionyr Immunotherapeutics and Foundery Innovations, which develop novel immunotherapeutics that target diseases including cancers. M.B. and J.L.P. are shareholders in Pionyr Immunotherapeutics.

relationship to patient outcome. Here, we have leveraged single-cell RNA-sequencing analysis of several mouse and human tumors and found that monocyte–macrophage diversity is characterized by a combination of conserved lineage states as well as transcriptional programs accessed along the differentiation trajectory. We also found in mouse models that tumor monocyte-to-macrophage progression was profoundly tied to regulatory T cell ( $T_{reg}$ ) abundance. In human kidney cancer, heterogeneity in macrophage accumulation and myeloid composition corresponded to variance in, not only  $T_{reg}$  density, but also the quality of infiltrating  $CD8^+$  T cells. In this way, holistic analysis of monocyte-to-macrophage differentiation creates a framework for critically different immune states.

## Introduction

A key component of most immune responses, including those to cancers, are mononuclear phagocyte cell populations, which share common features of phagocytosis, tissue repair, and immunoregulation but diverge in functional specialization. Conventional dendritic cells (cDCs) are positioned in tissues to initiate and sustain adaptive T-cell responses (1), whereas macrophages engage in high rates of phagocytosis and tissue remodeling (2). Self-renewing tissue-resident macrophages are seeded during embryonic development (3), whereas inflammatory stimuli prompt infiltration of adult hematopoietic stem cell–derived monocytes that give rise to tumor macrophages (4–7). These monocyte-derived macrophages preferentially accumulate as tumors progress (8) and may predominate in regulating the ongoing antitumor T-cell response (9).

Macrophages consist of numerous subset populations that have been identified across tissues (10–13). Therapeutic blockade of key epigenetic and signaling pathways has demonstrated their amenability to transcriptional reprogramming (14), but how phenotypic diversity arises remains poorly understood. Recruited bloodborne monocytes exhibit plasticity in differentiation potential and can acquire features of macrophages and/or DCs depending on the inflammatory setting (5,6,10,15–17). In addition, early studies demonstrated that macrophage exposure to type 1- or type 2-associated cytokines induces “M1” or “M2” cellular programs, respectively, and a model was put forth in which myeloid cells are polarized to be pro- (“M1”) or anti- (“M2”) inflammatory (18–20). Although this nomenclature was thereafter understood to require nuance to account for additional plasticity (21), it remains undetermined if these binary programs are applicable to describe tumor macrophage differentiation *in vivo*.

Myeloid phenotypic diversity has challenged efforts to utilize myeloid populations as biomarkers for patient treatment options and outcome. cDCs are critical for coordinating antitumor T-cell immunity (22–25) and higher cDC abundance is broadly associated with improved cancer patient survival, although additional tumor immune microenvironment (TIME) features may inform functionality (23,24,26). In contrast, macrophages have largely been considered to be pro-tumorigenic (2,14) and monocytes have often been described as myeloid-derived suppressor cells (MDSCs) (27). Yet, several studies have indicated that macrophages are not consistently a negative predictor of patient prognosis (28–31), and increased levels of circulating monocytes were unexpectedly linked to patient

responsiveness to immune checkpoint blockade (ICB) (32). These contrary findings speak to the need for improved resolution of myeloid-cell categorization and phenotype in order to dissect heterogeneous responses amongst cancer patients.

Using single-cell RNA-sequencing (scRNA-seq), we uncovered transcriptional heterogeneity amongst tumor-infiltrating myeloid cells and distinguished monocyte and macrophage lineage- and activation-induced programs shared between multiple mouse tumor models and human kidney cancer samples. Monocyte differentiation is dynamically regulated, and we found that regulatory T cell ( $T_{reg}$ ) density was one immunoregulatory axis capable of modulating macrophage density. Further comprehensive analysis of key myeloid populations revealed distinct network connections between different myeloid-cell types and T-cell subsets, including  $T_{regs}$  and effector T cells. This is consistent with an archetypal organization of immune systems in tumors — collections of cell types that move together as modules (33) — and improved classification of patients such that we could identify those with effective antitumor T-cell responses.

## Materials & Methods

### Mice

The following mice were housed and/or bred under specific pathogen-free conditions at the University of California, San Francisco Animal Barrier Facility: C57BL/6J (The Jackson Laboratory), MMTV-PyMT-mCherry-OVA transgenic (34), and *Foxp3*-DTR (The Jackson Laboratory). All mice were handled in accordance with NIH and American Association of Laboratory Animal Care standards, and experiments were approved by the Institutional Animal Care and Use Committee of the University of California, San Francisco.

### Human Tumor Samples

Renal cell carcinoma (RCC), melanoma, and head and neck tumor samples were transported from various cancer operating rooms or outpatient clinics. All patients provided informed written consent to the UCSF IPI clinical coordinator group for tissue collection under a UCSF IRB approved protocol (UCSF IRB# 20–31740) in accordance with the Declaration of Helsinki guidelines. Patients were selected without regard to prior treatment and 21 RCC (all primary tumors), 22 melanoma (20 primary and 2 metastasis tumors) and 4 head and neck tumors (all primary tumors) were collected. All samples were defined as primary tumor or metastasis by pathology assistants. Samples were obtained after surgical excision with biopsies taken to confirm the presence of tumor cells. Freshly resected samples were placed in ice-cold DPBS (Thermo Fisher Scientific, catalog no. 14190144) or Leibovitz's L-15 medium (Thermo Fisher Scientific, catalog no. 11415064) in a 50 mL conical tube and immediately transported to the laboratory for sample labeling and processing. As described below (*Human Tissue Processing and Flow Cytometry Analysis*), the whole tissue underwent digestion and processing to generate a single-cell suspension. In the event that part of the tissue was sliced and preserved for imaging analysis, the remaining portion of the tissue sample was used for flow cytometry analysis.

## Tumor Cell Lines

B16-F10 cells (ATCC, CRL-6475) were purchased in 2015 and stock vials were generated from an initial thaw. Cells in use were taken from early passages and maintained consistent and homogenous morphological characteristics, during which time they were tested for Mycoplasma. B16-F10-ZsGreen was previously generated in our laboratory as described (35) and tested for maintained expression of ZsGreen by flow cytometry. After thawing, tumor cells were cultured at 37°C in 5% CO<sub>2</sub> in DMEM (Thermo Fisher Scientific, catalog no. A4192101), 10% FCS (Benchmark, catalog no. 100–106), Penicillin, Streptomycin, and L-Glutamine (Thermo Fisher Scientific, catalog no. 10378016). Cells were generally cultured for 2–5 days (0–1 passages) before use for subcutaneous injection.

## Mouse Tumor Cell Injections and Growth

Prior to injection, adherent B16-F10 or B16-ZsGreen tumor cells were dissociated with 0.05% Trypsin-EDTA (Thermo Fisher Scientific, catalog no. 25300120) and washed 2–3X with DPBS (Thermo Fisher Scientific, catalog no. 14190144).  $1.0 \times 10^5$  –  $2.5 \times 10^5$  cells were resuspended in DPBS and mixed 1:1 with Matrigel GFR (Corning, catalog no. 356231). Mice were injected subcutaneously with a volume of 50 µl either unilaterally or bilaterally depending on the experimental setup. Tumor tissue was harvested approximately 12–16 days later.

MMTV-PyMT-mCherry-OVA transgenic mice were bred and genotyped for the transgene by PCR. Spontaneous tumor growth was monitored by measuring with electronic calipers. Tumors were harvested when the mice were approximately 20–30 weeks of age such that palpable tumors had developed but had not exceeded a size of 100mm<sup>2</sup>.

## In Vivo Mouse Treatments

To deplete T<sub>reg</sub> cells, *Foxp3*-DTR and control mice were injected intraperitoneally with 500ng of unnicked diphtheria toxin (List Biologics, catalog no. 150). Mice were typically injected 9, 10, and 12 days following initial inoculation with tumor cells (see Mouse Tumor Cell Injections and Growth).

For specified experiments, wild-type mice were injected intraperitoneally 7, 9, 10, 11, and 13 days following tumor injection with 250 µg of anti-mouse CTLA-4 IgG2c (modified clone 9D9, Bristol-Myers-Squibb), mouse IgG2C isotype, anti-mouse CTLA-4 IgG1 (modified clone 9D9, Bristol-Myers-Squibb), or mouse IgG1 isotype.

## Mouse Tissue Processing and Flow Cytometry Analysis

Mouse tumor tissue was harvested and enzymatically digested with 0.2mg/ml DNase I (Sigma-Aldrich, catalog no. D5025), 100U/ml Collagenase I (Worthington Biochemical, catalog no. LS004197), and 500U/ml Collagenase Type IV (Worthington Biochemical, catalog no. LS004189) for 30 minutes at 37°C while under constant agitation. Blood was collected via cardiac puncture from mice that were euthanized by overdose with 2.5% Avertin. Blood samples were treated with 175 mM NH<sub>4</sub>Cl for 5 minutes at room temperature to lyse red blood cells.

Samples were filtered, washed with stain media (DPBS, 2% FCS), and resuspended in stain media. Cells from this single-cell suspension were washed with DPBS and stained with Zombie NIR fixable viability dye (BioLegend, catalog no. 423106) for 30 minutes at 4°C. Cells were washed and resuspended in stain media containing anti-CD16/32 (BioXCell, catalog no. BE0307), 2% rat serum (Thermo Fisher Scientific, catalog no. 10710C), 2% Armenian hamster serum (Innovative Research, catalog no. IGHMA-SER), and antibodies against surface proteins of interest. Cells were stained for 30 minutes at 4°C. In some experiments, cells were then washed and stained for intracellular protein levels, for which they were fixed, permeabilized, and stained according to BD Cytofix/Cytoperm Kit (BD Biosciences, catalog no. 554655) or the FoxP3/Transcription Factor Staining Buffer Set (Thermo Fisher Scientific, catalog no. 00-5523-00).

The following antibodies were from Biolegend: anti-mouse CD45 (clone A20, catalog no. 110727), anti-mouse Ly-6C (clone HK1.4, catalog no. 128037), anti-mouse CD11b (clone M1/70, catalog no. 101257), anti-mouse CD11c (clone N418, catalog no. 117339), anti-mouse MHC-II (clone M5/114.15.2, catalog no. 107622), anti-mouse F4/80 (clone BM8, catalog no. 123135, 123107, or 123131), anti-mouse CD24 (clone M1/69, catalog no. 101822), anti-mouse Ly-6G (clone IA8, catalog no. 127645), anti-mouse NK1.1 (clone PK136, catalog no. 108749), anti-mouse CD90.2 (clone 30-H12, catalog no. 105331), anti-mouse/human CD45R/B220 (clone RA3-6B2, catalog no. 103246), anti-mouse CD301b (clone URA-1, catalog no. 146814 or 146803), anti-mouse CD64 (clone X54-5/7.1, catalog no. 139306), anti-mouse CD127 (clone A7R34, 135031). The following antibodies were from BD Biosciences: anti-mouse Siglec-F (clone E50-2440, catalog no. 740956), anti-mouse CD106 (clone 429, catalog no. 745672). The following antibodies were from R&D: anti-mouse/human ARG1 (polyclonal, catalog no. IC5868F), normal sheep IgG (polyclonal, catalog IC016F). The following antibodies were from Thermo Fisher Scientific: anti-mouse FoxP3 (clone FJK-16s, catalog no. 48-5773-82).

