1	A differential regulatory T cell signature distinguishes the immune landscape of
2	COVID-19 hospitalized patients from those hospitalized with other respiratory
3	viral infections
4	
5	Short Title: Immunity to SARS-CoV-2 versus other respiratory infections
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23					
24	Funding				
25	This work was supported by NIH grant R01 AI121129 and R01 AI141435.				
26					
27	Competing interests				
28	The authors declare that no conflicts of interest exist. R.G. has received consulting				
29	income from Takeda and Merck and declares ownership in Ozette Technologies. E.G				
30	declares ownership in Ozette Technologies.				
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33	Highlights				
34	1. The immune landscapes of hospitalized pre-pandemic RSV and influenza				
35	patients are similar to SARS-CoV-2 patients				
36	2. Serum cytokine and chemokine expression patterns are largely similar between				
37	patients hospitalized with respiratory virus infections, including SARS-CoV-2,				
38	versus healthy donors				
39	3. SARS-CoV-2 patients with the most critical disease displayed unique changes in				
40	the Treg compartment				
41	4. Rapid advances in understanding and treating SARS-CoV-2 could be leveraged				
42	for other common respiratory infections				
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44					

45 Abstract

SARS-CoV-2 infection has caused a lasting global pandemic costing millions of lives 46 47 and untold additional costs. Understanding the immune response to SARS-CoV-2 has 48 been one of the main challenges in the past year in order to decipher mechanisms of 49 host responses and interpret disease pathogenesis. Comparatively little is known in 50 regard to how the immune response against SARS-CoV-2 differs from other respiratory 51 infections. In our study, we compare the peripheral blood immune signature from SARS-52 CoV-2 infected patients to patients hospitalized pre-pandemic with Influenza Virus or 53 Respiratory Syncytial Virus (RSV). Our in-depth profiling indicates that the immune 54 landscape in patients infected by SARS-CoV-2 is largely similar to patients hospitalized 55 with Flu or RSV. Similarly, serum cytokine and chemokine expression patterns were 56 largely overlapping. Unique to patients infected with SARS-CoV-2 who had the most 57 critical clinical disease state were changes in the regulatory T cell (Treg) compartment. 58 A Treg signature including increased frequency, activation status, and migration 59 markers was correlated with the severity of COVID-19 disease. These findings are particularly relevant as Tregs are being discussed as a therapy to combat the severe 60 61 inflammation seen in COVID-19 patients. Likewise, having defined the overlapping 62 immune landscapes in SARS-CoV-2, existing knowledge of Flu and RSV infections could be leveraged to identify common treatment strategies. 63 64

Key Words: COVID-19, SARS-CoV-2, respiratory infections, immune signature,
 regulatory T cells

67 Introduction

68	The current coronavirus (CoV) pandemic began in Wuhan, China in 2019 with an
69	outbreak of what would later be designated SARS-CoV-2 ¹⁻³ . To date, SARS-CoV-2 has
70	led to devastating disease (called Coronavirus Disease 2019 (COVID-19)), death, and
71	economic instability on a global scale ⁴ . Despite the unprecedented rapid design and
72	large-scale testing of SARS-CoV-2 vaccines, vaccine supply shortages, vaccine
73	hesitancy, delays in global implementation, and emerging variants raise concerns that
74	SARS-CoV-2, as well as the next pandemic respiratory infection, will continue to pose a
75	threat to humans, underscoring the vital need for identification of additional
76	therapeutics.
77	Many investigations to date have focused on characterizing the immune
78	responses to natural SARS-CoV-2 infection in an effort to understand disease
79	pathogenesis and reveal potential therapeutic targets. We reasoned that these
80	extraordinary efforts to understand COVID-19 disease pathogenesis and improve
81	treatment options could be leveraged for other respiratory infections if there is
82	substantial congruence in the underlying immune response. In the vast majority of such
83	SARS-CoV-2 studies, immune responses have been measured using human blood
84	samples, comparing healthy controls to asymptomatic patients with SARS-CoV-2 or
85	COVID-19 patients with varying degrees of disease severity ⁵ . Both the innate and
86	adaptive arms of the immune response to SARS-CoV-2 have been profiled to date.
87	Initial studies focusing on innate immunity demonstrated that the type I and type III
88	interferon (IFN) response is blunted in early stages of the response to SARS-CoV-2,
89	though IL-6 and chemokines are elevated ^{6,7} . Notably, this varied from the response to

