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Single cell transcriptomic landscape reveals tumor specific innate lymphoid cells associated with colorectal cancer progression

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25 **Summary**

26 Innate lymphoid cells (ILCs) are tissue-resident lymphocytes **differing** from conventional T
27 lymphocytes in having no antigen-specific receptors. ILCs include natural killer (NK) cells,
28 helper-like ILC1s, ILC2s, ILC3s and lymphoid tissue-inducer (LTi) cells. Tumor ILCs are
29 frequently found in various cancers, but their roles in cancer immunity and immunotherapy remain
30 **largely unclear**. We report here the single-cell characterization of blood and gut helper-like ILC
31 subsets in healthy conditions and in colorectal cancer (CRC). The healthy gut contains ILC1s,
32 ILC3s, and ILC3/NKs, but no ILC2s. Additional tumor-specific ILC1-like and ILC2 subsets were
33 identified in CRC patients. Signaling lymphocytic activation molecule family member 1
34 (SLAMF1) was found to be selectively expressed on tumor-specific ILCs and higher levels of
35 SLAMF1⁺ ILCs were observed in the blood of CRC patients. The SLAMF1-high group of **CRC**
36 patients had a significantly higher survival rate than the SLAMF1-low group, suggesting that
37 SLAMF1 is an anti-tumor biomarker in CRC.

Introduction

T cell-based immunotherapy has been very successful clinically for the treatment of malignant tumors, but only in a small proportion of patients¹⁻⁶. Treatments targeting other immune components are required, to increase the proportion of patients benefiting from immunotherapy. Innate lymphoid cells (ILCs) are tissue-resident innate antigen-independent lymphocytes that regulate immunity to pathogens and commensal organisms for tissue homeostasis^{7,8}. ILCs form a heterogeneous population of cells that are currently classified into five major groups, natural killer (NK) cells, helper-like ILC1s, ILC2s, ILC3s, and lymphoid tissue-inducer (LTi) cells on the basis of their cytokine production and transcription factor expression profiles⁸. ILCs are involved in immune functions, including pathogen responses, inflammation, tissue development, remodeling, repair and homeostasis.

Given the large amounts and nature of the cytokines they produce, ILC subsets are likely to be involved in cancer immunity, but may also contribute to tumor-associated inflammation. NK cells are known to play a role in cancer, through their tumor-suppressive properties, and are efficient at controlling metastasis⁹. The role of helper-like ILCs in the context of tumorigenesis and cancer immunity is less clear and appears to depend on the tumor microenvironment. ILC1s produce large amounts of proinflammatory cytokines, such as IFN- γ and TNF- α , which favor tumorigenesis¹⁰. However, IFN- γ can also limit tumor growth in certain tumor microenvironments^{11, 12}. ILC2s have been shown to be mostly detrimental in various tumor settings. Indeed, large numbers of ILC2s are present in the peripheral blood of patients with gastric cancer¹³ and acute promyelocytic leukemia¹⁴. ILC2-derived IL-13 stimulates the immunosuppressive activity of myeloid-derived suppressor cells in acute promyelocytic leukemia¹⁴, and in human bladder cancer and murine prostate tumors¹⁵. However, ILC2-derived IL-5 may

help to suppress primary and metastatic lung tumors in mouse models ^{16, 17}. ILC2 could also secrete CXCR2 ligands to reinforce tumor cell-specific apoptosis in solid tumor mouse model ¹⁸, and ILC2s activate tissue-specific tumor immunity in pancreatic cancer ¹⁹. ILC3s also have tumor suppressor properties, in the B16 melanoma mouse model ^{20, 21} and in non-small cell lung cancer (NSCLC) patients ²², for example. By contrast, ILC3-derived IL-17 and IL-22 may contribute to gut cancer development ^{23, 24}. There is, therefore, a clear need to investigate the presence and role of helper-like ILC subsets in various cancer indications.

Colorectal cancer (CRC) is the third most prevalent cancer in both women and men, and the second most frequent cause of cancer-related deaths worldwide ²⁵, despite remarkable improvements in therapeutic strategies. Dysregulated ILC responses have been linked to the development of intestinal cancers. ILC2s are present at low levels in many pathological conditions in humans ^{26, 27}. By contrast, CRC patients have large numbers of ILC1s in the intestines ²⁶⁻²⁹, and abnormally low levels of ILC3s ^{28, 29}, which normally densely populate the colon at steady state ²⁷⁻²⁹. Indeed, decreases in the ILC3/ILC1 ratio have been associated with the severity of CRC ²⁹. The baseline helper-like ILC landscape, in terms of the composition, diversity, and functional status of these cells in the human gut, remains incompletely explored under tumor conditions.

We used unsupervised hierarchical clustering to investigate helper-like ILC heterogeneity at steady state and during CRC, in the blood, normal mucosa and gut tumors. The healthy gut is composed of ILC1s, ILC3s, and ILC3/NKs, but no ILC2s. Helper-like ILCs from CRC patients were found to contain two additional subsets: a CRC tissue-specific ILC1-like subset (ctILC1-like) and an ILC2 (ctILC2) subset. SLAMF1 (signaling lymphocytic activation molecule family member 1, CD150) was found to be selectively expressed on ctILCs, and higher frequencies of

84 SLAMF1-expressing helper-like ILCs were found in the blood of CRC patients. The group of
85 patients with SLAMF1-high colon and rectal cancers had a significantly higher survival rate than
86 the SLAMF1-low patients, suggesting that SLAMF1 is an anti-tumor biomarker in CRC.

Results

Healthy gut contains ILC1s, ILC3s, and ILC/NKs, but no ILC2s

We dissected the role of helper-like ILCs in CRC by studying paired CRC tissue and adjacent mucosal tissue (used as a control) samples, and comparing blood from patients with blood from age-matched healthy donors (Table S1 and Figure S1A). Lineage negative (Lin^-) ($\text{TCR}\gamma\delta^-$ $\text{TCR}\alpha\beta^-$ CD3^- CD19^- CD14^- CD16^- CD94^- CD123^- CD34^- CD303^- $\text{Fc}\epsilon\text{RI}^-$) CD127^+ helper-like ILCs were more abundant in both normal mucosa and CRC tissue than in blood, consistent with the known tissue residence properties of ILCs³⁰ (Figure S1B-C). The percentage of helper-like ILCs was lower in CRC tissues than in normal mucosa, but similar in normal and CRC blood samples (Figure S1B-C).

We performed scRNAseq on ~58,000 total purified helper-like ILCs from blood samples from CRC patients, healthy blood, normal mucosa and CRC tissue samples (Figure S1D-E). The heterogeneity of helper-like ILCs in normal mucosa was assessed with a total of 16,145 Lin^- CD127^+ cells from colon tissues adjacent to the colon tumor in CRC patients (Figure S1E). The projection of cells onto two dimensions in a uniform manifold approximation and projection (UMAP) analysis revealed segregation into six distinct clusters: normal mucosa cluster (nmC)0 to nmC5 (Figure 1A). Two clusters, nmC4 and nmC5, contained cells from all donors, suggesting that there was no donor-specific transcriptomic profile for these two helper-like ILC populations (Figure 1B-C). By contrast, most of the cells from nmC0 to nmC3 were single donor-specific (Figure 1B-C).

Using hierarchical clustering (Figure 1C) and gene signature heatmaps (Figure 1D and Table S2), principal component analysis (PCA) (Figure 1E-F), top 10 expressed gene analysis (Figure 1G), and module score analysis (Figure 1H), we then compared the gene signatures of nmC0 to nmC5

with previously described transcriptomic signatures of human helper-like ILC subsets³¹. nmC0 to nmC3 had a common transcriptomic signature characteristic of ILC3s, with *REL*, encoding a proto-oncogene member (c-Rel) of the NF-κB family³² and NF-κB signaling *via* the *IL22* promoter site in ILC3s³³, as a driver gene (Figure 1F), and *KIT*, *CXCL8*, *IL4I1* and *IL1R1* in the top 10 expressed genes (Figure 1G). nmC4 was characterized by *NKG7*, encoding a cytolytic granule membrane protein³⁴, and *KLRD1*, encoding CD94, expressed in T and NK cells, as driver genes, with *GNLY*, *GZMK*, *XCL2*, and *CCL4*, among the top expressed genes and with a whole signature common to NK cells and ILC3s from tonsils (Figure 1F-G). nmC4 was, thus, identified as an ILC3/NK subset. nmC5 resembled ILC1s, with higher levels of expression of T-cell markers (*CD3D*, *CD3G*, and *CD3E*), as previously described^{31,35,36}, specific transcription factors (*IKZF3*, *BCL11B*, *PRDM1*, and *ID3*), and NK/ILC1 cell functional cytokines (*GZMM*, *IFNG*, *IL32*, *CCL4*, and *CCL5*) (Figure 1F-H). nmC0-3 were enriched in response to lipid, glucocorticoid, and corticosteroid while nmC5 was involved in T cell activation and differentiation (Figure S2A). The assignments of each cluster were supported by the selective expression of known helper-like ILC markers, such as *IL7R*, *GATA3*, *NCR3*, *EOMES*, *TBX21*, *KIT*, *RORC*, *NCR1*, *NCR2* and *KLRF1* (Figure S2B). We found differences between nmC5 and previously reported healthy gut ILC1s³⁷, probably because the gating strategies used here did not exclude CD5⁺ cells (Figure S2C-D). Thus, the normal gut mucosa defined by scRNAseq profiling of Lin⁻CD127⁺ contains ILC1s, ILC3s, and ILCs/NKs but no ILC2s, consistent with the lack of *PTGDR2* gene expression (Figure S2B).