Following staining, cells were washed, resuspended in stain media, and analyzed on a BD Biosciences Fortessa or sorted with a BD Biosciences FACSAria Fusion. Flow cytometry data was analyzed using FlowJo software (BD Biosciences, version 9 or 10).

### Human Tissue Processing and Flow Cytometry Analysis

Human tumor or metastatic tissue was thoroughly chopped with surgical scissors and transferred to gentleMACS C Tubes (Miltenyi Biotec) containing 20 uL/mL Liberase TL (5 mg/ml, Roche, catalog no. 5401020001) and 50 U/ml DNase I (Roche, catalog no. 10104159001) in RPMI 1640 (Thermo Fisher Scientific catalog no. 11875093) per 0.3 g tissue. gentleMACS C Tubes were installed onto the gentleMACS Octo Dissociator (Miltenyi Biotec) and incubated for 45 minutes according to the manufacturer's instructions. Samples were then quenched with 15 mL of sort buffer (DPBS, 2% FCS, 2mM EDTA), filtered through 100 µm filters, and spun down. Red blood cell lysis was performed with 175 mM NH<sub>4</sub>Cl if needed. Cells were incubated with Human FcX (Biolegend, catalog no. 422301) to prevent non-specific antibody binding. Cells were then washed in DPBS and incubated with Zombie Aqua Fixable Viability Dye (Thermo Fisher Scientific, catalog no. L34957). Following viability dye, cells were washed with sort buffer and incubated with

cell surface antibodies that had been diluted in the BV stain buffer (BD Biosciences, catalog no. 563794) for 30 minutes on ice. Cells were subsequently fixed in either Fixation Buffer (BD Biosciences, catalog no. 554655) or in Foxp3/Transcription Factor Staining Buffer Set (Thermo Fisher Scientific, catalog no. 00–5523-00) if intracellular staining was required.

The following antibodies were from BD Biosciences: anti-human HLA-DR (clone G46–6, catalog no. 564040), anti-human CD56 (clone NCAM16.2, catalog no. 564448), anti-human CD127 (clone HIL-7R-M21, catalog no. 563225) anti-human CD25 (clone 2A3, catalog no. 340939), anti-human CD45RO (clone UCHL1, catalog no. 561889), anti-human PD-1 (clone EH12, catalog no. 563789), anti-human CTLA-4 (clone BNI3, catalog no. 565931), and anti-human CD64 (clone 10.1, catalog no. 564425). The following antibodies were from Thermo Fisher Scientific: anti-human CD45 (clone HI30, catalog no. 47–0459-42), anti-human CD3e (clone OKT3, catalog no. 46–0037-42), anti-human FoxP3 (clone 236A/E7, catalog no. 25–4777-41), anti-human Ki-67 (SolA15, catalog no. 11–5698-82), anti-human CD19 (clone H1B19, catalog no. 45–0199-42), anti-human CD20 (clone 2H7, catalog no. 45–0209-42), anti-human CD56 (clone CMSSB, catalog no. 46–0567-42), and anti-human CD11c (clone 3.9, catalog no. 56–0116-42). The following antibodies were from Biolegend: anti-human CD4 (clone S3.5, catalog no. 100455), anti-human CD8 $\alpha$  (clone RPA-T8, catalog no. 301039), anti-human CD38 (clone HIT2, catalog no. 303523), anti-human CD16 (clone 3G8, catalog no. 302039), CD1C/BDCA-1 (clone L161, catalog no. 331515), anti-human CD14, (clone M5E2, catalog no. 301837) anti-human CD304 (clone 12C2, catalog no. 354503), and streptavidin. Anti-human BDCA-3 (clone AD5–14H12, catalog no. 130–098-843) was purchased from Miltenyi Biotec.

Stained cells were washed and analyzed on a BD Biosciences Fortessa or sorted with a BD Biosciences FACSARIA Fusion. Flow cytometry data was analyzed using FlowJo software (BD Biosciences, version 10.6). Clustering and heatmap analyses were performed using Morpheus (Broad Institute).

### Single-Cell RNA-Sequencing Data Generation

Mouse B16 samples were generated over 2 independent experiments. Samples were pooled from at least 5 mice per experiment to ensure representation across a cohort of tumor-bearing mice. In the first experiment, CD45<sup>+</sup>CD90<sup>–</sup>B220<sup>–</sup>NK1.1<sup>–</sup>Ly6G<sup>–</sup> cells that were Ly6C<sup>–</sup>MHC-II<sup>+</sup> or Ly6C<sup>+</sup>CD11b<sup>+</sup> were sorted as 1 bulk myeloid sample. Individual monocyte (CD45<sup>+</sup>CD90<sup>–</sup>B220<sup>–</sup>NK1.1<sup>–</sup>Ly6G<sup>–</sup>Ly6C<sup>+</sup>CD11b<sup>+</sup>) and macrophage (CD45<sup>+</sup>CD90<sup>–</sup>B220<sup>–</sup>NK1.1<sup>–</sup>Ly6G<sup>–</sup>Ly6C<sup>–</sup>MHC-II<sup>+</sup>F4/80<sup>+</sup>CD24<sup>lo</sup>CD11c<sup>lo/hi</sup>) populations from these tumors were also sorted. Each of these samples were processed separately, but in parallel, for scRNA-seq analysis. In the second experiment, B16 tumor myeloid cells (CD45<sup>+</sup>CD90<sup>–</sup>B220<sup>–</sup>NK1.1<sup>–</sup>Ly6G<sup>–</sup> cells that were CD11b<sup>+</sup> and/or CD11c<sup>+</sup>) were sorted from control or *Foxp3*-DTR mice. Blood myeloid cells (CD45<sup>+</sup>CD90<sup>–</sup>B220<sup>–</sup>NK1.1<sup>–</sup>Ly6G<sup>–</sup> cells that were CD11b<sup>+</sup> and/or CD11c<sup>+</sup>) were also sorted from these B16 tumor-bearing wildtype mice. Each of these 3 samples were processed separately, but in parallel, for scRNA-seq analysis. In a subsequent experiment, myeloid cells (CD45<sup>+</sup>CD90<sup>–</sup>B220<sup>–</sup>NK1.1<sup>–</sup>Ly6G<sup>–</sup>CD11b<sup>+</sup> and/or CD11c<sup>+</sup>) from a mouse PyMT tumor were sorted. In addition, myeloid cells (CD45<sup>+</sup>CD3e<sup>–</sup>CD19<sup>–</sup>CD20<sup>–</sup>CD56<sup>–</sup>HLA-DR<sup>dim/hi</sup>) from a total of 1 RCC, 4



head and neck, and 6 melanoma biopsies were sorted and processed individually as they became available.

Once sorted, cells were resuspended at a concentration of  $1 \times 10^3$  cells/ $\mu$ l in media (DPBS, 0.04% BSA) and loaded onto the Chromium Controller (10X Genomics). Samples underwent single-cell encapsulation and cDNA library preparation using the Chromium Single Cell 3' v1 or v2 Reagent Kits (10X Genomics, catalog no. 120237). The cDNA library was sequenced on an Illumina HiSeq 4000 or Illumina Novaseq.

### Single-Cell RNA-Sequencing Data Processing

Sequencing data was processed using the 10X Genomics Cell Ranger V1.2 pipeline. Fastq files were generated from Illumina bcl files with the Cell Ranger subroutine *mkfastq*. Fastq files were then processed with Cell Ranger's *count* to align RNA reads against UCSC mm10 or GRCh38 genomics for mouse and human cells, respectively, using the aligner STAR (36). Redundant unique molecular identifiers (UMI) were filtered, and a gene–cell barcode matrix was generated with *count*. *Mkfastq* and *count* were run with default parameters.

For mouse B16 tumor samples, the gene–cell barcode matrix was passed to the R software package Seurat (v2.3.0) (37) for all downstream analyses. Genes that were expressed in at least 3 cells were included. Cells that did not express at least 200 genes were excluded, as were those that contained >5% reads associated with cell cycle genes (38,39). For mouse PyMT and human tumor samples, raw feature–barcode matrices were loaded into Seurat (v3.1.5) (40) and genes with fewer than 3 UMIs were dropped from the analyses. Matrices were further filtered to remove events with greater than 20% percent mitochondrial content, events with greater than 50% ribosomal content, or events with fewer than 200 total genes. The cell cycle state of each cell was assessed using a published set of genes associated with various stages of human mitosis (41).

Using Seurat's *ScaleData* function, read counts were log<sub>2</sub> transformed and scaled using each cell's proportion of cell cycle genes as a nuisance factor. A set of highly variable genes was generated by Seurat's *FindVariableGenes* function, which were used for principal component analysis (PCA). Genes associated with principal components (selected following visualization with scree plots) were used for graph-based cluster identification and dimensionality reduction using *t*-distributed stochastic neighbor embedding (*t*-SNE) or Uniform Manifold Approximation and Projection (UMAP) analysis. Seurat's *FindAllMarkers* function was used for subsequent cluster-based analyses, including cluster marker identification and differentially expressed (DE) gene analyses.

### Single-Cell RNA-Sequencing Signature Generation

To generate mouse monocyte- and macrophage-specific gene signatures, sorted monocyte, CD11c<sup>lo</sup> macrophage, and CD11c<sup>hi</sup> macrophage samples were aggregated, log<sub>2</sub> transformed, and scaled using Seurat. DE gene analysis was performed using *FindMarkers* with the parameters log<sub>2</sub> fold change > 1.5 and a min.pct of 0.25. Genes were selected by ranked fold change and the criteria that min.pct1/min.pct2 > 1.5. Genes used for cell cycle regression analysis were excluded. The top 10 genes (or fewer if less remained) were median normalized and aggregated, scaled 0–1, and plotted on specific *t*-SNE plots.



Gene signatures for cellular programs such as metabolism (42), “M1” and “M2” polarization (43), and MHC-II-associated genes (GSEA, REACTOME\_MHC\_CLASS\_II\_ANTIGEN\_PRESENTATION), previously published cell types (44,45), and cell populations identified here were generated by taking the mean of log-normalized expression for a particular set of genes related to the specific pathway or phenotype. To visualize the distribution of these scores across cells, we binarized the distribution of the score at the 70th percentile unless specified otherwise and overlaid on the calculated *t*-SNE coordinates.

For correlation analysis of “M1” and “M2” genes, the expression of each gene in the signatures was calculated for each B16 tumor *Csf1r<sup>+</sup> Mafb<sup>+</sup>* cluster cell and binarized at the median. A cross-correlation gene–gene matrix was obtained using the R *cor* function with *method="pearson"*.

### Single-Cell RNA-Sequencing Sample Aggregation

Pairwise comparison analyses were performed between B16 tumor myeloid-cell clusters from wildtype and T<sub>reg</sub>-depleted mice. For this, 1 sample from wildtype mice and 1 sample from *Foxp3*-DTR mice were used, along with an additional wildtype sample that had been generated in a previous independent experiment. The 3 objects were first transformed from Seurat v2 to Seurat v3. The raw UMI counts were renormalized using person residuals from “regularized negative binomial regression,” with sequencing depth a covariate in a generalized linear model via the R *sctransform* package (46). Pairwise “anchor” cells were identified between the 3 objects using the original wild-type mouse sample as a reference via the Seurat *FindIntegrationAnchors* function. Briefly, each pair of samples was reduced to a lower dimensional space using diagonalized Canonical Correlation Analysis (CCA) using the top 3,000 genes with the highest dispersions. The canonical correlation vectors were normalized using L2-normalization. Multiple Nearest Neighbors (MNNs) across datasets were identified for each cell in each dataset and cell–cell similarities are used as anchors to integrate the datasets together using the Seurat *IntegrateData* function.