90 other respiratory viral infections, including human parainfluenza virus 3 and respiratory syncytial virus (RSV), which induced potent type I and III IFN responses⁶ and could 91 92 suggest fundamental differences in the immune landscape of different respiratory 93 infections. Further, data derived from comparing healthy controls and patients with 94 severe COVID-19 identified an early reduction in type I IFNs in patients with the most 95 severe or critical disease, as well as enhanced pro-inflammatory IL-6 and TNF responses⁸⁻¹². In association with this depressed type I IFN response, patients with 96 97 critical cases of COVID-19 have a corresponding decrease in frequency of professional type I IFN producing cells, plasmacytoid dendritic cells (pDC)⁸. The frequency of NK 98 99 cells was significantly diminished in SARS-CoV-2 patients with acute respiratory 100 distress syndrome (ARDS) as compared to healthy donors, though patients with more 101 severe disease had NK cells with increased expression of activation and cytotoxic 102 molecules^{13,14}. Additionally, increased frequencies of neutrophils have been identified in 103 patients with severe COVID-19 as compared to patients with more mild disease or healthy donors^{10,11,13,15}, congruent with a hyper-inflammatory state. 104 105 Patients infected with SARS-CoV-2 also raise detectable adaptive immune responses, in the form of both B and T cell responses specific to SARS-CoV-2¹⁶⁻²⁴. 106 107 Additionally, circulating conventional T cell phenotypes have been extensively profiled in 108 patients infected with SARS-CoV-2 with varying degrees of disease, from asymptomatic 109 or mild to critical disease, and several differences in the dynamics of immune cells have

110 been noted, including increased abundance of activated T cells in patients with the most

severe COVID-19 disease as compared to healthy controls^{10,13,23-25}. Moreover, two

112 groups have noted a significant decrease in abundance of circulating regulatory T cells

(CD3+CD4+CD25+CD127lo) in patients with severe COVID-19 as compared to patients 113 with non-severe disease or healthy donors^{11,26}. Notably, one study identified a decrease 114 in airway regulatory T cells in patients with COVID-19 compared to healthy controls ²⁷. 115 116 raising the possibility that a Treg deficit at the lung site could be contributing to disease. 117 Altogether, these data suggest that a dysregulated state of hyper-inflammation is 118 associated with severe COVID-19. However, it remains largely unclear if this 119 dysregulated hyper-inflammatory state is unique to COVID-19 or is a feature of severe 120 disease with respiratory viral infections more generally. A recent study comparing 121 inflammatory profiles in patients infected with SARS-CoV-2 or influenza virus (Flu) 122 found several notable differences between such patients. These consisted of lower 123 cytokine levels and reduced circulating monocyte counts in patients with SARS-CoV-2 124 as compared to Flu, although circulating lymphocyte counts did not differ in patients with the two distinct infections²⁸. They concluded that SARS-CoV-2 patients have a less 125 126 inflamed peripheral immunotype as compared to patients infected with Flu, though other 127 respiratory viruses were not examined. Thus, we designed a study wherein circulating 128 immune signatures were compared among healthy human donors and hospitalized 129 patients with SARS-CoV-2, Flu, or respiratory syncytial virus (RSV) infection. 130 Hospitalized patients infected with either of the three viruses were further classified as 131 having moderate, severe, or critical disease based on the type of provided oxygen 132 supplementation, thereby allowing for comprehensive comparisons of immune cell 133 abundance and phenotype across a range of disease severity. In general, our deep 134 immune profiling revealed similar cellular and cytokine immune landscapes in 135 hospitalized patients infected with SARS-CoV-2, Flu or RSV compared to healthy