Tumor ILC1-like and ILC2 subsets are present in CRC patients

We then investigated the composition and diversity of 15,101 ILCs from the tumors of CRC patients. UMAP analysis identified four distinct clusters in CRC tissue (ctC short for CRC tissue

cluster): ctC0 to ctC3 (Figure 2A). Contrary to what was observed for normal mucosa, no overwhelming donor-dependent effect was observed, each cluster being present in all samples (Figure 2B-C). Based on the strategy applied to normal mucosa clusters (Figure 1), ctC0 was assigned to ILC3s, consistent with its overexpression of *KIT*, *CXCL8*, *NFIL3*, and *IL411*, like nmC0-3 (Figure 2C-H and Table S2). ctC1 resembled ILC1s and, like nmC5, displayed differential expression of genes encoding T-cell molecules (*CD3D*, *CD3G*), secreted effectors (*CCL4*, *IFNG*), and ILC-related transcription factors (*IKZF3*, *PRDM1* and *BCL11B*). The other two subsets present, ctC2 and ctC3, were absent from normal mucosa. ctC2 cells corresponded to an additional ILC1 subset, hereafter called the ctILC1-like subset (CRC tissue-specific ILC1-like subset), characterized by an enrichment in the expression of genes encoding inhibitory and costimulatory markers (*TIGIT*, *CTLA4*, and *TNFRSF4*). ctC3 cells, identified as ILC2s and hereafter referred to as ctILC2, had high levels of expression for genes encoding transcription factors required for ILC2 development (*GATA3*, *RORA*, and *ZBTB16*) and ILC2-responsive cytokine receptor genes (*IL1RL1* and *IL17RB*) (Figure 2C-H and Table S2). ctC1 was enriched in cytolysis, granulocyte chemotaxis, granzyme-mediated apoptotic signaling pathway, whereas ctC2 and ctC3 were respectively enriched in T cell anergy and interleukin-5 production and interleukin-13 secretion (Figure S2E). Subset assignments were supported by the selective expression of known ILC markers, such as *IL7R*, *GATA3*, *NCR3*, *EOMES*, *TBX21*, *KIT*, *RORC*, *NCR1*, *NCR2* and *KLRF1* (Figure S2F). In particular, *PTGDR2* and higher levels of *GATA3* expression were found in the ILC2s. *SLAMF1* (signaling lymphocytic activation molecule family member 1 or CD150), which encodes a soluble and membrane protein involved in the activation of T cells, B cells, and NK cells³⁸, was upregulated both in ctILC1-like and ctILC2 in tumors (Figure 2G). Thus, like nmILCs, ctILCs formed heterogeneous populations encompassing four different subsets:

ctC0 (resembling ILC3s), ctC1 (resembling ILC1s), ctC2 (named as ILC1-like), and ctC3 (resembling ILC2s).

Tumor tissue ILC3s seemed to be less heterogeneous than those in the normal mucosa. We therefore focused on nmC0-3, nmC4 and ctC0, comparing ILC3 heterogeneity between normal mucosa helper-like ILCs and gut ctILCs, with the same analysis pipeline as described above after applying a correction that removed the donor batch effect allowing the analysis of ILC3 heterogeneity (Figure S3, Table S2). Four different populations were found in ILC3s from both types of tissue (Figure S3 A-I), including a potentially immature *SELL*-expressing population, and a population enriched in HLA-encoding transcripts also present in human tonsils (Figure S3E and J). Each subset of normal mucosa ILC3 had a counterpart in tumor tissue (Figure S3K). Given the overlap in ILC3s heterogeneity between normal mucosa and gut ctILCs, we can conclude that CRC did not affect the subset heterogeneity of ILC3s. Thus, gut ctILCs differed from nmILCs in the appearance of a ctILC2 subset and a second ctILC1-like subset.

Blood helper-like ILC heterogeneity is stable in CRC

We searched for potential biomarkers of the disease, by investigating differences in blood helper-like ILCs between healthy individuals and CRC patients. A UMAP analysis of 19,603 helper-like ILCs from healthy donors revealed three distinct clusters, hereafter referred to as nbC0, nbC1, and nbC2 (Figure S4A-C and Table S2). nbC0 was considered to correspond to ILC1s, based on the upregulation of *CD3D*, *CD3E*, *CD3G*, the NK/ILC1 cell effector proteins (*CCL5*, *GZMK*, *GZMM*, and *GZMA*), and helper-like ILC transcription factors (*BCL11B*, *PRDM1*, and *IKZF3*) (Figure S4D-H). nbC1 was identified as ILC3s, and was characterized by ILC3 transcription factors (*MAFF*, *RUNX3*) and costimulation markers (*TNFRSF4*, *TNFRSF18*). nbC2

displayed an upregulation of genes from the ILC2 signature (*GATA3*, *RORA*), and genes encoding regulatory receptors (*KLRB1*, *KLRG1*) (Figure S4D-H). These assignments were supported by the selective expression of known helper-like ILC markers, such as *IL7R*, *GATA3*, *NCR3*, *EOMES*, *TBX21*, *PTGDR2*, *KIT*, *RORC*, *NCRI*, and *KLRF1* (Figure S4I).

A UMAP plot of 6,899 blood helper-like ILCs from CRC donors also identified three subsets, hereafter referred to as cbC0, cbC1 and cbC2 (Figure S5A-C and Table S2). Driver genes, top ten genes and module score signatures highlighted the similarity of cbILCs to nbILCs (Figure S5D-H). cbC0, like nbC1, had an ILC3 profile with enrichment for *MAFF*, *RUNX3*, *TNFRSF18*. cbC1 were identified as ILC2s, with high levels of *RORA*, *KLRB1*, *KLRG1*, and *PTGDR2* expression, like nbC2. Of note, similar to ctILC2, cbC1 exhibited high levels of *SLAMF1*. cbC2, like nbC0, displayed an enrichment in the genes of the ILC1 signature: *CD3D*, *CD3G*, *CD3E*, *CCL5*, *GZMK*, *GZMM*, *GZMA*, *BCL11B*, *PRDM1*, and *IKZF3* (Figure S5D-I). These assignments were also supported by the selective expression of *IL7R*, *GATA3*, *NCR3*, *EOMES*, *TBX21*, *PTGDR2*, *KIT*, *RORC*, *NCRI*, and *KLRF1* (Figure S5I). However, despite the similarity of cbILC subsets to nbILC subsets, velocity analysis predicted a possible conversion of ILC1s into ILC3s only in the context of CRC, in tumor blood (Figure S5J and data not shown). In summary, the blood helper-like ILCs of both healthy donors and CRC patients formed heterogeneous populations containing ILC1, ILC2 and ILC3 subsets.

Identification of a population of CRC tissue-specific ILC1s

Tumor tissue helper-like ILCs contained two additional populations not present in the helper-like ILCs of the normal mucosa, with transcriptomic signatures resembling those of ILC2s and ILC1s (Figure 1 and Figure 2). We investigated the relatedness of these two tumor tissue-specific

clusters and the helper-like ILC subsets from healthy blood and blood from CRC patients, by grouping the 41,603 helper-like ILCs into a single global analysis. This analysis revealed organ-specific imprinting in helper-like ILCs, with an overlap between the two types of blood samples, and ctILCs clustering separately (Figure 3A and Table S2). There was a high degree of similarity between nbILCs and cbILCs in gene signature, it was remarkably different from that of ctILCs (Figure 3B-C). We further investigated the relationship between defined ILC subsets from CRC tissue, normal blood and CRC blood samples. The ctILC1-like subset appeared to segregate away from the other clusters, including TILC1 in particular, despite having a core ILC1-transcriptomic signature in common with this subset (Figure 3D). Likewise, another TILC-specific subset, ctILC2, clustered away from the other ctILCs and the ILC2 in the blood. In the blood, each nbILC clustered with the corresponding cbILC subset (Figure 3D). We investigated whether the tumor-specific helper-like ILCs shared more genes to their normal blood or CRC blood counterparts, by creating Venn diagrams comparing their whole transcriptomic signatures (Figure 3E-F). The ctILC1-like subset shared more genes with cbILC1 (57 genes in common) than with nbILC1 (34 genes in common) (Figure 3E), suggesting a tumor imprinting, whereas ctILC2 shared comparable numbers of genes with cbILC2 and nbILC2, with which this subset had 39 and 34 genes, respectively, in common (Figure 3F).

Helper-like ILC signature is modified in CRC tumor

We searched for tumor-specific tissue features of ILCs, by clustering the 31,246 helper-like ILC cells from normal mucosa and tumor tissues. These two tissues had some helper-like ILC populations in common, but UMAP highlighted a shift between the two tissues, suggesting differences at the transcriptomic level (Figure 4A). Unsupervised hierarchical clustering also

showed the tissue-of-origin signature to be stronger than the helper-like ILC subset identity signature (Figure 4B-C, Table S2). The clustering of nbILCs and cbILCs revealed a similar pattern of separation for the 26,502 helper-like ILCs in the UMAP analysis (Figure 4D), and in unsupervised hierarchical clustering, which segregated blood samples according to health status, revealing differences in transcription between the two subsets (Figure 4E-F). One gene was found to be upregulated in normal blood and mucosa (*AQP3*). Four genes were identified as upregulated in both CRC blood and gut ctILCs relative to their healthy counterparts (*SLAMF1*, *HPGD*, *TLE4*, and *PRDM1*) (Figure 4G). Feature plots of these five genes of interest confirmed the specific upregulation of *SLAMF1*, *HPGD*, *TLE4*, and *PRDM1* in gut ctILCs, and the downregulation of *AQP3* (Figure 4H-I). *SLAMF1* was the principal surface protein gene upregulated in tumors. This gene was expressed in ctILC2, ctILC1-like subsets and cbILC2 (Figure 2G, 4H and Figure S5), but only weakly in their healthy counterparts (Figure 4H), suggesting that *SLAMF1* expression at the helper-like ILC cell surface can differentiate healthy individuals from CRC patients.

SLAMF1 is a biomarker of CRC

We confirmed, by flow cytometry, the expansion of the ILC1 subset accompanied by reduction of the ILC3 subset in tumor tissues from CRC patients relative to adjacent normal mucosa (Figure 5A-B). Consistent with the scRNAseq analysis revealing higher levels of *TIGIT* in an ILC1-like subset and the presence of ctILC2s (Figure 2G), we observed by flow cytometry a population of *TIGIT*⁺ ctILC1-like cells and ctILC2 in tumors, but not in normal tissue (Figure 5A-B). Higher levels of expression of the ILC2-activating cytokine *IL33* in tumors were correlated with longer survival in CRC patients from The Cancer Genome Atlas (TCGA) dataset, suggesting that ctILC2 might be indicative of a good prognosis in CRC patients (Figure 5C). In

contrast to the findings for gut helper-like ILCs, the frequency of each helper-like ILC subset among total helper-like ILCs in blood was similar in CRC patients and healthy donors (Figure 5D). Larger numbers of ILCs expressing SLAMF1 at their surface was found in tumors than in the adjacent tissues, from which SLAMF1 was almost absent (Figure 5E-F). By contrast, SLAMF1 was expressed by blood ILCs from healthy donors, but high frequencies of SLAMF1-expressing helper-like ILCs were also found in the blood of CRC patients (Figure 5G). Signatures of *SLAMF1*⁺ and *SLAMF1*⁻ ILCs from CRC tissue were then compared. While *RORA* and *IL32* expression were relatively high in *SLAMF1*⁺ ILCs, *XCL2* and *XCL1* expression were enriched in *SLAMF1*⁻ ILCs (Figure 5H). IL-32 was reported to be anti-tumor in several cancer types, including cervical, colon, prostate, liver and pancreatic cancer, as well as melanoma and chronic myeloid leukemia ³⁹, suggesting that *SLAMF1*⁺ ILCs might exhibit an *IL-32* dependent anti-tumor effect. We then investigated the potential role of SLAMF1 in CRC disease development and progression further, by studying the clinical outcome of cancer patients from the TCGA database. Survival was much higher in patients with *SLAMF1*-high colon and rectal cancer than in those with *SLAMF1*-low tumors (Figure 5I-J), strongly suggesting that SLAMF1 is an anti-tumor biomarker in CRC.