For the integration of all human samples, the individually processed samples were normalized, and variance stabilized using negative binomial regression via the *scTransform* method offered by Seurat (46). Counts matrices were merged into a single Seurat object and the batch (or library) of origin was stored in the metadata of the object. The log-normalized counts were reduced to a lower dimension using PCA and the individual libraries were aligned in the shared PCA space in a batch-aware manner (each individual library was considered a batch) using the Harmony algorithm (47). The resulting Harmony components were used to generate a batch-corrected UMAP, and to identify clusters of transcriptionally similar cells across each of the 11 samples.

### Single-Cell RNA-Sequencing Pseudotime Analysis

Raw UMI counts from the cleaned and processed Seurat objects for the control and T<sub>reg</sub>-depleted mouse experiment were extracted and coerced into Monocle2 (48,49). *CellDataSet* objects were generated, normalizing the data using a negative binomial distribution with fixed variance (*negbinom.size*). Each object was independently processed to identify a

pseudotime trajectory. Briefly, each object was processed to estimate per-cell coverage and sequencing depth (*estimateSizeFactors*) and gene dispersions (*estimateDispersions*). Cells were further filtered to retain high-quality cells with 500 genes and genes were filtered to retain only those in at least 10 cells. The dataset was reduced to 2 dimensions using the *DDRTree* algorithm and the marker genes that differentiated the *Ly6c2<sup>+</sup>Hp<sup>+</sup>* monocytes and *Clqa<sup>+</sup>* macrophage clusters from other cell types were used to guide the trajectory inference. Relative pseudotime was obtained through a linear transformation relative to the cells with the lowest and highest pseudotimes  $(1 - \min\_pseudotime) / \max\_pseudotime$ . The “wave” plots were constructed using the Seurat LogNormalized counts and the relative pseudotime described above for the top 5 genes per cluster as identified by scRNA-seq.

Human samples were analyzed with Monocle3 (48,49), and the *cell\_data\_set* object along with the batch-corrected PCA and UMAP embeddings were imported directly from the Seurat object. Each cell-specific trajectory was inferred by reverse embedding the UMAP coordinates using the *DDRTree* method. Relative pseudotime was obtained as described for the mouse tumor samples.

### TCGA Survival Analyses

Tumor RNAseq counts and transcripts-per-million (TPM) values for 985 kidney renal clear cell carcinoma (KIRC) samples from the Toil recompute data in the TCGA Pan-Cancer (PANCAN) cohort (50) were downloaded from the UCSC Xena browser (51). A gene signature score for each patient was calculated using the gene signature score method below. The feature gene signature scores were calculated using an  $m \times n$  matrix where  $m$  represented the TPM normalized log<sub>2</sub> counts per million (logCPM) expression of the feature signature genes and  $n$  represented the selected sample set (52). The expression of each gene was converted to percentile ranks across the samples using the SciPy Python module (53). The top and bottom 30 percentile were then used to define low and high patients for each respective signature unless otherwise noted.

### Statistical analysis and data visualization

Comparisons between groups were analyzed using GraphPad Prism software. Experimental group allocation was determined by genotype or by random designation when all wild-type mice were used. Error bars represent mean  $\pm$  SEM calculated with Prism unless otherwise noted. Comparisons between 2 groups were analyzed with Student's *t*-test. For statistical measures between more than 2 groups, one-way ANOVA was performed unless otherwise noted. Nonsignificant comparisons are not shown. Investigators were not blinded to experiment group assignment during experimental data generation or analyses. The R packages Seurat and ggplot2 were used to generate figures.

### Data Availability

The expression matrices for the scRNA-seq samples reported in this paper can be found with the following GEO accession numbers: GSE188548, GSE184096, GSE159913, and GSE184398. Code used to generate the scRNA-seq analyses are included on Github ([https://github.com/UCSF-DSCOLAB/mujal\\_et\\_al\\_MonoMac\\_2021](https://github.com/UCSF-DSCOLAB/mujal_et_al_MonoMac_2021)).

## Results

### Mouse B16 Tumors Harbor a Diversity of Myeloid States

Subcutaneous implantation of B16 melanoma cells is a well-established mouse tumor model with abundant infiltration of monocytes, macrophages, and cDCs (23). To study these cells along their differentiation trajectories, we used conventional markers to sort bulk myeloid populations, along with reference populations of Ly6C<sup>+</sup> monocytes and two tumor-associated macrophage (TAM) populations, distinguished based on level of expression of CD11c and MHC-II (23) (Fig 1A, Supplementary Fig S1A). Each of these samples were then subjected to scRNA-seq analysis.

Within the bulk myeloid population, *t*-SNE clustering yielded eight transcriptionally-distinct cell populations (Fig. 1B, Supplementary Fig S1B–C), including three *Flt3*<sup>+</sup>*Kit*<sup>+</sup> cDC populations (Clusters 4, 6, 7), which were marked by signatures specific to cDC1s, cDC2s, and conserved cDC activation programs (Supplementary Fig. S1D, Supplementary Table S1) (23,24,26). The remaining myeloid cells (Clusters 0, 1, 2, 3, 5) broadly expressed *Csflr* and *Mafb* (Fig. 1C), indicative of monocytes and macrophages. In addition, these cells broadly expressed *Ccr2* and modest but appreciable levels of *Cx3cr1* (Supplementary Fig. S1E). Having focused on the stimulatory capacity of cDCs in previous work (23,24,45), here we focused on the diversity of monocytes and macrophages as it related to the TIME.

To align transcriptional cell type categorization with flow cytometry analysis, we generated cell type-specific gene signatures from the scRNA-seq analysis of the FACS-sorted monocytes and TAMs (Fig. 1A, Supplementary Fig. S1F). When applied (Fig. 1D), these indicated that four *Csflr*<sup>+</sup>*Mafb*<sup>+</sup> populations (Clusters 0, 1, 2, 5) expressed monocyte-specific genes. The four monocyte populations expressed *Ly6c2*, but varied in levels of other monocyte-associated genes (e.g., *Hp*, *Chil3*) and, as found in Cluster 0, also expressed TAM-associated genes (e.g. *H2-Ab1*, *C1qa*, *Ms4a7*) (Fig. 1E–F). Monocyte-like clusters were differentiated from one another by cellular activation programs. For example, Cluster 1 (“IFN-responsive”) was specifically enriched for interferon (IFN)-inducible genes such as *Cxcl10*, *Gbp2*, and IFIT-family members. Cluster 2 (“stress-responsive”) cells expressed *Arg1* and were enriched for cellular stress processes, including oxidative stress-responsive genes and heat-shock protein genes such as *Hmox1*, *Hspala*, *Hilpda*, *Bnip3*, *Ero11*, and *Ndr1* (Fig. 1F, Supplementary Fig. S1G). In contrast to the heterogeneity observed amongst monocytes, signatures for both populations of TAMs localized within Cluster 3 (Fig. 1D).

We applied pseudotime analysis (48) to generate a model of tumor monocyte-to-macrophage differentiation (Fig. 1G–H, Supplementary Fig. S1H). This model placed Cluster 5 *Ly6c2*<sup>+</sup>*Hp*<sup>+</sup> monocytes and Cluster 3 *C1qa*<sup>+</sup> TAMs at opposite ends of a linear trajectory, consistent with our expectations. Cluster 0 monocytes occupied the continuum between them and expressed a combination of both monocyte- and TAM-associated gene signatures such that we designated these cells “Intermediate monocytes” (“Mono-Int”). Kinetic analysis of cluster-enriched genes confirmed gradual downregulation of *Ly6c2*<sup>+</sup>*Hp*<sup>+</sup> monocyte-associated genes and up-regulation of “Mono-Int”- and TAM-associated genes along the pseudotime trajectory (Fig. 1I). This transcriptional model thus supported a framework of progressive monocyte-to-TAM differentiation, in which

Ly6C down-regulation is paired with up-regulation of CD64, MHC-II, and F4/80 (15) (Fig. Supplementary S1I–J). In contrast, IFN- and stress-responsive cells occupied distinct branches that diverged from the dominant differentiation trajectory at intermediate timepoints (Fig. 1H–I, Supplementary Fig S1H).

### Heterogeneous Acquisition of ‘Stress-’ and ‘IFN-Responsive’ Cellular Programs

To gain higher resolution on the differentiation trajectories within the monocyte/macrophage lineage, we performed cluster analysis on the sorted monocyte and TAM samples. Sorted monocytes expressed *Ly6c2* and contained clusters similar to those identified within the bulk myeloid-cell sample (Fig. 2A, Supplementary Fig S2A), indicating that these cells may not consist purely of early-stage monocytes but also include some cells that have acquired macrophage attributes (Supplementary Fig. S1J). Cluster analysis of CD11c<sup>lo</sup> and CD11c<sup>hi</sup> TAMs, however, resolved diversity beyond the *C1qa*<sup>+</sup> TAM signature (Fig. 2B, Supplementary Fig. S2B–C) including identifying clusters enriched for cell cycle-related genes, and an *Mgl2*<sup>+</sup> TAM subset that expressed immune modulators such as *Ccl6*, *Iilb*, and *Retnla* as compared to the *C1qa*<sup>+</sup> cluster, which more highly expressed genes such as *Ms4a7*. Although these cells had not formed a distinct population in our original analysis of bulk myeloid cells (Fig. 1), we did retrospectively detect *Mgl2*<sup>+</sup> cells in that scRNA-seq dataset, as well as by flow cytometry (Supplementary Fig. S2D). TAM-subset clusters were also accompanied by an *Arg1*<sup>+</sup> stress-responsive cluster akin to that found in the sorted monocytes (Fig. 2B, Supplementary Fig. S2B–C). Indeed, re-clustering of the entire stress-responsive cluster from the bulk tumor myeloid sample revealed that this program was acquired by monocytes, “Mono-Int” and TAMs (Fig. 2C, Supplementary Fig. S2E).

Segregated expression of stress-responsive genes and canonical TAM-associated genes suggested divergent transcriptional programs and we sought to determine if these populations could also be distinguished by flow cytometry. Differential gene expression analysis of the stress-responsive and *C1qa*<sup>+</sup> TAM clusters from our bulk myeloid-cell sample revealed cluster-specific expression of cell surface genes *Ii7r* and *Vcam1*, respectively (Fig. 2D). Using the same gating as in Supplementary Fig. S1A, we confirmed this split in both “Mono-Int” and TAMs (Fig. 2E) and we found enriched arginase 1 (ARG1) expression in both IL-7R $\alpha$ <sup>+</sup> populations (Fig. 2E–F, Supplementary Fig. S2F). As expected from the single-cell transcriptional analysis, VCAM1<sup>+</sup> cells were more abundantly found within TAMs (Fig. 2E–F, Supplementary Fig. S2F).