- donors. However, unique to COVID-19 patients with the most critical disease was a
- 137 significant increase in the frequency of regulatory T cells (Treg) in the circulation, as
- 138 well as phenotypic changes indicating increased suppressive capacity and tissue-
- 139 migratory patterns. Our novel findings have clinical implications, as treatments used for
- 140 COVID-19 may be useful in mitigating severe Flu or RSV, as well as future pandemic
- 141 respiratory diseases. Furthermore, Tregs may provide a potential therapeutic target for
- 142 COVID-19.

143 **Results**

144 Deep immune profiling of a unique cohort of patients reveals shared circulating immune 145 cell composition between respiratory infections.

146

147 We analyzed PBMCs from a unique cohort of age- and sex- matched patients 148 hospitalized with respiratory infections including Flu, RSV, or SARS-CoV-2 compared to 149 PBMCs from healthy donors (Figure 1A). The patients infected with SARS-CoV-2 150 required varying degrees of oxygen supplementation, and patients experienced varying 151 COVID-19 outcomes, from moderate disease to death (Table 1). The PBMCs from 152 hospitalized patients with RSV or Flu A or B were all collected before the SARS-CoV-2 153 pandemic. To extensively characterize the cellular immunotypes present in the 154 peripheral blood of patients hospitalized with Flu, RSV, or SARS-CoV-2 infection 155 compared to healthy donors, we combined several high-parameter flow cytometry 156 panels to profile myeloid cells, T cells, NK cells, or regulatory T cells (Treg) 157 (Supplemental Table 1). For exploratory analysis of this high-dimensional data set we utilized clustering by Flow-SOM^{29,30} and dimensionality reduction with uniform manifold 158 approximation projection (UMAP)³¹, which revealed strikingly similar distributions of cell 159 160 populations between healthy donors and all three respiratory infections (Figure 1B). A 161 heatmap of markers to identify cell populations distinguished the main clusters as Lin 162 HLADR⁺ myeloid cells, B cells, T cells, and NK cells (Figure 1C). A key feature of SARS-CoV-2 infection that has emerged through recent studies is lymphopenia^{2,7,32,33}. 163 164 Lymphopenia can also result from other respiratory infections such as Flu and RSV, but this generally occurs early after onset of symptoms and is rapidly resolved³⁴. Thus, we 165

166 wanted to compare alterations in immune subsets across respiratory infections to 167 determine if patients within our SARS-CoV-2 cohort were experiencing similar levels of 168 immune alteration to patients with RSV or Flu versus healthy donors. Manual gating of 169 the flow cytometry data by a conventional gating strategy to determine the main immune 170 populations confirmed the observations seen in the meta-clustering data from FlowSOM 171 (Figure 1D). In the Lin HLA-DR⁺ compartment, we did not see significant alterations in 172 the overall frequency across groups. We observed a significant increase in the 173 frequency of B cells in patients hospitalized with RSV compared to patients hospitalized 174 with Flu or to healthy donors. We saw no significant alterations in the frequency of total 175 circulating T cells across all respiratory infections compared to healthy donors. Finally, 176 the frequency of NK cells was significantly reduced only in patients infected with RSV 177 compared to healthy donors (Figure 1E). While previous studies have indicated a 178 reduction in NK cell populations after infection with SARS-CoV-2 as compared to healthy donors^{13,14}, our data indicates that this phenomenon is likely not specific to 179 180 SARS-CoV-2 infection but is seen across additional respiratory infections as well. While 181 the frequencies of these cell population may not directly correlate with the total number 182 of cells found in the blood, we concluded that the overall immune populations remain 183 similar between respiratory infections.