Discussion

Over the last decade, helper-like ILCs have emerged as key elements in protection against pathogens, tissue remodeling and homeostasis⁸. The contribution of helper-like ILCs to cancer remains poorly understood, as they may promote tumor-associated inflammation or, conversely, may display anti-tumor properties, depending on the tumor microenvironment.

We investigated the heterogeneity of helper-like ILCs in the human gut and blood by building a single cell transcriptomic landscape of Lin⁻CD127⁺ cells at steady state and in CRC patients. This unbiased helper-like ILC characterization differed from the analysis of gut ILC transcriptomes provided by another recent study, in which these cells were subjected to sorting by flow cytometry on the basis of the CD103, CD300LF and CD196 cell surface markers before transcriptomic profiling⁴⁰. We show here by single-cell RNA sequencing that the healthy gut contains ILC1s, ILC3s, a population of ILC3/NKs, but no ILC2s. Indeed, only few ILC2s can be detected by flow cytometry as Lin⁻CRTH2⁺ in our analysis and in⁴¹. In a recent study³⁷, only 2 donors out of 18 exhibited reliable ILC2 population in colon lamina propria (2.7% and 3.9% of Lin⁻CRTH2⁺), but the vast majority (16 donors) did not possess a solid ILC2 subset (0 to 0.6% of Lin⁻CRTH2⁺). Thus, purification of these cells for RNA sequencing was not successfully achieved³⁷. Importantly, even if few ILC2s may be present in the intestine of some donors, these cells did not give rise to a robust cluster detectable by scRNA sequencing taking into account the minimal percentage of cells needed to exclude a possible doublet contamination. Indeed, and by contrast to what has been reported for mice, ILC2s are almost entirely absent from healthy human tissues, with the exception of the lungs, adipose tissue and the blood connective tissue⁴¹. In our study, we detected tumor infiltrating ctILC2 in CRC patients. ctILC2 were also observed in breast⁴², gastric⁴², and pancreatic¹⁹ tumors and in urine from bladder cancer patients¹⁵.

Several data support a model in which ILC2s infiltrate tumors via an IL-33-dependent pathway^{15, 16, 19} and mediate tumor immune surveillance by promoting cytolytic CD8⁺ T-cell responses. IL-33 expression showed different survival prognosis in different cancer types, with better prognosis in melanoma patients but not in lung squamous cell carcinoma and pancreatic adenocarcinoma⁴³. IL-33 is overexpressed in colorectal tumors⁴⁴ and high levels of IL-33 are frequently observed in low-grade adenocarcinomas and early colorectal tumors⁴⁵. Survival rate is higher in the IL-33-high group of colon cancer patients than in IL-33-low patients, suggesting that ctILC2 might be indicative of a good prognosis in CRC. However, PD-1 expression on ctILC2 from late stage of CRC may be of bad prognosis⁴⁶. There is, therefore, a clear need to investigate further the role of ctILC2s in anti-tumor immunity in CRC and other cancer indications.

We identified an additional helper-like ILC1 subset, named ctILC1-like TIGIT⁺, present in tumors from CRC patients, but absent from the blood. ctILC1-like TIGIT⁺ had a transcriptional profile more closely resembling the ILC1 gene signature than that of any other ILCs, but they segregated away from ctILC1, suggesting that they differed markedly from ‘conventional’ gut ctILC1. ILC1-like cells known as ‘intermediate ILC1s’ (intILC1s) have also been described in a mouse model of methylcholanthrene (MCA)-induced tumors⁴⁷. In humans, CD56⁺CD16⁻ ILC1-like cells have been found in solid tumors and in peritoneal and pleural fluids from cancer patients⁴⁸, and the cytotoxic functions of these cells are altered in the peripheral blood of donors with acute myeloid leukemia⁴⁹. Intratumoral intILC1 may emerge from NK cell differentiation driven by TGF- β signaling, a phenomenon known as ILC plasticity^{47, 50}. The conversion of ILC3s into ILC1s upon TGF- β signaling has been demonstrated in humanized mice and a transitional ILC3-ILC1 population has been identified in the human intestine⁴⁰. We observed no such phenomenon in our

gut ILC dataset and none of the algorithms tested was able to establish a relatedness between ctILC1-like TIGIT⁺ and another gut ILC subset reflecting possible differentiation (data not shown). The mechanisms by which ctILC1-like TIGIT⁺ emerge in CRC tumors thus remain to be determined. We observed a plasticity of ILC1 towards ILC3 in the blood of CRC patients, but not in healthy donors, suggesting the presence of soluble signals driving ILC1-ILC3 plasticity, such as sustained IL-23 levels ⁵¹. The biological relevance of such ILC1-ILC3 plasticity in the blood of CRC patients is not clear.

intILC1s and ILC1s produced large amounts of TNF- α and were found to be ineffective at controlling carcinogenesis, potentially even promoting metastasis in mouse models ⁴⁷. In human, CD56⁺CD16⁻ ILC1-like cells express the pro-angiogenic factor VEGF, which may also favor tumor growth ⁴⁸. In CRC patients, the frequency of ILC1s has been shown to be higher in tumor tissues than in the normal mucosa ^{28, 29}, and to increase, at the expense of ILC3s, with tumor progression ²⁹. These results suggest that high ILC1 levels may be predictive of a poor prognosis in cancer. The issue of the specific biological function of the ctILC1-like subset relative to classical TILC1 in CRC tumors also needs to be addressed, because ctILC1-like cells have high levels of PD1 and TIGIT, and may be further unleashed by anti-PD1 and anti-TIGIT immunotherapies.

We characterized the levels of three subsets: ILC3, ILC3/NK and ILC1, in the normal mucosa of all donors. A donor-specific effect was observed in the ILC3 subsets, suggesting possible ILC3-imprinting by the microbiota. This effect was absent in blood ILC3 population from healthy donors, which was similar to CRC patient blood. Thus, alteration of gut-microbiota did not seem to influence ILC3 population in the blood. One explanation could reside in the fact that ILC3 are largely resident in tissues ⁵². Interestingly, CRC tumors had much lower levels of ILC3s and

displayed a loss of this apparent donor specificity. CRC is frequently associated with tumor dysbiosis, involving massive changes to the composition of the microbiota⁵³⁻⁵⁷. ILC3s are major regulators of intestinal barrier integrity and immune homeostasis. It might therefore be beneficial to promote both ILC3 recolonization and diversification in CRC patients. ILC3 heterogeneity could potentially be boosted by increasing microbial diversity.

We also defined a population of ILC3/NK cells in healthy gut mucosa. These cells had transcriptomic features in common with both ILC3 and NK cells. They differ from ILC3s mostly in terms of their *NKG7*, *KLRD1* (CD94), *GNLY*, *GZMK*, *XCL2* and *CCL4* expression. The biological role of this ILC3/NK subset and its relatedness to ‘classical’ ILC3 remain to be addressed.

A recent study in a mouse model of CRC confirmed the diversity of ILC populations present within the tumor⁴⁶. The authors identified 6 subsets of helper ILC encompassing 1 ILC1, 3 ILC2 (A, B and C), 1 ILC3 and 1 ‘ILCreg’. This study also presented results obtained by flow cytometry in human colorectal tumors that corroborated the presence of PD1⁺ ILC2 and ILCreg in patients with advanced CRC. We did not find these populations in our study, which is based on the analysis of donors with early stage disease. However, these results suggest the need for an additional comparative scRNAseq study to understand the evolution of the heterogeneity of helper-like ILC as the disease progresses.

SLAMF1 was the only cell surface marker for which transcript levels were higher in ctILCs and blood ILCs from CRC patients. ILCs expressing SLAMF1 on their surface were also present at higher frequency in tumors and blood from CRC patients than in healthy donors. SLAMF1 is a single-chain type I transmembrane receptor bearing two immunoreceptor tyrosine-based switch motifs (ITSM) in its cytoplasmic tail, thus recruiting Src homology 2 (SH2) domain-containing

signal transduction molecules like SLAM-associated protein (SAP) to initiate downstream signaling cascades^{38, 58, 59}. SLAMF1 is a self-ligand but also a microbial receptor for morbilliviruses and a bacterial sensor involved in the elimination of Gram-negative bacteria^{38, 60-62}. SLAMF1 is expressed by almost all hematopoietic cells except NK cells, particularly those with an activated phenotype, and is upregulated upon cell activation^{38, 63}. A large proportion of ILCs in the bloodstream expressed SLAMF1 on their surface at steady state, but no such expression was observed on ILCs from normal gut mucosa. By contrast, SLAMF1 was expressed on ctILCs from CRC patients, suggesting that ctILCs may be more activated in the tumor bed than in the normal adjacent mucosa. Nevertheless, the effect of SLAMF1 engagement at the cell surface of helper-like ILCs on the biology of these cells remains to be investigated. High levels of SLAMF1 were correlated with better survival of CRC patients. Our results therefore suggest that SLAMF1 is an anti-tumor biomarker in CRC.