Together, this dissection of sorted cell populations lent support to a model in which monocytes and TAMs exist in a differentiation trajectory, along which cells can adopt specialized cellular programs (Fig. 2G–H). Some programs, such as those associated with *Mgl2*<sup>+</sup> or *Vcam1*<sup>+</sup> TAMs, selectively emerged later, in mature TAMs. Others, such as IFN-induced signaling or stress-responsiveness may be more universally accessible across differentiation stages. In addition, we detected populations of IFN-responsive monocytes in the peripheral blood of B16 tumor-bearing mice (Supplementary Fig. S2G–H), perhaps suggesting that systemic IFN signaling, or other induction of this program, may define monocytes prior to tumor entry. In contrast, stress-responsive populations were not detected in the blood, suggesting that microenvironmental cues in the TIME likely induce this

activation program locally. Further studies are warranted to explore if these programs directly influence monocyte differentiation processes or act as ‘layers’ that accessorize a canonical differentiation trajectory.

### Mouse Tumor Macrophage Subset Heterogeneity Does Not Reflect “M1/M2” Polarization

Macrophage exposure to type-1 or type-2 cytokines *in vitro* results in “M1” and “M2” transcriptional signatures that are often used to describe ‘pro-inflammatory,’ or ‘anti-inflammatory’ and wound-healing processes, respectively (18–20). To address whether “M1/M2” polarization was a useful construct to define tumor macrophage diversity *in vivo*, we tested how “M1” and “M2” gene signatures (43) corresponded to the tumor myeloid-cell subsets profiled here. Using correlation and clustering analyses (Fig. 3A, Supplementary Fig. S3A), we found that, contrary to *in vitro* findings, tumor myeloid cells were marked by broad expression of both “M1”- and “M2”-associated genes, and we did not observe substantial correlation of gene expression within “M1” or “M2” gene groups across single cells. These data suggest that although tumor myeloid cells can express individual “M1” and “M2” genes, they rarely do so in any distinguishably consistent way during unperturbed tumor growth. We next processed tumor myeloid cells from MMTV-PyMT spontaneous mammary carcinomas for scRNA-seq analysis, sorting on Lin<sup>-</sup>CD11c<sup>+</sup> and/or CD11b<sup>+</sup> cells to capture the full cadre of myeloid populations including MHCII<sup>+/-</sup> cells (Supplementary Fig. S1A). We found that MMTV-PyMT tumors shared populations with the identical signatures as those defined for B16 tumors in Figure 1, albeit in different proportions, and also showed a lack of co-association between “M1” and “M2” signatures amongst the clusters (Fig 3B–C, Supplementary Fig. S3B–E).

While myeloid-cell populations appeared to be largely defined by differentiation stage and activation programs, we considered whether other core cellular features could help to further distinguish subsets across diverse microenvironments. It is now increasingly appreciated that metabolic reprogramming accompanies differentiation of immune cells, including macrophages (54). Indeed, assessment of metabolism-related genes (42) demonstrated that glycolysis-associated genes were specifically enriched in the stress-responsive cell cluster, whereas genes pertaining to oxidative phosphorylation were specifically enriched in *C1qa*<sup>+</sup> TAMs in two distinct mouse models (Fig. 3D–E, Supplementary Fig. S3F). This suggests that these populations have additional important biological features in common—namely those coupled to distinct bioenergetic processes and demands.

Together, our data provides compelling evidence that “M1” and “M2” pathways have limited use in defining *in vivo* tumor myeloid-cell differentiation and subset plasticity during normal tumor development. Rather, common microenvironmentally-induced programs and associated metabolic programs may yield greater insight in efforts to transcriptionally define and selectively target monocyte/TAM subsets.

### Human RCC-infiltrating monocytes and macrophages mirror murine populations

We next assessed how the mouse monocyte/macrophage transcriptional programs we identified might compare to those from human cancers. We performed scRNA-seq analysis on HLA-DR<sup>dim/+</sup>Lin<sup>-</sup> myeloid cells sorted from an RCC sample, which are described to

have substantial myeloid-cell infiltration (55), as well as 6 melanoma and 4 head and neck cancer samples (Fig. 4A–B, Supplementary Fig. S4A). Signatures derived from previously described blood myeloid-cell populations (11,44) guided cluster identification and exclusion of cDCs (Supplementary Fig. S4B). Analysis of the *CSF1R*<sup>+</sup>*MAFB*<sup>+</sup> clusters revealed a heterogeneous collection of monocytes and macrophages with varying levels of CD14 and CD16 (Fig 4C–E).

As in mouse models, we detected early-stage *CD14*<sup>+</sup>*S100A8*<sup>+</sup> classical monocytes along with terminally-differentiated *CIQC*<sup>+</sup> TAMs (Fig. 4 E–F, Supplementary Table S2). Another population was *CD14*<sup>+</sup> and differentially expressed *LYPD3* and MHC-II genes, consistent with intermediate differentiation of monocytes towards TAM (“Mono-Int”; Fig. 4E–F). A population of *FCGR3A*<sup>+</sup> non-classical monocytes also expressed IFN-stimulated genes and thus appears to functionally represent ‘IFN-responsive’ cells (Fig. 4E–F, Supplementary Fig. S4C).

Finally, we found that there were a mix of cells on the monocyte–macrophage trajectory that expressed the stress-responsive program identified in mice, including the gene *SPP1* (Fig. 4F, Supplementary Fig. S4C). When compared further to *CIQC*<sup>+</sup> TAMs, this *SPP1*<sup>+</sup> cluster was less mature based on higher expression of monocytic markers (i.e. *S100A* genes) and lower expression of MHC-II–related genes (Fig. Supplementary S4D). This analysis revealed also a population marked by expression of the antioxidant gene *SEPP1* (Fig. 4F). These cells largely resembled *CIQC*<sup>+</sup> TAMs but were enriched for *FOLR2* (Fig. 4F, Supplementary Fig. S4E). *FOLR2* is a marker previously associated with tissue-resident macrophages in breast cancer (56). Pseudotime analysis recapitulated a monocyte-to-macrophage differentiation trajectory (Fig. 4G–H) but did not connect the *SEPP1*<sup>+</sup> cluster to the other monocyte–macrophage subsets, potentially due to the distinct ontogeny of tissue-resident macrophages, and thus this cluster was not considered for further trajectory analysis (Fig. 4G–H).

As in the mouse samples, the stress- and IFN-responsive programs aligned over the monocyte-to-macrophage trajectory, although in these samples, IFN-responsive monocytes appeared more advanced in differentiation stage. Again, there was broad co-expression of “M1”- and “M2”-associated genes across the populations (Supplementary Fig. S4G). Also, as in mice, there was a striking enrichment of a glycolytic signature (42) within the stress-responsive (*SPP1*<sup>+</sup>) cluster as compared to the *CIQC*<sup>+</sup> TAMs, supporting the notion that these cells were functional orthologs in the two species (Fig 4I). Altogether, these data confirm the limitation of “M1” and “M2” applicability in human tumors and illustrate the ability of other pathways to better define myeloid-cell subsets *in vivo*.

### **T<sub>reg</sub> depletion elicits reprogramming of the tumor myeloid-cell compartment**

Myeloid-cell density can vary across patients (55), but how myeloid-cell infiltration and differentiation is collectively regulated in human cancer is still not well understood. When we quantified myeloid-cell populations in 20 RCC patient biopsies using flow cytometry we found that the proportion of myeloid cells amongst live immune cells was increased in tumors of greater size and later stages (Supplementary Fig. S5A). Closer examination revealed that the ratio of macrophages-to-monocytes was also specifically increased in more



advanced tumors (Fig. 5A, **top**). This suggested that the balance between monocytes and macrophages is dynamically regulated and that tumor growth is tied to higher macrophage density.

We thus sought other immunosuppressive parameters that might work in concert with increased macrophage accumulation.  $T_{\text{regs}}$  are a potent immunosuppressive force in the TIME and ablation can result in tumor clearance (24,57). We found that  $T_{\text{regs}}$  accumulated as kidney tumor size increased (Fig. 5A, **bottom**), and that  $T_{\text{reg}}$  abundance correlated well with macrophage-to-monocyte ratios in RCC as well as melanoma (Fig. 5B). The positive correlation between  $T_{\text{reg}}$  and macrophage density spurred us to ask whether one caused the other. Using *Foxp3*-DTR mice, we found that depletion of  $T_{\text{regs}}$  dramatically reduced the macrophage-to-monocyte ratio in mouse B16 tumors (Fig. 5C, **top**) as assessed by flow cytometry. These results were phenocopied by treatment of mice with an anti-CTLA-4 that specifically depletes tumor  $T_{\text{regs}}$  (24,58) (Fig. 5C, **bottom**, Supplementary Fig. S5B–C). The shift in macrophage-to-monocyte ratio observed following both methods of  $T_{\text{reg}}$  loss preceded subsequent tumor growth control (24,58).

To further examine how  $T_{\text{regs}}$  may be influencing monocyte and macrophage proportions, we performed scRNA-seq analysis on mouse tumor  $\text{Lin}^- \text{CD11b}^+$  and/or  $\text{CD11c}^+$  myeloid cells from B16 tumor-bearing control and *FoxP3*-DTR mice. *Csf1r*<sup>+</sup>*Mafb*<sup>+</sup> clusters from this experiment were aggregated with those from the original wild-type B16 tumor sample in Figure 1 and we observed similar cell populations across both experiments and treatment conditions (Fig. 5D, Supplementary Fig. S5D–E). Cluster proportions were modestly shifted with  $T_{\text{reg}}$  loss (Fig. 5D), but cells from control and  $T_{\text{reg}}$ -depleted tumors shared similar differentiation trajectories (Fig. 5E). However, Monocle analysis revealed differences in the accumulation of cells along the trajectory. Namely, whereas tumor monocytes, “Mono-Int”, and TAMs from the control sample acquired progressively increased pseudotime scores, “Mono-Int”, and TAM populations in the *Foxp3*-DTR sample did not exhibit sequential increases in pseudotime scores (Fig. 5E). In effect, TAM progression appeared stunted following depletion of  $T_{\text{regs}}$ .

In addition to increased expression of inflammatory and immunomodulatory genes (e.g., *Ccl24*, *Arg1*, *Retnla*, *Mmp12*, *Mmp13*, *Nos2*), expression of monocyte-associated genes was sustained in TAMs from  $T_{\text{reg}}$ -depleted tumors (Fig. 5F–G, Supplementary Table S3). Moreover, expression of genes tied to macrophage differentiation (e.g., *C1qa*, *H2-Ab1*, *ApoE*, *Ms4a7*) were decreased across stages of differentiation (Fig. 5H, Supplementary Fig. S5F), further indicating these TAMs were more immature. Our analysis suggests that  $T_{\text{reg}}$ -depletion may impair implementation of TAM transcriptional programs, a remodeling detected early during tumor monocyte differentiation. Altogether these findings support a model in which  $T_{\text{reg}}$  abundance promotes an accumulation of terminally-differentiated TAMs in both mouse and human tumors.