184

A decreased frequency of dendritic cell subsets is common across hospitalized
individuals with respiratory infections compared to healthy donors.

187

188 For an in-depth analysis of these immune cell populations, we leveraged 4 high-189 parameter flow cytometry panels focusing on antigen presenting cells (APC panel), NK 190 cells (NK cell panel), as well as T cells (T cell panel) and Treqs (Treq panel) 191 (Supplemental Table 1). For APC, we followed recently suggested phenotyping 192 guidelines to separate classical and non-classical monocytes, as well as 4 distinct 193 dendritic cell (DC) subsets: the pDC, cDC1, cDC2 and the newly defined inflammatory cDC3^{35,36} (**Supplemental Figure 1A**). None of the infections led to a significant 194 195 alteration in frequency of classical monocytes compared to healthy donors. While a 196 decrease in non-classical monocyte frequency has been reported with SARS-CoV-2 infection³⁷, our data only showed a significant decrease of the non-classical monocytes 197 198 for Flu while a trend toward reduction was observed for RSV and SARS-CoV-2 infected 199 patients (Figure 2A). In a similar manner as Zhou et al., we observed a reduced frequency across several DC subsets in SARS-CoV-2 compared to healthy donors³⁸. Of 200 201 note, this decrease in the frequency of pDC, cDC1, cDC2, and inflammatory cDC3 was 202 also observed in Flu and RSV-infected patients (Figure 2B). When we assessed the frequencies of the CD56^{bright}CD16⁻ as well as the CD56^{dim}CD16⁺ NK cell subsets 203 204 (Supplemental Figure 1B), we found no significant differences when compared across 205 respiratory infections and healthy donors (Figure 2C).

Finally, we observed a reduction in peripheral mucosal-associated invariant T (MAIT) cells across all respiratory infections (**Figure 2D** and **Supplemental Figure 1C**), similar to what has been previously documented in patients with severe COVID-19 compared to healthy donors³⁹. We did not observe significant reductions compared to healthy donors in the T cell compartment of patients with any respiratory infection when

211	we examined individual CD4 and CD8 T cell subsets (Figure 2D). Furthermore, there
212	was no statistically significant difference in the frequency of CD25 ⁺ CD127 ⁻ Foxp3 ⁺ Tregs
213	in patients with any of the respiratory infections compared to healthy donors (Figure
214	2D). Thus, in terms of overall immune cell subset distribution, we found that the NK cell
215	family and T cell family remained unchanged between infected patients and healthy
216	donors. We also found a congruent reduction in circulating DC subsets for Flu, RSV,
217	and SARS-CoV-2 patients as compared to healthy donors. Overall, our results indicate
218	that these immune cell changes are a general feature of immune responses to
219	respiratory virus infections rather than a unique signature of SARS-CoV-2 infection.
220	
221	Immune cell phenotypic changes are consistent with both a respiratory virus signature
222	as well as a SARS-CoV-2 specific signature.
223	
224	After observing minimal changes in the frequency of various immune cell subsets
225	between respiratory viral infections, we next wanted to more comprehensively assess

the expression of various markers of activation, maturation, and migration among
 monocytes, DC, NK cells, CD8⁺ T cells, CD4⁺ conventional T cells (Tconv), and CD4⁺

regulatory T cells (Tregs). Some markers did not show any change either across

infection or compared to healthy donors and are displayed unabridged in **Supplemental**

Figures 2-4. Interestingly, in instances wherein we observed a significant difference for

one of the infections compared to healthy donors, this difference was usually seen

across multiple respiratory infections, consistent with a respiratory virus signature

233 (Figure 3A-D). Specifically, we observed in the monocyte population an increase in