ILCs have emerged as tissue-specific modulators of cancer immunity that can control various aspects of immunotherapy. As ILCs and T cells co-exist in human cancers and have stimulatory and inhibitory pathways in common, immunotherapy strategies targeting anti-cancer ILCs may be as important as strategies targeting T cells. Our results suggest that ILCs are part of the tumor microenvironment, as subsets of ctILCs are present in CRC. It is tempting to speculate that they may regulate immunity at the tumor bed or have a direct effect on tumor cells. Further studies are required to determine whether it is possible to define more tumor-specific subsets differing in terms of activation status, with either pro- or anti-tumor immunity effects, in cancers arising in different tissues.

Limitations of the Study

This study mainly used the scRNAseq technology to decipher the heterogeneity of ILCs in healthy donor and CRC patients. We did not found ILC2s in normal mucosa by scRNAseq but in tumors. The mechanisms involved in the recruitment/differentiation of ILC2s in CRC tumors remain to be investigated. The functions of tumor-specific ILC1-like cells and *SLMAFI*⁺ ILCs have not been addressed in this first study.

Acknowledgments

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Author contributions

Conceptualization, J.Q., A.C., E.V., and B.S.; Investigation, J.Q., A.C.; Formal Analysis, J.Q., A.C. B.E., Y.Y., and L.B.; Validation, J.Q.; Resources, Z.W., T.Z., L.H., Y.L., H.L., N.W., M.Z., L.C.; Writing – Original Draft, J.Q., A.C., L.S., Y.Y., B.S., E.N.M., E.V.; Writing –Review & Editing, J.Q., A.C., L.S., B.S., E.N.M., E.V.; Funding Acquisition, L.S., and B.S.; Supervision, L.S., E.N.M., E.V., and B.S.

Declaration of Interests

Eric Vivier is Innate Pharma employee. The others authors declare no competing interests. Patents related to this work were under application.

Main figure tiles and figure legends

Figure 1. scRNAseq analysis reveals the presence of ILC1s, ILC3s and ILC3/NKs, but not ILC2s, in normal mucosa.

(A) Uniform manifold approximation and projection (UMAP) plot of 16,145 ILCs from normal mucosa from four patients. Cells are color-coded according to the defined subset. (B) UMAP with color coding according to donor origin. (C) Unsupervised hierarchical clustering of the 6 clusters from each donor based on mean expression levels for genes with variable expression within cells. Samples are color-coded according to their relatedness to a particular subset. (D) Heatmap of the 542 genes (256 in nmC0-3, 97 in nmC4, 189 in nmC5) tested with a Wilcoxon rank-sum test distinguishing the three groups of ILCs in normal mucosa. Cells are plotted in columns and genes are shown in rows and ranked by adjusted p value < 0.05 . Gene expression is color-coded with a scale based on z -score distribution from -2.5 (purple) to 2.5 (yellow). Squares identify specific transcriptomic signatures of ILC subsets. (E) Principal component analysis (PCA) on the 3 groups of ILC clusters of each sample based on the mean level of expression for genes with variable expression. (F) Driving genes for each cell subset, accounting for 20% of the total information in each PC from (E). (G) Top 10 expressed genes from the total gene set, and top 10 expressed genes encoding transcription factors, secreted proteins and cell membrane markers significantly differentiating between the groups of ILCs. Gene symbols and annotations were retrieved from public databases. Transcription factor genes are color-coded in red, secreted protein genes in orange, cell membrane protein genes in blue, and other protein-encoding genes in black. Genes encoded both secreted and cell membrane proteins are color-coded in violet. Genes are ranked by p -value. (H) Module score for tonsil ILC gene expression programs for each of the 3 groups of ILCs, at the single-cell level. Kruskal-Wallis with Dunn's multiple-comparison tests were

performed with Benjamini-Hochberg adjusted p -values. Each comparison was statistically significant and values are shown in Supplementary Table 3.

Figure 2. scRNA-seq analysis reveals tumor-specific ILC1 and ILC2 subsets in CRC tissues.

(A) UMAP plot of 15,101 CRC tissue ILCs (ctILCs) from the CRC tissues of 4 patients. Cells are color-coded according to the defined subset. (B) UMAP with color coding for donor origin. (C) Unsupervised hierarchical clustering of the 4 clusters from each donor based on mean expression levels for genes with variable expression. (D) Heatmap of the 982 genes (463 in ctC0, 100 in ctC1, 314 in ctC2, 105 in ctC3) tested with a Wilcoxon rank-sum test distinguishing between the 4 ctILC subsets in tumor tissue. Cells are plotted in columns and genes are shown in rows and ranked by adjusted p values (< 0.05). Gene expression is color-coded with a scale based on z -score distribution from -2.5 (purple) to 2.5 (yellow). Squares identify specific transcriptomic signatures of ctILC subsets. (E) Principal component analysis (PCA) on the 4 ctILC subsets of each sample based on the mean level of expression of genes with variable expression. (F) Driving genes for each cell subset accounting for 20% of the total information in each PC from (E). (G) Top 10 expressed genes from the total gene set, and top 10 expressed genes encoding transcription factors, secreted proteins and cell membrane markers significantly differentiating between the groups of ctILCs. Gene symbols and annotations were retrieved from public databases. Transcription factor genes are color-coded in red, secreted protein genes in orange, cell membrane protein genes in blue and other protein-encoding genes in black. Genes encoded both secreted and cell membrane proteins are color-coded in violet. Genes are ranked by p -value. (H) Module score for tonsil ILC gene expression programs, at the single-cell level, for each of the 4 ctILCs subsets. Kruskal-Wallis with Dunn's multiple-comparison tests were

performed with Benjamini-Hochberg adjusted p values. Each comparison was statistically significant and values are shown in Supplementary Table 3.

Figure 3. Characterization of tumor tissue-specific ILC subsets.

(A) UMAP plot of 41,603 ILCs from normal blood, CRC blood and CRC tissue. Cells are color-coded according to the defined subset. (B) Unsupervised hierarchical clustering of normal blood, CRC blood and CRC tissue ILCs from each donor, based on the mean level of expression of genes with variable expression. (C) Heatmap of the 899 genes (44 in normal blood, 70 in CRC blood, 775 in CRC tissue) tested in a Wilcoxon rank-sum test distinguishing between the three organs. Cells are plotted in columns and genes are shown in rows and ranked by adjusted p values (< 0.05). Gene expression is color-coded with a scale based on z -score distribution from -2.5 (purple) to 2.5 (yellow). Squares identify specific transcriptomic signatures of ILC subsets. (D) Unsupervised hierarchical clustering of normal blood ILCs (nbILCs), CRC blood ILCs (cbILCs) and CRC tissue ILCs (ctILCs) from each donor, at the subset level, based on the mean expression level for genes with variable expression. (E) Venn diagram representing the intersection between the gene signatures of the 4 ILC1 subsets from normal blood, CRC blood, normal mucosa, and CRC tissue. (F) Venn diagram representing the intersection between the gene signatures of the 3 ILC2 subsets from normal blood, CRC blood, and CRC tissue.

Figure 4. Specific gene signature of ILC in CRC.

(A) UMAP plot of 31,246 ILCs from normal mucosa and CRC tissue. Cells are color-coded according to the defined subset. (B) Unsupervised hierarchical clustering of normal mucosa and CRC tissue ILCs from each donor based on the mean level of expression for genes with variable

expression. (C) Heatmap of the 331 genes (266 in CRC tumor, 51 in normal mucosa) tested with a Wilcoxon rank-sum test distinguishing between the two organs. Cells are plotted in columns and genes are shown in rows and ranked by adjusted p value (< 0.05). Gene expression is color-coded with a scale based on z -score distribution from -2.5 (purple) to 2.5 (yellow). Squares identify specific transcriptomic signatures of ILC subsets. (D) UMAP plot of 26,502 ILCs from normal blood and CRC blood. Cells are color-coded according to the defined subsets. (E) Unsupervised hierarchical clustering of normal blood and CRC blood ILCs from each donor, based on the mean level of expression of genes with variable expression. (F) Heatmap of the 254 genes (233 in CRC blood, 23 in normal blood) tested with a Wilcoxon rank sum test distinguishing between the 2 organs. Cells are plotted in columns and genes are shown in rows and ranked by adjusted p value (< 0.05). Gene expression is color-coded with a scale based on z -score distribution from -2.5 (purple) to 2.5 (yellow). Squares identify specific transcriptomic signatures of ILC subsets. (G) Venn diagram representing the intersection of gene signatures between normal blood and CRC blood, and between normal mucosa and CRC tissue. (H) Feature plots of relative levels of *SLAMF1* expression on each of the ILCs from normal blood, CRC blood, normal mucosa, and tumor tissue. (I) Feature plots of the relative expression levels of *AQP3*, *HPGD*, *TLE4* and *PRDMI* in normal blood, blood from CRC patients, normal mucosa and tumor tissue.

Figure 5. SLAMF1 is a biomarker in CRC.

(A) Representative flow cytometry profile of TIGIT cell surface expression on the ctILC1-like subset. (B) Flow cytometry analysis of ILC subsets from normal mucosa ($n=8-16$) and CRC tissues ($n=7-16$). Data show the frequencies of the indicated subset among total ILCs. (C)

Kaplan-Meier curves of overall survival stratified by IL-33 expression in CRC patients from TCGA. The optimal cut-off for patient stratification was obtained with a Cox proportional hazards model and the *p*-value was calculated in a log-rank test. IL-33-high group (*n*=369); IL-33-low group (*n*=84). **(D)** Flow cytometry analysis of blood ILC subsets from healthy donors (*n*=18) and CRC patients (*n*=16). **(E)** Representative FACS profile of SLAMF1 cell surface expression on ILCs. **(F)** Flow cytometry analysis of SLAMF1 expression on total ILCs from normal mucosa (*n*=7) and CRC tissues (*n*=7). The data show frequencies of SLAMF1⁺ cells among total ILCs. **(G)** Flow cytometry analysis of SLAMF1 expression on total blood ILCs from healthy donors (*n*=14) and CRC patients (*n*=5). Data show frequencies of SLAMF1⁺ cells among total ILCs. **(H)** Differentially expressed (DE) genes between *SLAMF1*⁺ ILCs and *SLAMF1*⁻ ILCs in CRC tissues. The DE transcriptional factors and cytokines are labeled by red and orange text, respectively. Red dots mean genes up-regulated in *SLAMF1*⁺ ILCs, and blue dots represent genes up-regulated in *SLAMF1*⁻ ILCs. Kaplan-Meier curves for overall survival stratified by SLAMF1 expression level in colon **(I)** and rectum **(J)** cancer patients from TCGA. The optimal cut-off for patient stratification was obtained with a Cox proportional hazards model and the *p*-value was calculated in a log-rank test. In **(I)**, *SLAMF1*-high group (*n*=393); *SLAMF1*-low group (*n*=60). In **(J)**, *SLAMF1*-high group (*n*=119); *SLAMF1*-low group (*n*=46). In **(B)**, **(D)**, statistical significance was calculated in Kruskal-Wallis tests with Dunn's multiple comparison tests, and *p*-values were adjusted with the Benjamini-Hochberg method. In **(F)**, **(G)**, Mann-Whitney tests of unpaired nonparametric *t* tests were used. In **(H)**, statistical analysis is performed by Wilcoxon test.

p*-value<0.05; *p*-value<0.01; ****p*-value<0.001; *****p*-value<0.0001.