### Multiparametric immune-cell analysis improves classification of kidney cancer patients

Given this association between T-cell subset density and TAM maturation, we sought to further explore how features of tumor macrophage infiltration could be harnessed to reliably inform features of patient outcome, such as survival. Analysis of TCGA KIRC samples



using a myeloid gene signature from CiberSort (59) demonstrated that patients with varying levels of overall myeloid-cell density did not significantly differ in their survival (Fig. 6A, **left**). We next stratified TCGA patient data based on levels of the monocyte–macrophage lineage genes *CSF1R* and *MAFB*, finding that patients with higher levels of these had modest improvements in outcome (Fig. 6A, **middle**). As these genes are not strictly macrophage-specific, we leveraged our scRNA-seq analyses of human RCC samples to generate signature scores based on the ratio between macrophage and monocyte (Fig 4E). However, no significant differences in survival were revealed using this metric (Fig. 6A, **right**).

As TAM density did not appear to robustly inform patient outcome, we sought to test how TAM abundance corresponds with other immune parameters and may stratify kidney cancer patients, using flow cytometry analysis of their biopsies. We thus performed unbiased clustering analysis using measurements of myeloid-cell,  $T_{reg}$  and conventional T cell ( $T_{conv}$ )-frequencies. This revealed three groups of patients that were characterized by nearly binary (all high or all low) levels of  $CD8^+$  T cells,  $CD4^+$   $T_{conv}$ , cDC2s, and cDC1s (Fig. 6B). These groups could be further parsed by varied macrophage–monocyte density: low (pink), moderate (yellow) and high (red) (Fig. 6B, **right**). Consistent with our previous finding (Fig. 5), the group with the highest degree of macrophage differentiation was associated with the consistent presence of  $T_{reg}$  infiltration ( $T_{reg}$ -Mp). Of two groups with lowest macrophage differentiation, one ( $CD8$ -Mo-cDC1; **pink**) was distinguished by notable infiltration of cDC1s, which are critical for  $CD8^+$  T-cell responses (22,23), and that group presented with uniformly high  $CD8^+$  T-cell infiltration. A second group had higher frequencies of both  $CD4^+$  T cells and cDC2s along with a variable amount of  $T_{regs}$ , consistent with the demonstrated role of cDC2s in supporting both  $CD4^+$   $T_{conv}$  and  $T_{reg}$  responses (24). Further, the same patients clustered together again based on phenotypic analysis of the  $CD8^+$  T-cell compartment (Fig. 6C). Notably,  $CD8^+$  T cells from the  $CD8$ -Mo-cDC1 group (**pink**) expressed low levels of the exhaustion markers PD-1 and CD38 (Fig. 6C–D) and were also distinguished by higher expression of the checkpoint regulator CTLA-4, which may indicate ongoing activation (60) (Fig. 6C–D). In contrast, the  $T_{reg}$ -Mp (**red**) group showed the highest levels of both exhaustion markers and proliferative capacity (i.e., Ki-67).

In testament to the heightened antitumor  $CD8^+$  T-cell profile associated with low macrophage and  $T_{reg}$  abundance but high cDC1 density, the subset of patients with these attributes (**pink**) had dramatically improved survival, showing no mortality for over three years (Fig. 6E). This multiparametric clustering parsed patients with the highest survival rates more profoundly from our data set than the sole metric of cDC1 infiltration (Fig. Supplementary Fig. S6A). Similarly, although sole measurement of a cDC1 signature alone corresponded to higher survival rates amongst TCGA patients (Fig. Supplementary Fig. S6B) in support of previous studies (23,45), a combined measurement of the ratio of cDC1s to macrophages through combined gene signatures using the  $CIQ^+$  macrophage gene signature (Fig. Supplementary Fig. S6C–D) allowed for identification of kidney cancer patients with better survival. Thus, fine-tuned stratification of the kidney cancer TIME provided the resolution critical for identifying three biologically-distinct patient classes

including this CD8<sup>+</sup>Mo-cDC1 group, which defines patients with the best CD8<sup>+</sup> T-cell infiltration and outcome.

## Discussion

Here we undertook scRNA-seq analysis of tumor monocytes and macrophages to determine the key hallmarks of their transcriptional diversity. We found two types of differentiation manifest during tumor development. On the one hand we found a classical lineage differentiation trajectory that progresses from monocytes-to-macrophages in a way that has been long appreciated (61) with a discernable ‘intermediate’ monocyte (“Mono-Int”) cell population. A “Mono-Int” population is, for reference, well-described in other settings. For example, Randolph and colleagues detect ‘intermediate’ monocytes in lymphoid and non-lymphoid tissue in steady-state conditions (62), and fluorescent real-time lineage tracing identifies cells undergoing that transition during allergic challenge (63).

On the other hand, we found two differentiation layers – ‘stress-responsive’ and ‘IFN-responsive’ – that co-exist along that trajectory and that were shared across multiple mouse models as well as a profiled human RCC biopsy (Fig. 1, 4). These programs were also present in other recently published studies (11,13,64,65). For example, in a pan-cancer study, Cheng et al. discern myeloid populations whose primary distinction is their expression of IFN-induced genes (e.g., *ISG15*<sup>+</sup> TAMs) (11). Similarly, we noted that the stress-responsive population shares characteristics with cells historically contained within MDSCs (i.e. *Arg1* expression and glycolytic programming) (27). A notable difference in our interpretation compared to these previous reports lies in our incorporation of these layers within the monocyte–macrophage differentiation axis, rather than proposing them as a unique trajectory. Through independent profiling of purified monocytes and macrophages in our study and pseudotime analysis (Fig. 1–2), we find the stress-responsive signatures evident in both cell populations and indeed across them. In additional support of such a view, we found that an IFN-responsive signature was enriched amongst monocytes in one mouse model and macrophages in another (Fig. 1, 3). We believe that this indicates that macrophages can differentiate in two dimensions – progression through the classical lineage as well as acquisition of specialized states characterized by examples of IFN or stress exposure. For these reasons, we prefer employing a nomenclature system that integrates the degree of monocyte-to-macrophage differentiation first, followed by additional transcriptional and functional qualities. Intuitively, this is similar to CD4<sup>+</sup> T cells that can differentiate along a naïve–effector–memory axis while also being able to layer on Th1/Th2/Th17 programs.

Despite the comparison with CD4<sup>+</sup> T cells, we do not find any populations, nor indeed any cells, that have an exclusively “M1” or “M2” signature (Fig. 3). Individual genes such as *Arg1* are associated with certain clusters, as some have observed (11), but both correlation and signature analyses fail to identify any of the described ‘M1’ or ‘M2’ genes as either being selectively linked with one another in single cells, or as key classifiers of cell clusters. To this extent, the ‘M1/M2’ nomenclature has provided direction in the fruitful study of myeloid-cell signaling and differentiation but does not appear to be accurately categorize distinct differentiation states, at least for tumors *in vivo*. We note the absence of data to the

contrary of this conclusion in other recent reports (43,55,65), although of course individual nomenclature (e.g., “M2-like”) is clearly a matter of choice and needs only discussion as to which part of the *in vitro* signature might be biologically relevant.

One important aspect of myeloid cell biology that requires further elaboration is how to identify IFN- and stress-responsive phenotypes. For example, Gubin et al. use iNOS as a marker by flow cytometry to define the IFN-stimulated population induced by ICB (12), whereas Cheng et al. utilize *ISG15* (11). Particularly in the former study, which studied macrophage identity following ICB therapies, varied levels of type I and II IFNs may also modulate properties of this differentiation layer. In the case of ‘stress-responsive’ populations, our data also point to IL-7R $\alpha$  expression, which may indicate involvement of TSLP signaling through heterodimeric pairing with TSLPR (66). An important set of conserved genes for ‘stress-responsive’ macrophages, taken from our manuscript, is their consistent and significant enrichment for glycolytic genes, particularly in comparison to conventional C1q ‘mature’ TAMs. Given that HIF-1 is known to induce glycolytic genes under inflammatory and/or hypoxic conditions (54), this finding raises the question of whether these cells are selected for hypoxic environments where oxidative phosphorylation may not proceed, as well as their specific function. Going forward, the use of multiplexed imaging technologies such as ion beam imaging (MIBI) and single-cell spatial transcriptomics will enable this question to be addressed.

Our investigation of monocyte–macrophage differentiation led us to explore how its regulation could inform our understanding of antitumor immunity. Analysis of RCC and melanoma patient cohorts revealed an increase in macrophage-to-monocyte ratios with tumor grade, a rise that coincided with T<sub>reg</sub> density and was T<sub>reg</sub>-dependent. T<sub>regs</sub> exert potent immunosuppression and are thought to restrain T-cell activity and antitumor responses through modulation of DC stimulatory capacity, production of immunosuppressive cytokines and substrates, and competitive usage of growth factors and metabolic byproducts (24,67,68). It is becoming clear now that tumor T<sub>regs</sub> also strongly influence the monocyte–macrophage lineage, likely through multiple mechanisms. In a recent study, tumor T<sub>regs</sub> promoted tumor macrophage numbers by supporting their mitochondrial capacity and viability (69). Here, our scRNA-seq data demonstrates that early-stage monocytes and “Mono-Int” cells are already unable to properly implement TAM-associated transcriptional programs in the absence of T<sub>regs</sub>, indicating that T<sub>regs</sub> also fuel macrophage differentiation processes. This liaison between T<sub>regs</sub> and macrophages mirrors one identified in the adipose fat of lean mice, where T<sub>regs</sub> are thought to actively maintain homeostasis and hold inflammatory macrophages at bay (70,71). Similarly, during the resolution of injury and inflammation in skeletal muscle and heart tissue, a transition from pro- to anti-inflammatory macrophages occurs in a manner that appears to rely on T<sub>reg</sub> accumulation (72,73). That T<sub>regs</sub> may act on tumor macrophages in a similar fashion offers another example of how the TIME can exploit immune programs of “accommodation” that are otherwise in place to achieve tissue homeostasis in the face of perturbations (74).

Accumulation of a broad swath of macrophages in the TIME has previously been implicated with poor outcome (75). Consistent with this but at higher resolution, we detected a group of kidney cancer patients for whom high macrophage-to-monocyte abundance was associated

with diminished T-cell infiltration and exhaustion of those cells detected, concurring with other reports (55,64). Our manuscript thus points to an emerging trio of T<sub>regs</sub>, macrophages, and exhausted T cells, whereby effector T cells may be corrupted through direct cellular interactions with TAMs, as has been suggested by observations of TAM-CD8<sup>+</sup> T-cell colocalization in clear cell RCC (ccRCC) (64), or indirectly through macrophage-induced T<sub>reg</sub> expansion and activity (8,76) or DC suppression (24,77).

Yet, high myeloid cell infiltration or skewed macrophage-to-monocyte ratios alone were not prognostic for KIRC patient survival. Indeed, although macrophages have often been found to be negatively associated with patient outcome, macrophage abundance as a sole biomarker has not been universally useful with prior studies similarly reporting instances in which macrophage abundance is not informative for patient cohorts with specific cancer sub-types, treatment regimens, or tumor stage (78–81). Clustering analysis of kidney TIME composition using comprehensive immune parameters, however, uncovered an archetype characterized by low macrophage-to-monocyte differentiation in conjunction with high cDC1 infiltration. These patients (CD8–Mo–cDC1) had elevated infiltration of CD8<sup>+</sup> T cells with low surface expression of proteins associated with exhaustion and highly enhanced survival rates (Fig. 6, **pink**). Notably, recent work focused on ascertaining the different immune archetypes across solid tumors suggests that these patient groups, though most frequent in kidney cancer, span cancer types including frequent representation in colorectal and bladder tumors (33).