234 CD40 and CD206 expression in multiple, but not all, respiratory infections. Non-classical 235 monocytes had a significant increase in CD11b and CD206 across all respiratory 236 infections compared to healthy donors (Figure 3A). We observed few significant 237 changes in the DC subsets, one being in the cDC3 population; the fraction of CD86-238 expressing cells was significantly lower in patients with Flu and RSV, while CD206 was 239 significantly higher in patients with SARS-CoV-2 (Figure 3B). The frequency of pDCs 240 expressing CD32 or CD38 was significantly increased in patients with any respiratory 241 infection as compared to healthy donors (Figure 3B). In the two NK cell subsets, we 242 observed a strong NK cell activation signature in patients hospitalized with respiratory 243 viral infections, characterized by an increased frequency of CD38, CD69, HLA-DR, 244 Ki67, and Granzyme B (Figure 3C). While others have shown this activated phenotype in NK cells following SARS-CoV-2 infection^{13,14}, we demonstrate that this phenotype is 245 246 also a feature of NK cells in patients with other severe respiratory infections compared 247 to healthy donors (Figure 3C).

248 Finally, we found T cell subsets to have increased frequency of markers related 249 to activation and effector function in individuals who were hospitalized for SARS-CoV-2 250 and other respiratory virus infections compared to healthy donors (Figure 3D). In 251 particular, CD8 and CD4 Tconv cells positive for HLA-DR and CD38 were increased in 252 patients hospitalized with Flu, RSV, and SARS-CoV-2 compared to healthy donors. 253 There was also an increase in the fraction of CD4 Tconv cells expressing CTLA-4 or 254 Ki67 across all infections compared to healthy donors (**Figure 3D**). Finally, we also 255 observed an increased frequency of Tregs expressing activation and suppression 256 markers CTLA-4, ICOS, Ki67, HLA-DR/CD38, and PD-1 in patients with respiratory

257	viruses compared to healthy donors (Figure 3D). It has been demonstrated during
258	SARS-CoV-2 infection that NK and T cell subsets have increased activation and
259	function compared to healthy donors ^{13,14,40} , and we hereby demonstrate that this
260	phenomenon is not specific to SARS-CoV-2 infection, but rather spans multiple
261	respiratory infections. We highlighted phenotypic marker alterations consistent between
262	Flu, RSV, and SARS-CoV-2 infections compared to healthy donors, and we propose
263	that these markers indicate a common circulating immune signature to respiratory virus
264	infection.

265

266 Unsupervised complex phenotype discovery analysis reveals a SARS-CoV-2 specific
267 signature including complex Treg phenotypes.

268

To specifically search for infection-specific changes in immune cell subsets in a 269 270 unsupervised manner, we applied a recently developed non-parametric method for 271 unbiased complex phenotype discovery called <u>Full Annotation Using Shape-constrained</u> **Trees** (FAUST)⁴¹. Briefly, FAUST performs data-driven phenotype discovery and annotation 272 273 on a per-sample basis, enabling the identification of statistically different complex immune 274 phenotypes between the different groups of our cohort (Supplemental Table 2). We 275 tested for differences in immune phenotypes between SARS-CoV-2 cohorts relative to 276 Flu and RSV to determine if there were any complex immune cell phenotypes unique to 277 SARS-CoV-2 infection using our high parameter flow panels (Supplemental Table 1). 278 Data from the APC panel revealed 8 distinct phenotypes with significant differences in 279 cell frequency when comparing SARS-CoV-2 (all severity levels) to Flu and RSV