514 **STAR Methods**

515 **RESOURCE AVAILABILITY**

516 **Lead Contact**

517 Further information and resource requests should be directed to and will be fulfilled by the Lead
518 Contact, Bing Su (bingsu@sjtu.edu.cn).

519 **Materials Availability**

520 This study did not generate new materials.

521 **Data and Code Availability**

522 Raw sequence data of each sample is available to download at Genome Sequence Archive for
523 Human, GSA-Human (Accession number, HRA000919).

524 **EXPERIMENTAL MODEL AND SUBJECT DETAILS**

525 Clinical samples were obtained from colorectal cancer (CRC) patients without chemo-radiation
526 therapy before resection of the tumor and healthy individuals who gave informed consent, after
527 approval had been obtained from the local medical ethics committee of Ruijin Hospital and
528 Xinhua Hospital Affiliated to Shanghai Jiao Tong University School of Medicine. Four CRC
529 patients were recruited for scRNAseq at diagnosis (Table S1). Adjacent tissue (normal mucosa),
530 and CRC tissue were collected from these four CRC donors whereas blood samples were collected
531 except P4. Healthy blood for scRNAseq were recruited from individuals undergoing routine
532 colonoscopy who were generally in good health, with no other relevant medical history, such as
533 inflammatory bowel disease (IBD) or CRC (Table S1).

534 **METHOD DETAILS**

535 **Isolation of human lymphocytes**

Fresh intestine tissues were quickly placed into 50 mL tubes containing RPMI 1640 medium plus 10% FBS, and were transported on ice to laboratory for cell preparation usually within 2 hours. Adipose tissue and visible blood vessels were removed from the tissue manually. Specimens were weighed and washed with PBS and then cut into small pieces. Normal tissue was incubated with 10 mL freshly prepared intraepithelial lymphocyte solution (5 mM EDTA, 15 mM HEPES, 10% FBS, 1 mM DTT in PBS), for 1 hour at 37°C, with shaking at 200 rpm. CRC tissue was washed with 10 mL freshly prepared 6.5 mM DTT in PBS for 15 min at 37°C, with shaking. After incubation, the tissue pieces were rinsed twice with PBS and subjected to enzymatic digestion for 1 hour at 37°C, with shaking (0.38 mg/mL collagenase VIII, 0.1 mg/mL DNase I, 100 U/ml penicillin, 100 mg/mL streptomycin, 10% FBS in RPMI 1640 medium). The digested tissues were then shaken vigorously by hand for 5 min and mechanically dissociated with a 21-gauge syringe. The resulting cell suspension was filtered through a cell strainer with 100 µm pores into a new 50 mL conical tube, and PBS was added to a final volume of 30 mL. Cells were then centrifuged at 1,800 rpm for 5 min. The supernatants were discarded and the cell pellets were resuspended in RPMI 1640 medium supplemented with 10% FBS. Cells were centrifuged on a Ficoll gradient and then washed with PBS before use.

Peripheral blood mononuclear cells (PBMCs) were obtained from human blood samples centrifuged on a Ficoll gradient. Briefly, blood was mixed with an equal volume of 2% FBS in PBS and gently layered on the Ficoll gradient. Cells were centrifuged at 1000 x g for 25 min, without braking. The cells in the middle layer were then washed once with PBS and resuspended in 2% FBS in PBS for use.

Sorting of ILCs

Freshly prepared human cells were resuspended in PBS and incubated with a live/dead cell marker, Fixable Viability stain 520 (BD 564407), for 10 min at 4°C. Cells were washed and suspended in 2% FBS, 2 mM EDTA in PBS (FACS buffer), supplemented with 10% mouse serum and 40% Brilliant Strain Buffer. Cells were first stained with 1:50 human Fc Block for 10 min at 4°C and then incubated with antibodies directed against CD45, CD127, CD117, CRTH2, and against lineage markers (TCR $\gamma\delta$, TCR $\alpha\beta$, CD3, CD19, CD14, CD16, CD94, CD123, CD34, CD303 and Fc ϵ RI) for 30 min at room temperature. Human cells were washed with FACS buffer, centrifuged and resuspended in FACS buffer. Live ILCs in RPMI 1640 supplemented with 20% FBS were sorted in a BD FACSAria III cell sorter (BD Biosciences).

Flow cytometry for ILCs

For cell surface staining of ILCs, freshly prepared human cells were stained with live/dead cell markers, Fixable Viability stain 520 (BD 564407), and Fc Block as for ILCs sorting. Cells were stained with surface antibodies against CD45, CD127, CD117, CRTH2, CD5, TIGIT and SLAMF1 and antibodies against same lineage markers for ILCs sorting for 30 min at room temperature. For each of the staining, paired samples from same patients were used. PBMC from more healthy donors was stained at same time. Cells were kept at 4°C and analyzed on a BD Symphony (BD Biosciences). Flow data was analyzed with FlowJo software (FlowJo LLC). Statistical analysis was performed by Mann-Whitney tests of unpaired nonparametric *t* tests or Kruskal-Wallis tests with Dunn's multiple comparison tests. *p*-values were adjusted with the Benjamini-Hochberg method for multiple comparison tests. * *p*-value < 0.05, ** *p*-value < 0.01, *** *p*-value < 0.001, **** *p*-value < 0.0001.

Single-cell RNA sequencing

Purified ILCs were resuspended in PBS supplemented with 0.04% BSA, and kept on ice. Cells were counted and cell density was adjusted to that recommended for 10x Genomics Chromium single-cell 3' v3 processing and library preparation. Sequencing was performed on an Illumina platform (NovaSeq 6000), by GENERGY BIO (Shanghai, China), at a sequencing depth of about 90,000 reads per single cell.

Raw 10X read alignment, quality control and normalization

Raw sequencing reads were subjected to quality control with FastQC software v0.11.9 (<https://www.bioinformatics.babraham.ac.uk/projects/fastqc/>). Sequencing data in a bcl file were converted to FASTQ format with Illumina bcl2fastq2 Conversion Software v2.20 (<https://support.illumina.com/downloads/bcl2fastq-conversion-software-v2-20.html>). We then used Cell Ranger Single Cell Software Suite v. 2.2 to process, align, and summarize unique molecular identifier (UMI) counts, according to the standard pipeline and default parameters described at <https://support.10xgenomics.com/single-cell-gene-expression/software/pipelines/latest/>. Briefly, we used the standard Cell Ranger Count pipeline to align FASTQ reads with the GRCh38 genome. We then filtered sequencing reads on the basis of base-calling quality scores, and assigned cell barcodes and UMIs to each read. The Cell Ranger aggr pipeline was used to normalize all scRNAseq data with default parameters, to obtain a uniform sequencing depth. The combined feature-barcode matrix was used for downstream analysis.

During quality control with Seurat analysis, raw UMI count matrices were filtered to remove genes expressed in fewer than three cells, cells with fewer than 200 genes, cells with more than

4000 genes, and cells with high percentages of mitochondrial genes (more than 8%). The resulting matrix was then normalized by a global-scaling method, converted with a scaling factor (10,000 by default) and log-transformed with the “LogNormalize” function in Seurat for downstream analysis.

Filtering contaminated cells

We used the R package SingleR ⁶⁷ and default parameters to assign individual cells to cell types, with the Human Primary Cell Atlas Data as the reference dataset. Each single cell was annotated with a cell type in “label.main” of the dataset. As the dataset did not include the human ILC dataset, and, given the similarities between ILCs and T cells or NK cells, we retained cells labeled as both NK and T cells. We removed cells considered as doublets with an range from 0.14% to 3.69%. In addition, when analyzing the ILC3 in tumor tissue, two small clusters with percentage ranging from 0.35% to 3.59% that were not present in each donor were removed. Donor-specific clusters with a strong specific NK cell signature were considered to be true NK cell contaminants and were removed from downstream analysis.

Reduction of the number of dimensions and clustering

The top 2000 variable genes were selected with the “FindVariableGenes” function of Seurat ⁶⁸ and used for principal component analysis (PCA). For ILCs in normal mucosa, we retained the first 40 PCs. For normal blood, CRC blood and tumor tissue, we retained the top 20 PCs. Clusters were identified with the “FindClusters” function, with the algorithm based on the optimization of nearest-neighbor modularity implemented in Seurat and visualized with the uniform manifold

approximation and projection (UMAP) algorithm. For comparisons of different tissues, the “merge” function was used to pool the individual Seurat objects. For donor and tissue data visualization, the “group.by” parameters were set as intended information when plotting with “DimPlot” function in Seurat.

Batch effect correction for ILC3 subsets in normal and tumor mucosa

ILC3 clusters in tumor tissue and both ILC3 and ILC3/NK clusters in normal mucosa were subsampled for downstream clustering. The batch effect was corrected with the “IntegrateData” function of the standard workflow of Seurat, based on previously identified anchors (Butler et al., 2018).

Unsupervised hierarchical clustering

Mean gene expression was analyzed for single cells in each cluster. Only genes previously shown to display variable expression were used. We used the Heatmap.plus package to plot the unsupervised clustering map. The Euclidean distance was calculated for genes in all clusters. For normal mucosa, only the major donor-derived ILCs for cluster 0-4 were used for analysis.

Principal component analysis

Principal component analysis (PCA) was performed on the mean level of expression of variable genes in clusters. The top 20 genes contributing to PC1 and PC2 or PC1 and PC3 were plotted. For the analysis of ILCs in normal mucosa, we removed ILCs from donors other than the major source of cluster 0-4. PCA gene loadings for the PCs corresponded to the 20 genes making the

largest contribution to the total amount of information represented by PC1 and PC2 or PC1 and PC3.