Identification of a CD8–Mo–cDC1 archetype emphasizes the value of integrating multiparametric biomarkers as a means to better parse patient outcome and to establish principles of TIME organization. Given that T-cell activity appears to be collectively influenced by multiple immune cell populations with distinct partnering patterns, our analysis suggests that dual targeting of TIME axes may elicit the best CD8<sup>+</sup> T-cell responses. For example, reprogramming and/or depletion of macrophages may relieve active suppression (2,14) and strategies that boost cDC1 recruitment and survival (1) may further benefit even those with favorable macrophage-to-monocyte density. It is also notable that this protective archetype is specifically enriched for monocytes. Indeed, monocyte differentiation into macrophages may not be inevitable and accumulation of “Mono-Int” cells have been detected in multiple forms of inflammation (10,16,82,83). Additionally, the potential importance of monocytes is indicated by their increased numbers in the blood of ICB responsive as compared to non-responsive melanoma patients (32). In ccRCC patients, IFN-responsive TAMs exhibited lower levels of *HLA-DR*, reminiscent of the “Mono-Int” cells described here, and higher levels of these ISG<sup>hi</sup> TAMs were predictive of survival after tyrosine kinase inhibitor treatment (79). Such a relationship opens questions across cancer type; namely, whether “Mono-Int” are distinct in their antitumor function, and how might monocytes be additive or synergistic with cDC1s to drive antitumor CD8<sup>+</sup> T cells?

Altogether these findings contribute to the endeavor of clarifying useful distinctions in myeloid cell gene expression and highlight settings in which multiparametric analysis of tumor myeloid cell composition can inform patient immune archetype and guide development of relevant therapies.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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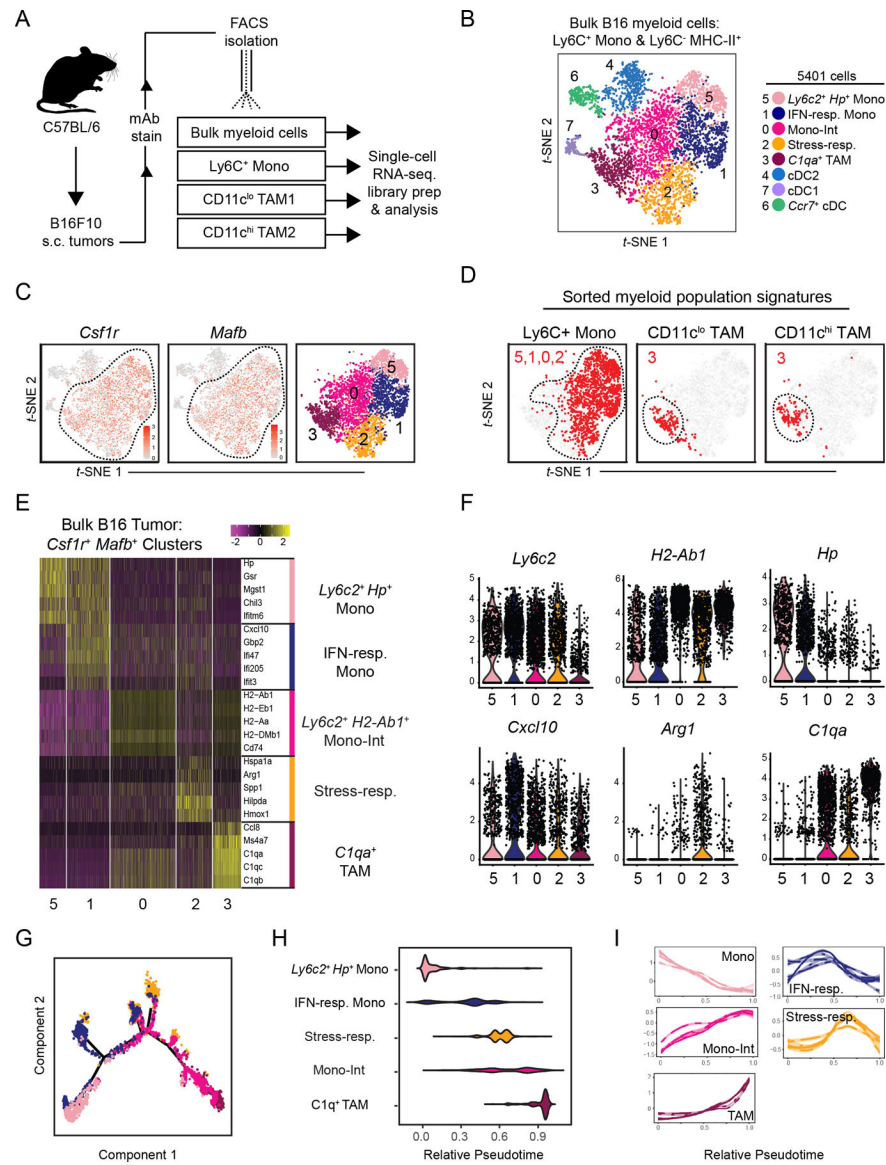


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### Synopsis

Single-cell RNA-sequencing analyses of mouse and human tumor-infiltrating myeloid cells show that monocyte-to-macrophage differentiation is marked by conventional lineage-associated and microenvironmental-induced cellular programs. Multiparametric analysis of myeloid composition, including monocyte-to-macrophage differentiation, helps to identify patients with improved survival.



**Figure 1. scRNA-seq analysis of mouse B16 tumor myeloid cells maps transcriptional heterogeneity amongst monocytes and TAMs.**

(A) Schematic illustration of workflow for isolation of specified myeloid cell populations from B16 tumors subcutaneously implanted in wild-type C57BL/6 mice.

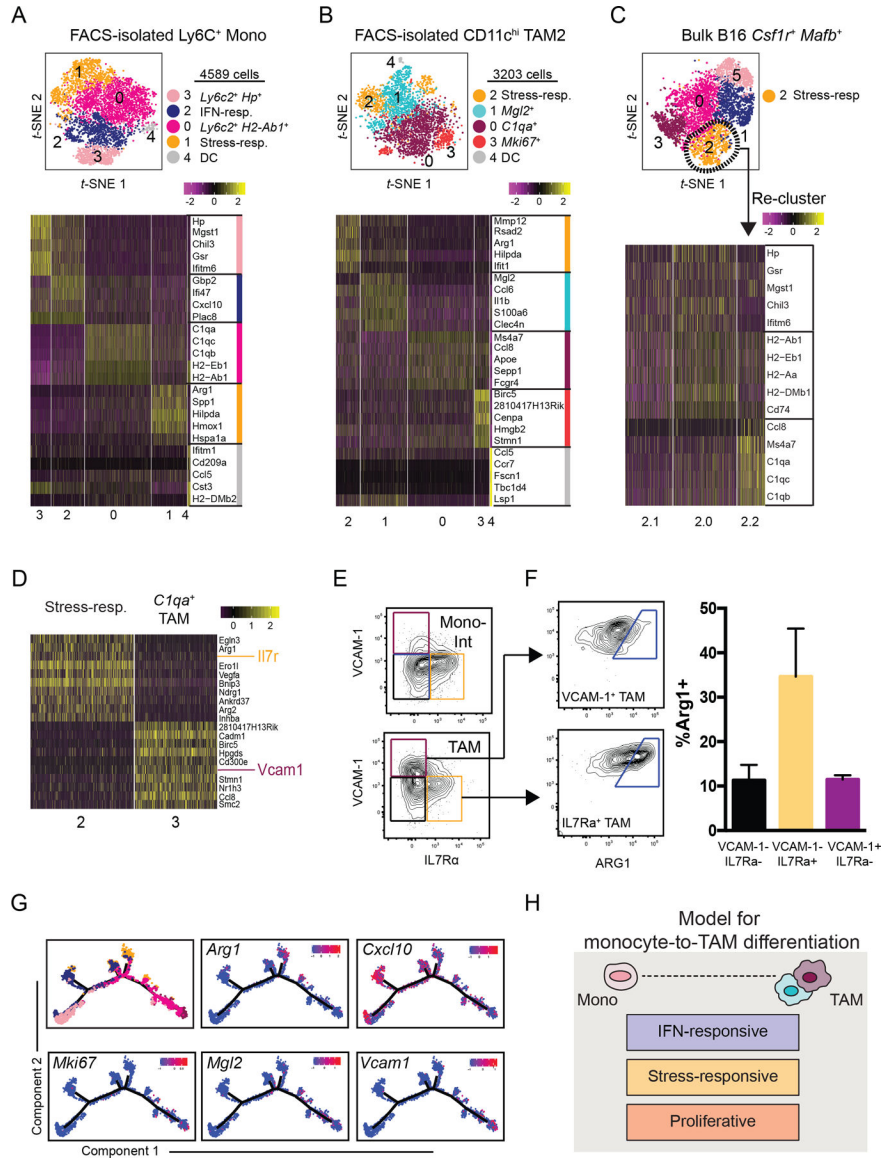
(B) t-SNE plot of graph-based clustering of Ly6C<sup>+</sup>CD11b<sup>+</sup> monocytes and Ly6C<sup>-</sup>MHCII<sup>+</sup> myeloid cells that were sorted and pooled from at least 5 B16 tumors, and underwent scRNA-seq (A). Each dot represents a single cell.

(C) Expression of *Csf1r* (left) and *Mafb* (middle) on t-SNE plot of bulk myeloid cells (B), and display of selected *Csf1r*<sup>+</sup> *Mafb*<sup>+</sup> clusters (right).

(D) Expression of gene signatures specific to Ly6C<sup>+</sup> monocyte, CD11c<sup>lo</sup> TAM1, or CD11c<sup>hi</sup> TAM2 populations (A, Supplementary Fig. S1F) displayed on t-SNE plot of *Csf1r*<sup>+</sup> *Mafb*<sup>+</sup> myeloid cells (C). Cells with top median of signature expression level labeled in red.

(E) Heatmap displaying expression levels of top 5 DE genes between *Csf1r*<sup>+</sup> *Mafb*<sup>+</sup> cell clusters (C). Genes ranked by fold change.

- (F)** Expression levels of selected genes amongst *Csf1r*<sup>+</sup>*Mafb*<sup>+</sup> cell clusters **(C)**.
- (G)** Differentiation trajectory model using Monocle analysis of cells from *Csf1r*<sup>+</sup>*Mafb*<sup>+</sup> clusters **(C)**. Color coding corresponds to previous labels **(B)**.
- (H)** Graph of relative pseudotime values of *Csf1r*<sup>+</sup>*Mafb*<sup>+</sup> cluster cells **(C)** from Monocle analysis **(G)**.
- (I)** Expression levels of cluster-specific genes **(E)** over relative pseudotime **(H)**. Each line corresponds to an individual gene.



**Figure 2. scRNA-seq analysis highlights layering of microenvironment-induced programs during tumor monocyte-to-macrophage differentiation.**

(A) t-SNE plot of graph-based clustering (**top**) of Ly6C<sup>+</sup> monocytes sorted from B16 tumors and processed for scRNA-seq (Fig. 1A), and heatmap displaying expression levels of top 5 DE genes between clusters (**bottom**) with genes ranked by fold change.