280 (Figure 4A and Supplemental Table 2). There were no significant complex phenotypes 281 discovered using the NK cell panel when patients with all SARS-CoV-2 severity levels 282 were compared to patients with RSV or Flu (Figure 4A and Supplemental Table 2), in 283 agreement with the NK cell analysis shown in **Figure 3** demonstrating that alterations in 284 immune cell populations are largely consistent between respiratory infections. However, 285 using the T cell panel in combination with FAUST analysis revealed 26 complex 286 immune cell phenotypes that differed significantly in patients with SARS-CoV-2 infection 287 with any level of disease severity compared to Flu and RSV (Figure 4A). Notably, the 288 majority of these significantly different T cell phenotypes were CD4+CD25+CD127-, and 289 thus comprising a Treg population (Figure 4B and Supplemental Table 2). Several 290 subsets of CD4+CD25+CD127- Treg that were CD45RA-CCR7- (effector memory 291 phenotype) were decreased in SARS-CoV-2 samples compared to the other respiratory 292 infections and healthy donors, including a CD27+CD28+ICOS+HLA-DR+Ki67- and a 293 CD27+CD28+ICOS+HLA-DR-Ki67- subset (Figure 4B). In contrast, a subset of 294 CD4+CD25⁺CD127⁻ Treg that is CD45RA⁻CCR7⁺ (central memory phenotype) that co-295 expresses CD27, CD28, Ki67, and HLA-DR was significantly increased in the circulation 296 of patients with SARS-CoV-2 and critical disease compared to Flu or RSV (Figure 4B). 297 We confirmed these populations by manual gating of our flow cytometry data (Figure 298 **4C**). While the functional relevance of these cells is unclear, it is noteworthy that these 299 complex Treg phenotypes distinguish SARS-CoV-2 infection compared to other 300 respiratory infections, Flu and RSV. In summary, while much of the immune landscape 301 is shared across these respiratory infections, our unsupervised analysis approach

302	reveals unique complex phenotypes in the circulating Treg population that distinguishes
303	patients infected with SARS-CoV-2 compared to Flu or RSV.

304

305 Pro-inflammatory cytokines and chemokines are increased during respiratory infections
 306 compared to healthy donors.

307

308 We next sought to determine if measuring cytokine and chemokine concentrations in 309 the serum would provide additional insight to explain the overlap in immune phenotypes 310 as well as the differences in Treg phenotypes. We tested serum samples from a subset 311 of the cohort described in Table 1 to quantify 71 different cytokines and chemokines 312 (Supplemental Table 3). This analysis revealed a significant increase in serum IL-6 313 levels compared to healthy controls in both SARS-CoV-2 and RSV patients (Figure 314 **5A**). Others have shown an increase in IL-6 to be consistent with SARS-CoV-2 infection^{7,42,43}, and here we demonstrate that IL-6 is significantly elevated in the serum 315 316 of RSV patients as well. As IL-6 is an important pro-inflammatory cytokine during mucosal infections⁴⁴, we wanted to examine whether other pro-inflammatory cytokines 317 318 were increased during respiratory viral infections compared to SARS-CoV-2. We 319 observed a significant increase in IL-8, IL-15, and IL-10 during both SARS-CoV-2 320 infection and RSV infection (Figure 5A). We did not see a large increase in pro-321 inflammatory cytokine levels in patients infected with Flu. However, this could be due to 322 the reduced number of serum samples available in our cohort from Flu patients (N=3). 323 Inflammatory mediators such as interferons (IFNs), IL-1 α , and IL-1 β have also been reported to be increased in patients with COVID-19², although some reports have 324

demonstrated very low levels of type I IFNs (IFN α and IFN β)⁶. In our cohort of patients, 325 326 we observed increased levels of IL-1 β and IL-1 α in patients with RSV compared to 327 healthy donors, but no difference between healthy donors and SARS-CoV-2 or Flu 328 patients. Furthermore, there was no difference in type I or type II interferons in patients 329 infected with SARS-CoV-2 compared to healthy donors, although serum IFN α was 330 significantly increased during RSV infection compared to either healthy donors or 331 SARS-CoV-2 patients (Figure 5A). We also observed a significant elevation of IL-1RA 332 during both SARS-CoV-2 and RSV infection (Figure 5A). Inflammatory chemokines 333 were significantly increased during respiratory infection compared to healthy donors. 334 with serum levels of CXCL9 and CXCL10 elevated during SARS-CoV-2 infection, 335 though CXCL9 was also significantly increased in the context of RSV infection 336 compared to healthy donors (Figure 5B). TRAIL has previously been correlated with viral load during SARS-CoV-2 infection¹⁰, but we found it to be significantly decreased in 337 338 the serum of RSV and SARS-CoV-2 patients compared to healthy donors in our cohort 339 (Figure 5B). Additionally, CCL17 and CCL22, chemokines known to be involved in the mobilization of immune cell to the lungs^{45,46} and reported to be increased in SARS-CoV-340 2 infection^{10,47,48}, were decreased or unchanged in the serum compared to healthy 341 342 donors in our cohort. These findings are most likely due to the timing of the sample 343 collection from symptom onset; studies have shown that trafficking of immune cells by these chemokines are most elevated as early as 1 week after infection⁴⁷, and since all 344 345 of our samples came from hospitalized patients, some were collected weeks after 346 symptom onset (**Table 1**). Finally, due to variability in the quantities of these cytokines 347 and chemokines detected in serum of SARS-CoV-2 patients, we next assessed whether