Differential expression analysis

We used the “FindAllMarkers” function in Seurat to identify genes differentially expressed between samples, for each cluster. The non-parametric Wilcoxon rank-sum test was used to obtain *p*-values for comparisons, and the adjusted *p*-values, based on Bonferroni correction, for all genes in the dataset. We used the following parameters for the calculation of log fold-change (logFC) in expression values and to obtain *p*-values for all the variable genes for each cluster: min.pct = 0.05, min.diff.pct = 0.1, logfc.threshold = 0.25. The log-transformed and scaled expression values of the genes were used to generate a heatmap.

Gene annotations

Genes encoding transcription factors (TFs) were retrieved from four TF-related public datasets: JASPAR⁶⁹ (<http://jaspar.genereg.net/>), DBD⁷⁰ (<http://www.transcriptionfactor.org/>), AnimalTFDB⁷¹ (<http://bioinfo.life.hust.edu.cn/AnimalTFDB/>), and TF2DNA⁷² (http://www.fiserlab.org/tf2dna_db/). Genes encoding cell membrane and secreted proteins were obtained from The Human Protein Atlas⁷³ (<https://www.proteinatlas.org/humanproteome/tissue/secretome>). Genes were ranked by the adjusted *p*-value for each ILCs cluster in tissue. The top 10 genes within each category (TF, cell membrane, or secreted protein) was selected based on their original adjusted *p*-value in each cluster.

670

671 **RNA velocity estimation**

672 We analyzed expression dynamics, using scRNA-seq data, by estimating the RNA velocities of
673 single cells by distinguishing between unspliced and spliced transcripts on the basis of the
674 previously aligned bam files of scRNA-seq data. The RNA velocity values for each gene in each
675 cell and the embedding of RNA velocity vectors in a low-dimension space were calculated with
676 the R package velocity.R ⁷⁴ (<https://github.com/velocyto-team/velocyto.R>). RNA velocities were
677 then visualized on the UMAP projection by Gaussian smoothing on a regular grid.

678

679 **Scoring samples for ILC signatures**

680 ILC and NK cell signatures from tonsil tissue were defined by Björklund et al., ³¹. ILC1 and ILC3
681 signatures from jejunum, and ILC2 signatures from spleen were obtained from Yudanin et al., ³⁷.
682 Module scores were calculated with “AddModuleScore” in Seurat, for each ILC. Briefly, the mean
683 level of gene expression in a single cell was calculated, and the aggregate expression of control
684 feature sets was then subtracted from it. The control features were selected at random from all
685 features. For the module scores of ILC3 subsets from normal mucosa, the differentially expressed
686 gene signatures for each ILC3 subset were used, at single-cell level, on each ILC3 subset in CRC
687 tissues. Violin plots were used to visualize the module scores of each cluster.