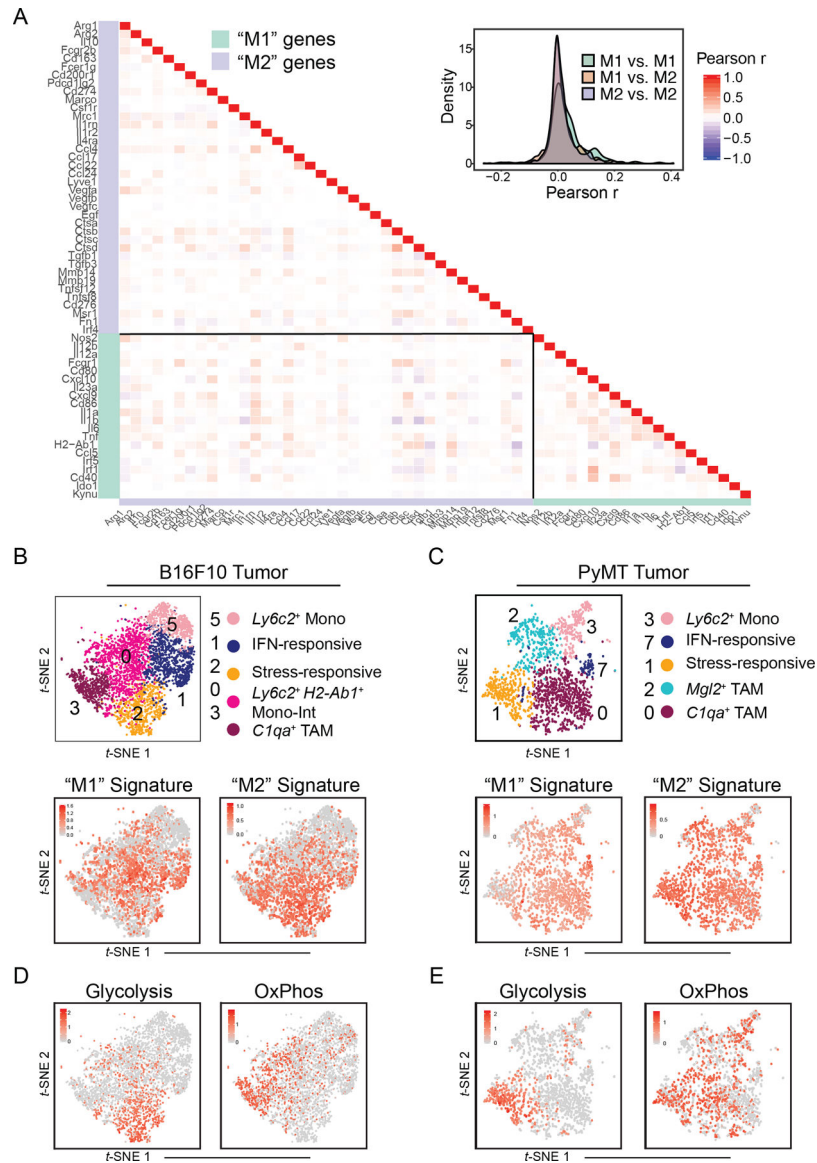
(B) t-SNE plot and graph-based clustering (**top**) of CD11c<sup>hi</sup> TAMs sorted from B16 tumors and processed for scRNA-seq (Fig. 1A), and heatmap displaying expression levels of top 5 DE genes between clusters (**bottom**) with genes ranked by fold change.

(C) Stress-responsive cells (Cluster 2) from bulk B16 myeloid cells (Fig. 1B) were selected for further clustering analysis (**top**). Heatmap of expression levels of monocyte- and macrophage-specific genes (Fig. 1E) by Cluster 2 sub-cluster (**bottom**).

(D) Heatmap of DE gene expression levels between Cluster 2 and Cluster 3 of bulk tumor myeloid cell sample (Fig. 1B). Genes ranked by degree of exclusivity to a given cluster (min.pct1/min.pct2).

- (E)** Expression levels of IL7R $\alpha$  and VCAM-1, as assessed by flow cytometry, of “Mono-Int” (Ly6C<sup>+</sup>CD64<sup>+</sup>) (**top**) and TAMs (Ly6C<sup>-</sup>F4/80<sup>+</sup>CD64<sup>+</sup>) (**bottom**) from B16 tumors.
- (F)** Example (**left**) and quantification (**right**) of intracellular ARG1 expression by VCAM-1<sup>+</sup> (**top**) or IL7R $\alpha$ <sup>+</sup> (**bottom**) TAMs from B16 tumors using flow cytometry. ARG1<sup>+</sup> gating determined by isotype control. Data are representative of 2 independent experiments with 3–5 mice per experiment (mean  $\pm$  SEM).
- (G)** Expression levels of selected genes along differentiated trajectory generated by Monocle (Fig. 1G).
- (H)** Schematic model of tumor monocyte-to-macrophage differentiation that integrates lineage-associated and microenvironmentally-induced transcriptional programs.

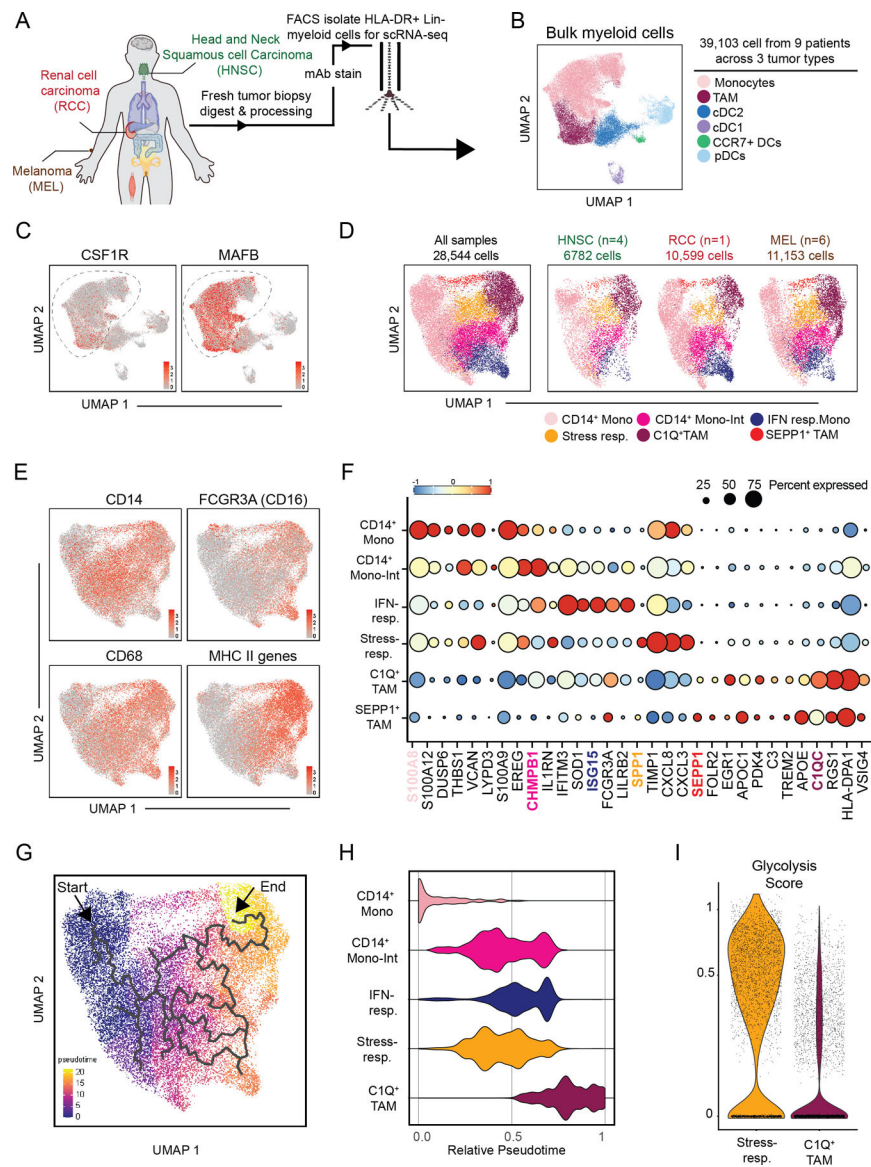




**Figure 3. B16 and PyMT tumor monocyte-macrophage heterogeneity can be attributed to diversity in transcriptional and metabolic programs, but not “M1/M2” polarization.** (A) Heatmap (left) and density plot (right) of Pearson r coefficient scores between “M1”- and “M2”-associated gene expression levels within *Csf1r*<sup>+</sup>*Mafb*<sup>+</sup> cells from B16 tumors (Fig. 1C). (B) t-SNE plot of *Csf1r*<sup>+</sup>*Mafb*<sup>+</sup> clusters from B16 tumors (top; Fig. 1C) with expression levels of “M1” (bottom, left) and “M2” (bottom, right) gene signatures (A) displayed. Cells with top median of signature expression level labeled in red. (C) t-SNE plot and graph-based clustering of *Csf1r*<sup>+</sup>*Mafb*<sup>+</sup> clusters of myeloid cells that were sorted from 1 PyMT tumor and processed for scRNA-seq in an independent experiment (top; Supplementary Fig. 3B). Expression levels of “M1” (bottom, left) and “M2” (bottom, right) gene signatures (A) displayed. Cells with top 70 percentile of signature expression level labeled in red.

**(D)** Expression levels of glycolysis (**left**) and oxidative phosphorylation (“OxPhos”) (**right**) gene signatures (Supplementary Fig. 3F) displayed on *t*-SNE plot of *Csf1r*<sup>+</sup>*Mafb*<sup>+</sup> clusters from B16 tumors (Fig. 1C). Cells with top 70 percentile of signature expression level labeled in red.

**(E)** Expression levels of glycolysis (**left**) and oxidative phosphorylation (“OxPhos”) (**right**) gene signatures (Supplementary Fig. 3F) displayed on *t*-SNE plot of *Csf1r*<sup>+</sup>*Mafb*<sup>+</sup> clusters from PyMT tumors (**C**). Cells with top 70 percentile of signature expression level labeled in red.



**Figure 4. Human RCC and mouse tumor myeloid cell compartments exhibit shared transcriptional features.**

(A) Schematic of the 1 human RCC, 6 melanomas, and 4 head and neck biopsy samples processed for scRNAseq analysis.

(B) *UMAP* plot of graph-based clustering of bulk myeloid ( $\text{Lin}^- \text{HLA-DR}^+$ ) cells sorted from human biopsy samples (A).

(C) Gene expression levels of *CSF1R* (left) and *MAFB* (right) displayed on *UMAP* plot of human tumor-infiltrating myeloid cells (B).

(D) *UMAP* plot of graph-based clustering of *CSF1R*<sup>+</sup>*MAFB*<sup>+</sup> cells (C) with cells from all human biopsy samples (left) or specified cancer type (right) displayed.