348	levels of these cytokines and chemokines differed by severity of COVID-19, as defined
349	by oxygen supplementation requirements (COVID-19 moderate, severe, or critical).
350	Serum levels of IL-6, IL-8 and IL-10 were all significantly increased in patients with
351	critical COVID-19 as compared to healthy donors, thereby suggesting that these
352	cytokines are a feature of critical disease (Figure 5C). Additionally, the chemokines
353	CXCL9 and CXCL10 were significantly elevated in patients with increased COVID-19
354	severity (Figure 5D). Overall, we demonstrated that several cytokines and chemokines
355	previously associated with SARS-CoV-2 infection were also elevated in the serum of
356	patients hospitalized with other respiratory infections, and so may not be a unique
357	feature of COVID-19.
358	
359	Markers of cellular activation among NK and T cells are increased after COVID-19 to
360	varying degrees.
361	
362	Based on the increase in pro-inflammatory cytokines and chemokines with increasing
363	COVID-19 disease severity, we wanted to determine if effector immune cell subsets
364	were also altered with COVID-19 severity in our cohort. In the CD56 ^{bright} CD16 ⁻
365	population of NK cells, characterized as being cytokine producers with proliferative
366	potential ⁴⁹ , we observed an increased expression of both CD38 and CD69 for both
367	patients with severe and critical COVID-19 compared to healthy donors (Figure 6A).

368 We also observed an increased expression of Ki67 among CD56^{bright}CD16⁻ NK cells of

369 patients with severe COVID-19 compared to healthy donors.