688

689 **TCGA analysis**

690 RNAseq data from primary tumors and clinical annotations were downloaded using the package
691 TCGAbiolinks in September 2019. Kaplan-Meier curves were plotted using the R package

survminer. In order to split the expression levels in two groups, the cut-off which gave the lowest p-value was used. Optimal cut-off for patient stratification was obtained with a Cox proportional hazards model and p-value indicated in the plot was calculated with a log-Rank test.

Quantification and statistical analysis

Data are presented as the mean \pm standard error of the means (SEM), or standard deviations (SD). GraphPad Prism 6 was used for statistical analysis, two-sided Wilcoxon test and Mann–Whitney test were used for unpaired data. Kruskal-Wallis tests with Dunn’s multiple comparison tests was used for multiple comparisons. Kaplan–Meier survival data were analyzed using two-sided log-rank test. p values <0.05 were considered significantly statistical difference.

SUPPLEMENTARY FILES

Table S1. Clinical characteristics of CRC patients and healthy blood donors analyzed by scRNAseq, Related to STAR Methods.

Table S2. Gene signatures of each clusters, related to Figure 1, 2, 3, 4 and Figure S3, S4, S5.

Adjusted p-values for non-parametric Wilcoxon rank-sum tests are provided.

Table S3. Statistical analysis of the module score for each cluster, Related to Figure 1H, Figure 2H, Figure S2B, S3K, S4H and S5H.

Kruskal-Wallis with Dunn’s multiple-comparison tests were performed with Benjamini-Hochberg adjusted p-values.

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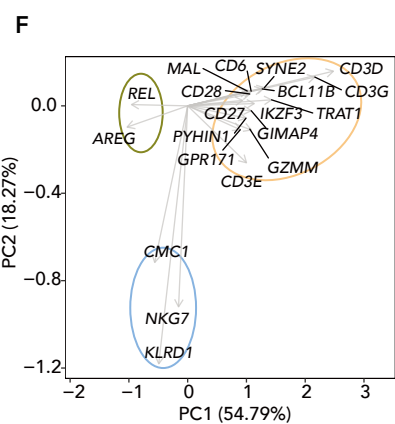
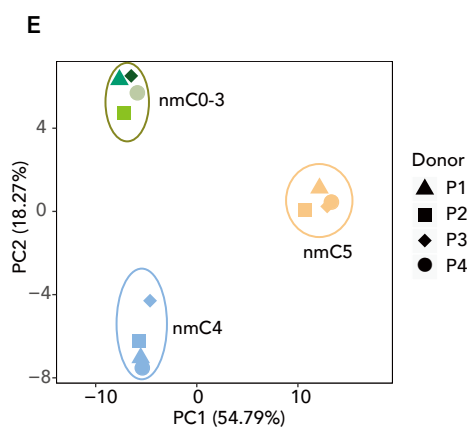
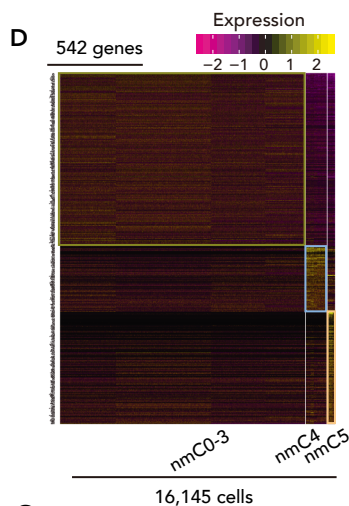
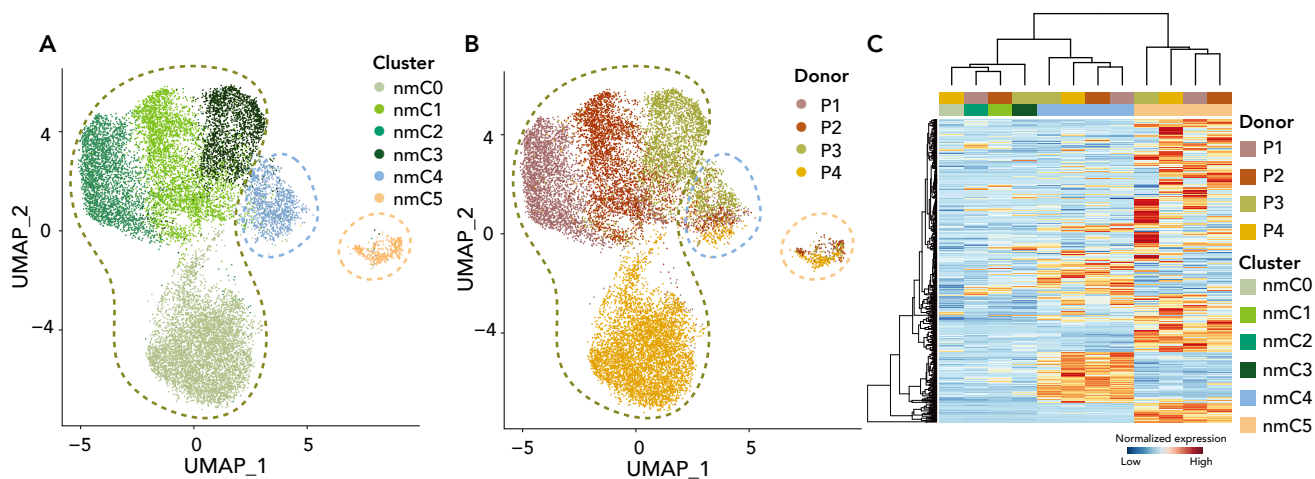
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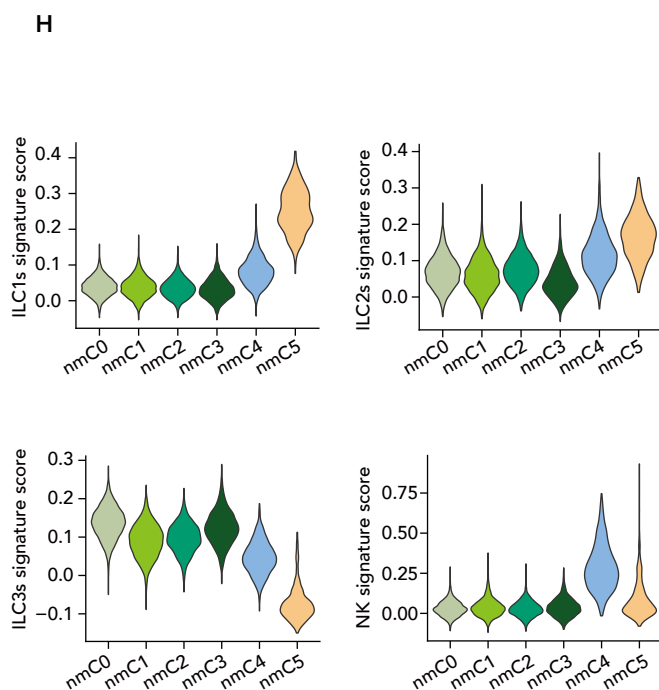
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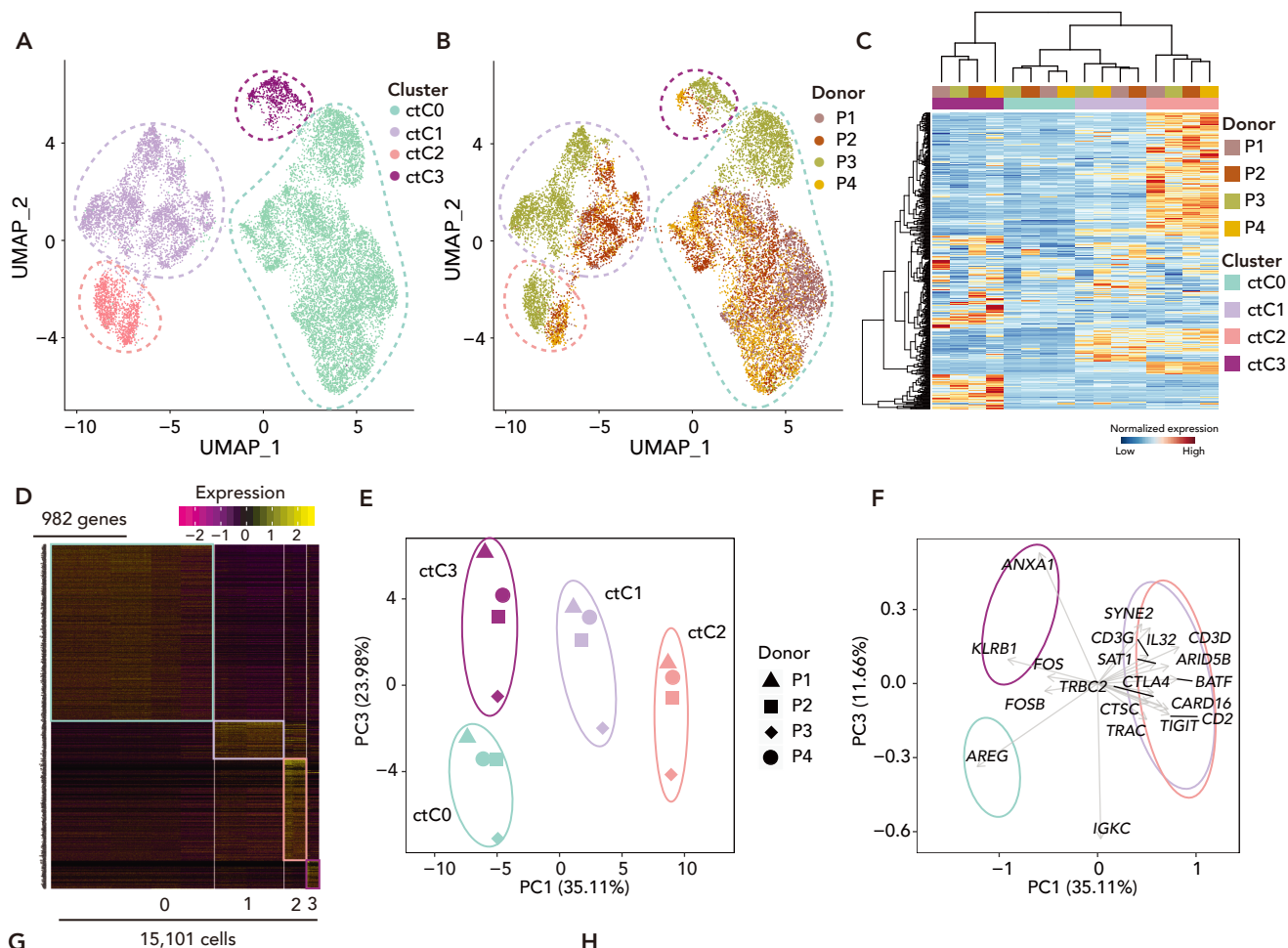
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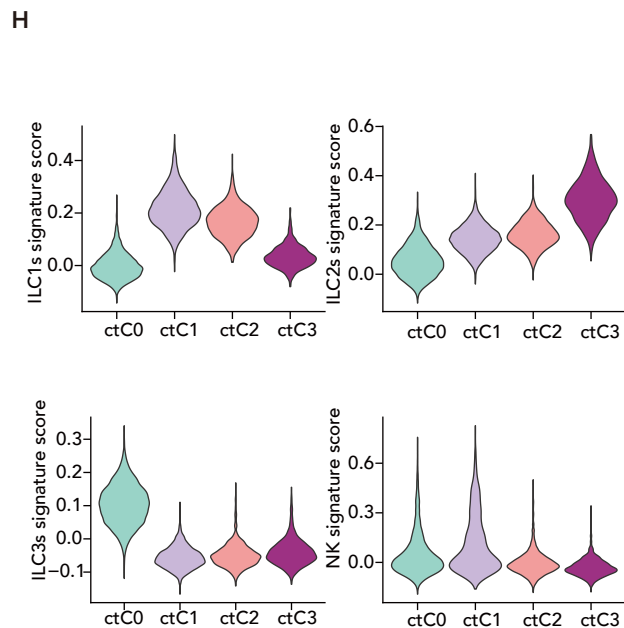
	Top 10	Transcription factors	Secreted	Cell membrane
nmC0-3	CXCL8 IL4I1 CD83 LST1 IL1R1 CXCL2 ATP1B3 NRIP1 VEGFA NCOA7	ZFAND5 HES1 ZNF331 ATF3 RBPJ NR4A3 ID2 NFKB1 NFIL3 IRF4	CXCL8 IL4I1 IL1R1 CXCL2 VEGFA LGALS3 TNFRSF25 CSF2 SDC4 TNFSF13B	CD83 LST1 IL1R1 ATP1B3 PCDH9 KIT MPV17L ICOS SCN1B TNFRSF25
nmC4	GNLY KLRD1 CCL4 CMC1 NKG7 CTSW HCST EMP3 CD7 IFITM2	HOPX IRF8 CEBPB GATA3 YBX3 ZEB2	GNLY CCL4 CTSW CST7 XCL2 LGALS1 CD55 GZMK NUCB2 TNFRSF1B	KLRD1 NKG7 HCST EMP3 CD7 IFITM2 CRTAM LITAF SELL FCER1G
nmC5	CCL4 CD3D CD3G SYNE2 CCL5 HSPA1B CD3E FYB1 TRAT1 DNAJB1	IKZF3 BCL11B BATF ZNF831 PRDM1 PBX4 ID3 SP140	CCL4 CCL5 CD40LG CST7 LGALS1 IFNG IL32 GZMM IL6ST CD6	CD3D CD3G SYNE2 CD3E TRAT1 GPR171 S100A10 CLEC2D CD48 CD40LG