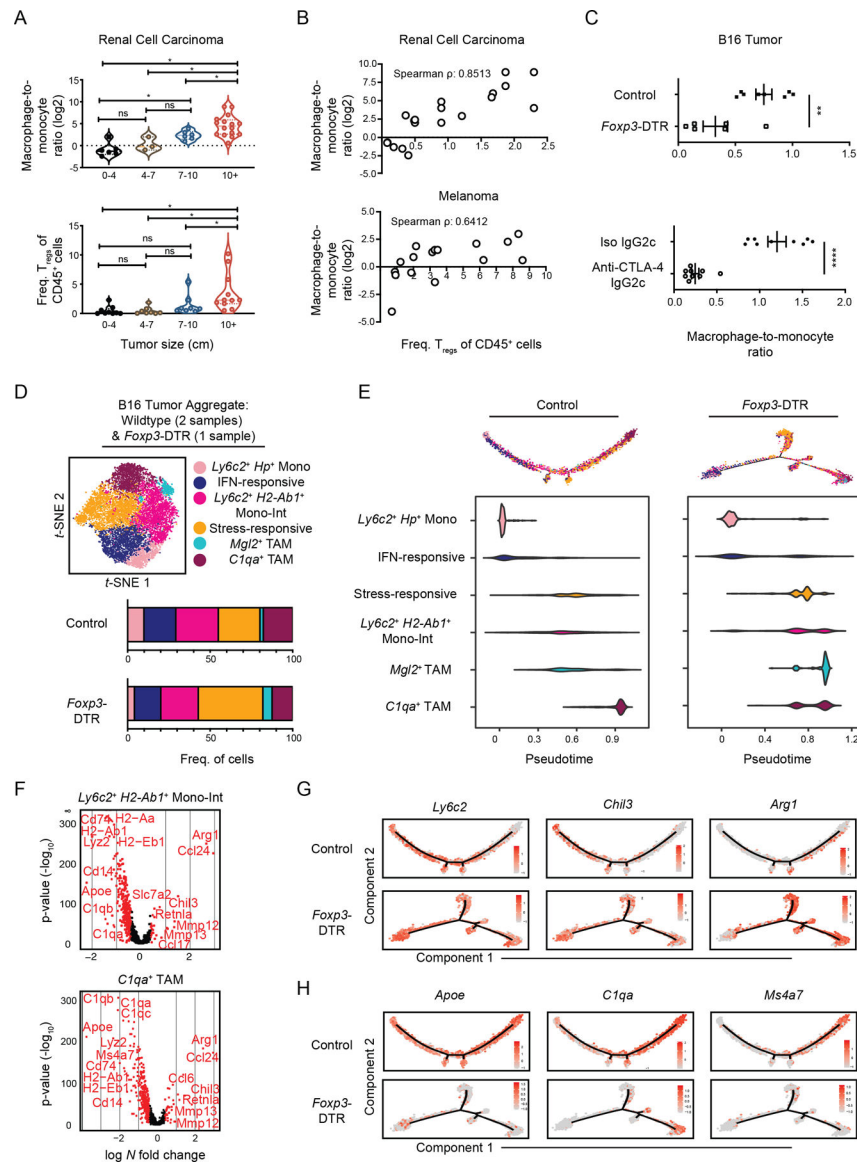
(E) Expression levels of selected genes (*CD14*, *FCGR3A*, *CD68*) or gene signature (MHC-II-associated genes) displayed on *t-SNE* plot of *CSF1R*<sup>+</sup>*MAFB*<sup>+</sup> clusters (C).

(F) Expression of selected genes expressed by *CSF1R*<sup>+</sup>*MAFB*<sup>+</sup> clusters (C).

**(G)** Differentiation trajectory model generated by Monocle analysis of *CSF1R*<sup>+</sup>*MAFB*<sup>+</sup> clusters (**C**).

**(H)** Relative pseudotime values of early-stage *CD14*<sup>+</sup> monocytes, *CD14*<sup>+</sup> “Mono-Int”, *CIQ*<sup>+</sup> TAMs, IFN-responsive cells, and stress-response TAM clusters (**C**) from Monocle analysis (**G**).

**(I)** Expression levels of glycolysis-associated gene signature by cells in stress-responsive and *CIQ*<sup>+</sup> TAM cells (**B**).



**Figure 5. Immunosuppressive  $T_{reg}$  cells promote tumor monocyte-to-macrophage differentiation.**

(A) 20 human RCC biopsies were measured and processed for flow cytometric analysis. The ratio of macrophage-to-monocyte ( $\log_2$ ) cell numbers (**top**) and  $T_{reg}$  frequency amongst CD45<sup>+</sup> cells (**bottom**) were quantified. Samples were acquired and pooled for analysis. \* $p < 0.05$ , Kruskal Wallis rank test. Dashed lines represent the median and dotted lines represent 25<sup>th</sup> percentile and 75<sup>th</sup> percentile.

(B) Dot plot and Spearman's correlation coefficient of macrophage-to-monocyte cell number ratio ( $\log_2$ ) and  $T_{reg}$  frequency within CD45<sup>+</sup> cells in 20 human RCC (**top**) and 16 melanoma (**bottom**) biopsies that were analyzed by flow cytometry. Samples were acquired and pooled for analysis.

(C) Quantification of the ratio between macrophages (Ly6C<sup>+</sup>F4/80<sup>+</sup>CD64<sup>+</sup>) and monocytes (Ly6C<sup>+</sup>CD11b<sup>+</sup>) cell number ratio in B16 tumors of DT-treated control and *Foxp3*-DTR mice (**top**), or of wild-type mice treated with depleting anti-CTLA-4 (IgG2c clone) or

isotype antibody (**bottom**). Data is representative of at least 2 independent experiments with 3–9 mice per group per experiment (mean  $\pm$  SEM). \*\*p < 0.01, \*\*\*\*p < 0.0001, unpaired *t*-test.

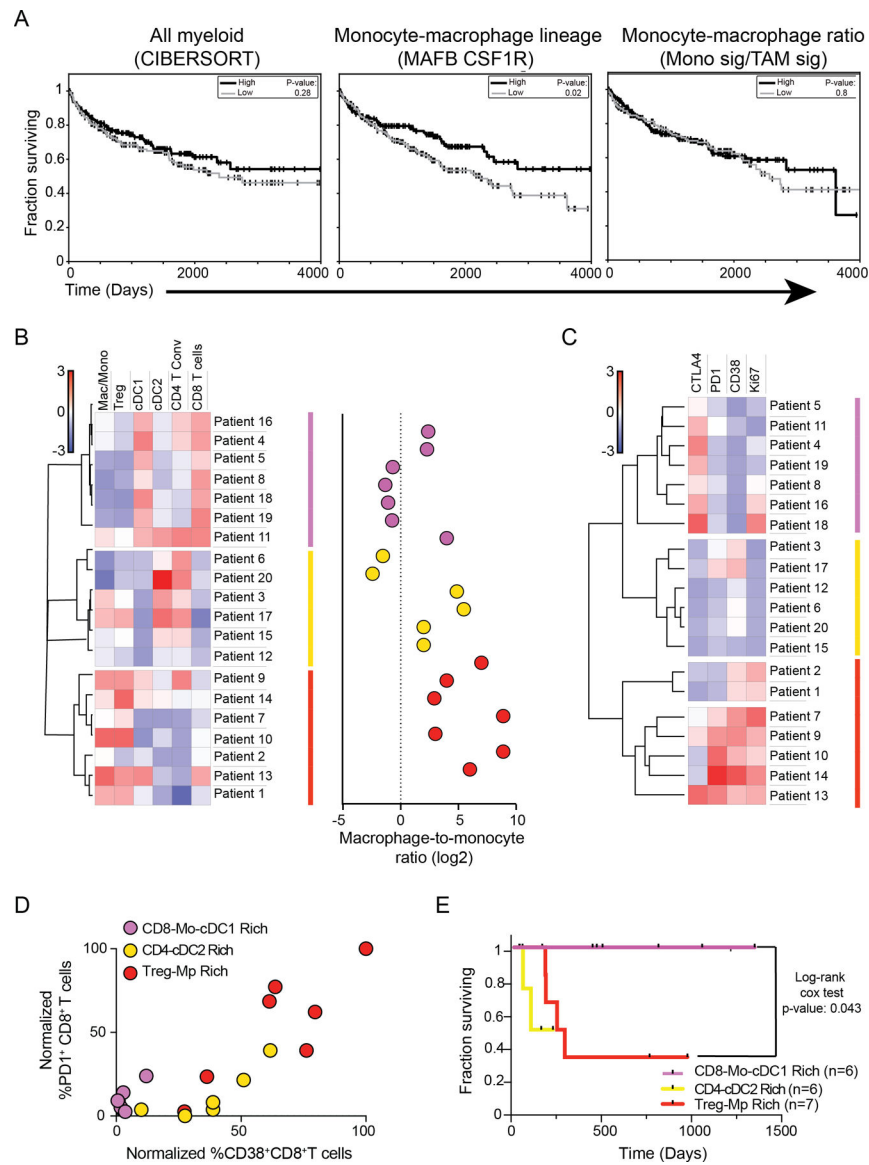
**(D)** *t*-SNE plot of graph-based clustering (**top**) of B16-infiltrating *Csf1r*<sup>+</sup>*Mafb*<sup>+</sup> cells from wildtype mice (Fig. 1) which were aggregated with DT-treated control and *Foxp3*-DTR mice (Supplementary Fig. 5D) from a second independent experiment in which tumors from at least 5 mice were pooled. Cell numbers in specified clusters were quantified (**bottom**).

**(E)** Differentiation trajectory model generated from Monocle analysis (**top**) and relative pseudotime values (**bottom**) of *Csf1r*<sup>+</sup>*Mafb*<sup>+</sup> cluster cells from B16 tumors from DT-treated control (**left**) and *FoxP3*-DTR mice (**right**).

**(F)** Volcano plot displaying DE genes between B16 tumor “Mono-Int” (**top**) and *Clqa*<sup>+</sup> TAM (**bottom**) cluster cells from DT-treated control and *FoxP3*-DTR mice (**D**). Genes with > 0.4 log-fold changes and an adjusted p value of 0.05 (based on Bonferroni correction) are highlighted in red. Genes of interest labeled.

**(G)** Expression of selected monocyte-associated genes displayed on the differentiation trajectory (**E**) of control (**top**) or *Foxp3*-DTR (**bottom**) B16 tumor-infiltrating *Csf1r*<sup>+</sup>*Mafb*<sup>+</sup> cells.

**(H)** Expression of selected macrophage-associated genes displayed on the differentiation trajectory (**E**) of control (**top**) or *Foxp3*-DTR (**bottom**) B16 tumor-infiltrating *Csf1r*<sup>+</sup>*Mafb*<sup>+</sup> cells.



**Figure 6. Multiparametric analysis of tumor myeloid composition identifies kidney cancer patients with effector CD8<sup>+</sup> T-cell responses and improved survival rates.**

(A) Survival curves of kidney tumor patients whose TCGA tumor samples exhibited high (33%) or low (33%) levels of expression levels of pan-myeloid cell gene signatures derived from CIBERSORT (left), *MAFB* and *CSF1R* (middle), or ratio of monocyte-to-TAM gene signatures (Fig. 4) (right), analyzed with log-rank test.

(B) Heatmap of specified immune cell population frequencies (left) and the ratio of macrophage-to-monocytes (right) detected in 20 human kidney tumor samples by flow cytometry.

(C) Heatmap of specified surface receptor or Ki-67 expression frequencies amongst CD8<sup>+</sup> T cells from 20 human kidney tumor samples that were analyzed with flow cytometry.

(D) Quantification of the frequency of CD8<sup>+</sup> T cells from 20 human tumor kidney samples that are PD1<sup>+</sup> or CD38<sup>+</sup>. Labeling of dots corresponds to patient groups (B,C).



(E) Survival curves of kidney cancer patients in cohort analyzed with log-rank test (B-D).

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