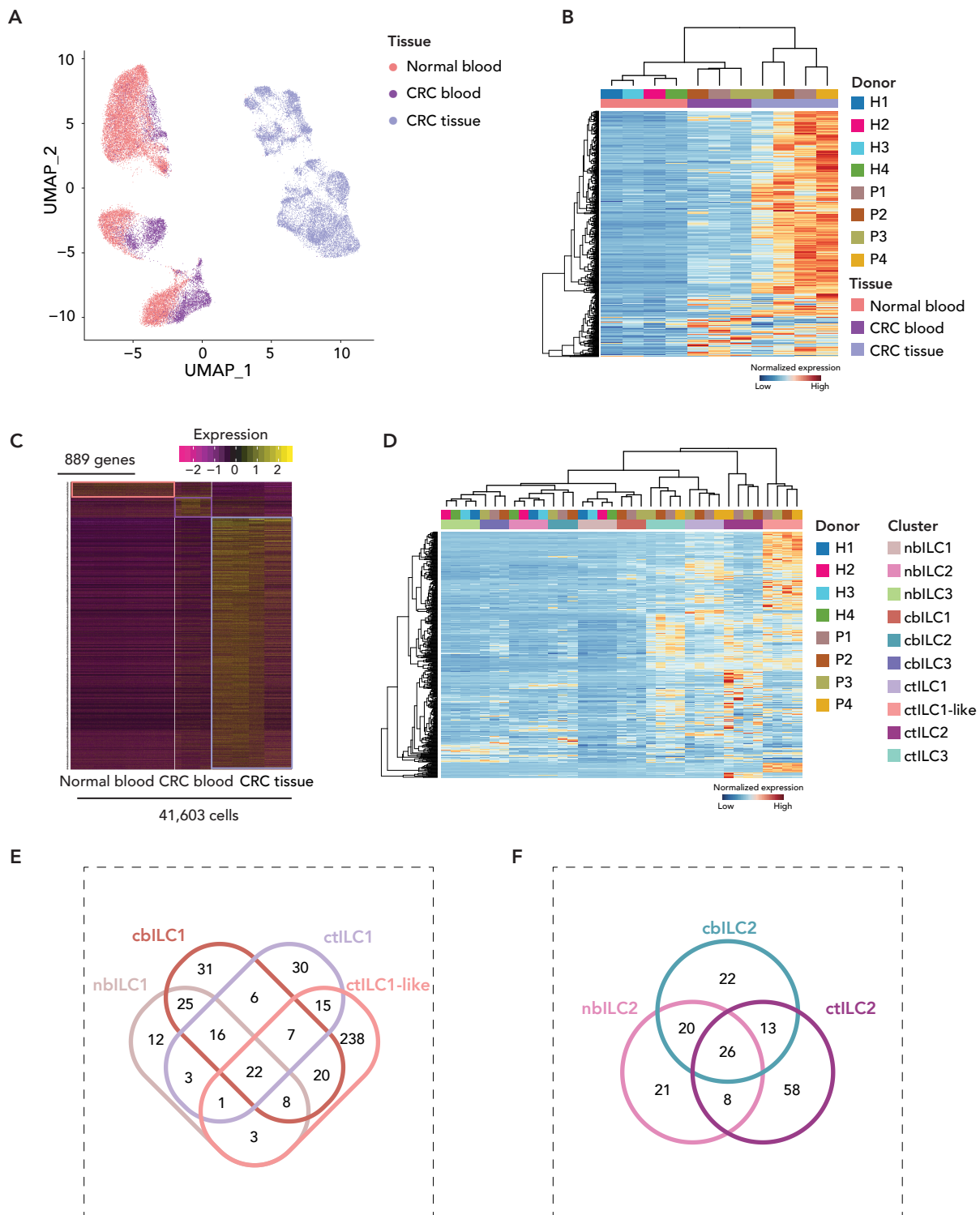


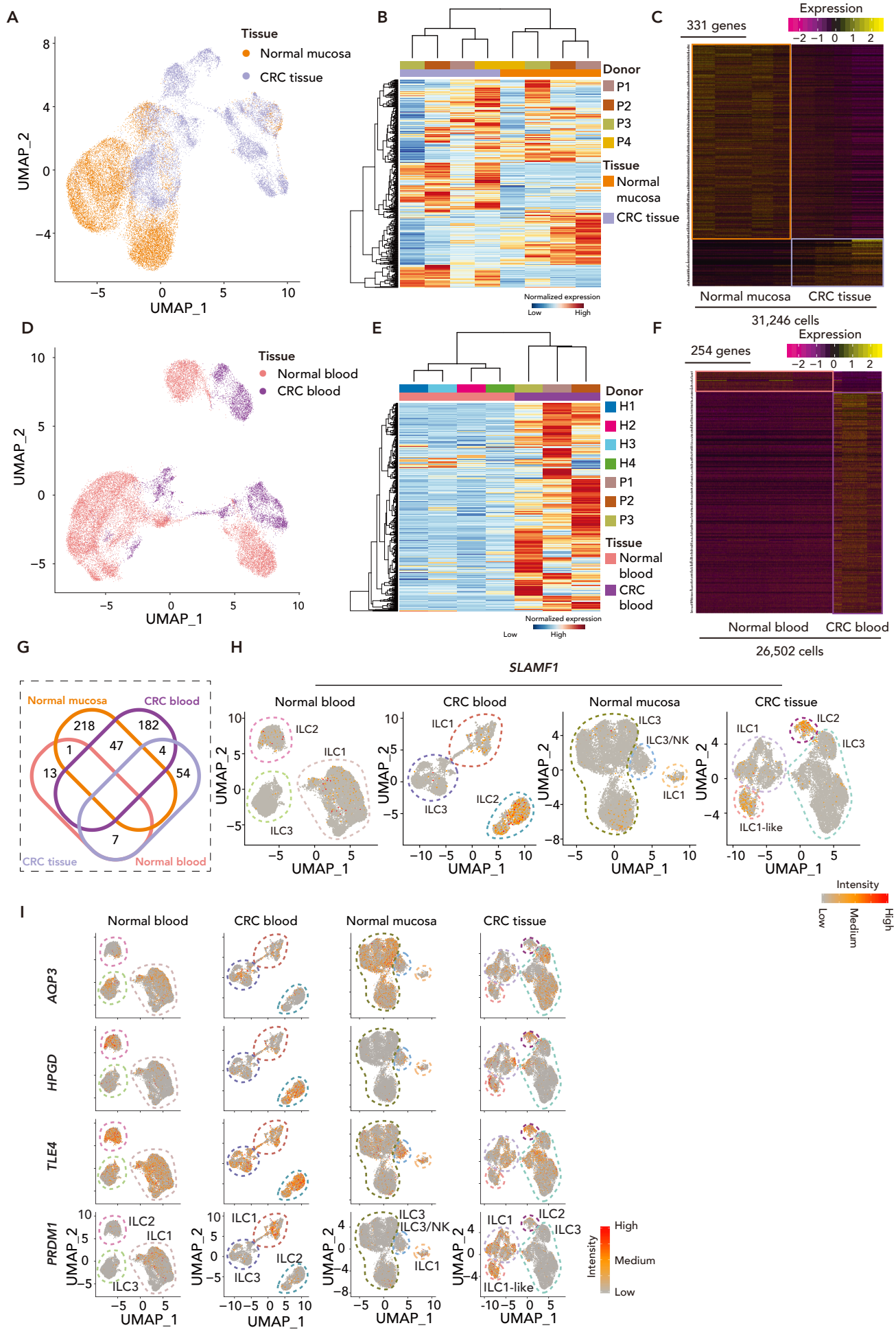


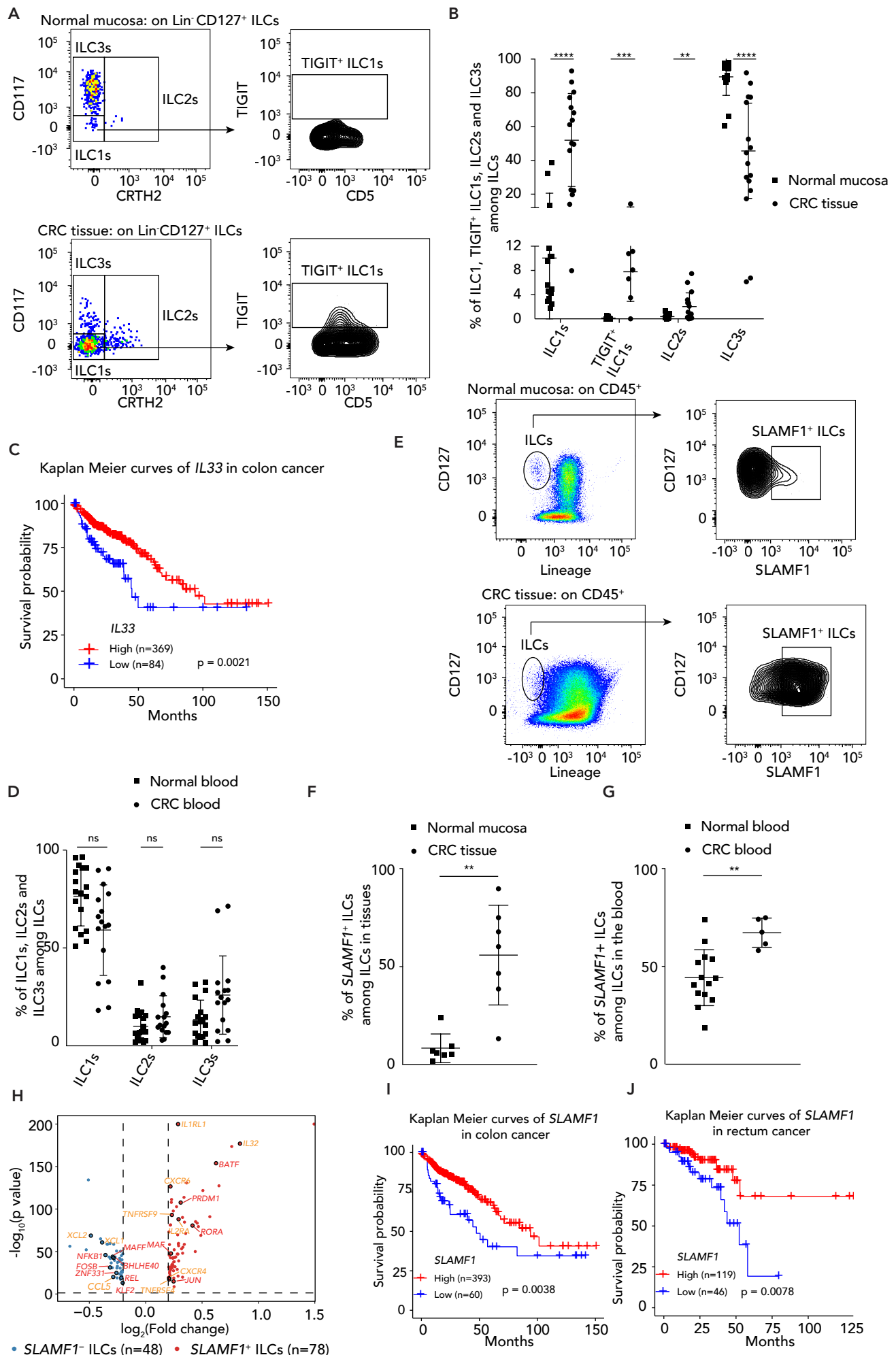
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	Top 10	Transcription factors	Secreted	Cell membrane
ctC0	AREG KIT XCL1 GNLY XCL2 TYROBP NFKB1 CTSW CXCL8 ZFP36L1	NFKB1 MAFF FOSB REL BHLHE40 ZNF331 RBPJ NFIL3 AFF3 RERE	XCL1 GNLY XCL2 CTSW CXCL8 IL4I1 VEGFA EREG TNFSF11 SPINK2	AREG KIT TYROBP LST1 PCDH9 FCER1G CD81 SELENOS CD83 EREG
ctC1	CCL4 CCL4L2 GZMK CD3D IFNG CCL5 GZMA CD3G NKG7 GZMH	PRDM1 ZNF831 PBX4 BATF IKZF3 BCL11B SP140	CCL4 CCL4L2 GZMK IFNG CCL5 GZMA GZMH CST7 ANXA1 GZMM	CD3D CD3G NKG7 TRAT1 SYNE2 GPR171 CD3E RARRES3 CD40LG CD8A
ctC2	BATF TIGIT CARD16 SAT1 CTLA4 MAGEH1 CTSC LINC01943 CD27 ICA1	BATF FOXP3 PRDM1 ZBTB38 IKZF2 BLOC151 MAF CREM ETV7 PBX4	IL32 LAIR2 TNFRSF1B SLAMF1 IL1R2 LGALS1 ISG15 NAMPT C4orf48 SPOCK2	TIGIT CTLA4 MAGEH1 CD27 TNFRSF4 TNFRSF9 CLEC2D TNFRSF1B CD3D IL2RA
ctC3	IL1RL1 HPGDS SLAMF1 PLIN2 IL17RB PTGS2 PMAIP1 ZFP36L2 IL2 HPGD	GATA3 HES4 RORA ZBTB16 EGR1 PPARG KLF9	IL1RL1 SLAMF1 IL2 TNFSF10 IL32 DPP4 FSTL4 ANXA1	IL1RL1 SLAMF1 IL17RB C1orf162 CD69 KLRB1 PTGER2 CYSLTR1 FFAR3 TNFSF10

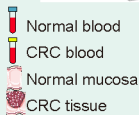
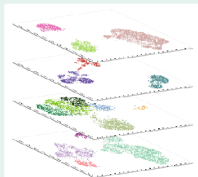




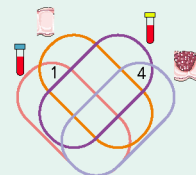
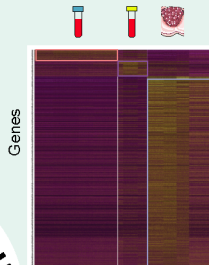




ILCs heterogeneity

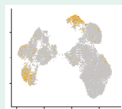


Tissue-specific phenotype

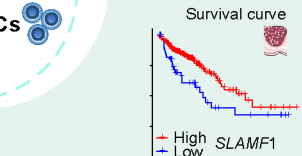


Overlapping up/down regulated genes

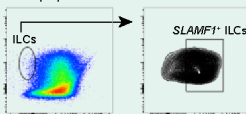
Gene expression



Inter-tissue common signature



Cell population



Validation & clinical relevance