370 Upon examination of T cell activation status, we observed that the frequency of 371 CD8⁺ T cells was not altered based on COVID-19 severity, nor was the frequency of 372 CD8⁺ T cells expressing the cytotoxic molecule granzyme B (**Figure 6B**). However, the 373 frequency of CD8⁺ T cells expressing Ki67 was significantly elevated for both patients 374 with severe and critical COVID-19 (Figure 6B). We also found an increased CD69 375 expression among circulating CD8⁺ T cells in both patients with moderate and critical 376 COVID-19 (Figure 6B). Finally, CXCL9 and CXCL10 are inflammatory chemokines induced by IFNy that share the chemokine receptor CXCR3⁵⁰. Since these chemokines 377 378 were increased in patients with severe COVID-19 (Figure 5D), we next wanted to 379 determine if CXCR3 expression was altered on T cells, thereby potentially accounting 380 for the increased fraction of activated cells present in the circulation of patients with 381 critical COVID-19. However, the expression of CXCR3 was not significantly increased 382 by CD8⁺T cells from patients with any degree of COVID-19 severity (Figure 6B). A 383 similar expression pattern of activation markers was observed in CD4⁺ Tconv cells; there was no change in the frequency of CD4⁺ T cells based on COVID-19 severity, and 384 385 there was limited expression of granzyme B within the CD4⁺ T cell subset that did not 386 vary by disease severity. However, the frequency of CD4⁺ T cells expressing either Ki67 387 or CD69 was increased in patients with COVID-19, with Ki67 increasing with disease 388 severity (Figure 6C). We did not see any increase in the fraction of CD4⁺ T cells that 389 expressed CXCR3 (Figure 6C), suggesting that these activated T cells would not have 390 the potential to migrate to the lung using the mucosal tissue homing molecule CXCR3, 391 though they may utilize other chemokine receptors to enter this critical site of virus 392 replication. We sought to confirm that any increase in markers of cellular activation were 393 in fact due to COVID-19 severity and not related to days post-symptom onset. When we 394 examined these markers of cellular activation on NK cells and T cells by days post 395 symptom onset to sample collection, we found no significant difference in cellular 396 activation relating the days post-symptom onset in our SARS-CoV-2 cohort 397 (Supplemental Figure 5). This suggests that our findings are associated with COVID-398 19 severity rather than timing of sample collection. 399 400 Regulatory T cells in patients with critical COVID-19 disease are increased in frequency 401 and display a heightened activation signature. 402 403 A hallmark of the immune response to SARS-CoV-2 infection in individuals with severe disease has been identified as a state of dysregulated and pro-inflammatory immunity⁶⁻ 404 ^{8,10,13,14,28,32,40,51,52}. We and others have previously demonstrated that Tregs play a role 405 406 in orchestrating the anti-viral immune response by potentiating the antigen-specific T cell response⁵³⁻⁵⁸. However, it is also evident that in the context of infections, including 407 408 RSV and Flu, Tregs can assist in restraint of immunity to reduce immunopathogenesis associated with a robust immune response^{54,58} ⁵⁹⁻⁶⁴. Because we identified significant 409 410 changes in the frequency of complex Treg phenotypes in patients with SARS-CoV-2 411 compared to Flu and RSV infection (Figure 4), we sought to further examine Treq 412 phenotype based on COVID-19 severity. Since we also observed increased proliferation

413 of CD4⁺ Tconv cells with increased COVID-19 severity, we hypothesized that Tregs

414 could be involved in restraining this exuberant anti-SARS-CoV-2 immune response. A

415 previous study found no significant difference in the frequency of Tregs in the circulation

by COVID-19 severity⁷, while two subsequent studies have identified a slight decrease 416 in Trea frequency with increasing COVID-19 severity^{11,26}. However, when we measured 417 418 Treg frequency in healthy donors compared to patients with COVID-19 disease, we saw 419 a significant increase in the frequency of CD25⁺CD127⁻Foxp3⁺ Tregs in COVID-19 420 critical patients only (Figure 7A). We additionally measured the median fluorescent 421 intensity of Foxp3 in the Tregs, as this has been shown to be an indicator of suppressive capabilities⁶⁵. We detected an increase in the level of Foxp3 expression by 422 423 Tregs in the COVID-19 critical patients compared to patients with moderate disease 424 (Figure 7A). To test if circulating Tregs from COVID-19 patients showed a more 425 suppressive phenotype, we measured Ki67, CTLA-4, GITR, and ICOS, all of which were 426 significantly increased with COVID-19 disease severity (Figure 7B). TCF1, a transcription factor that has been shown to dampen Foxp3 activity^{66,67}, appeared to be 427 428 decreased with COVID-19 severity, albeit non-significantly, consistent with the notion of 429 more functional Tregs in COVID-19 critical patients (Figure 7B). Finally, we wanted to 430 determine if Treqs were licensed to migrate to the lungs in COVID-19 patients, and so 431 we examined CXCR3 expression. We observed a significant increase in the frequency 432 of CXCR3 expressing Treqs with increasing COVID-19 severity (Figure 7B). Our data 433 indicated that Treqs are highly activated in patients with critical COVID-19 and are 434 potentially able to migrate toward a gradient of increasing CXCL9 and CXCL10 during 435 SARS-CoV-2 infection.

436

437 **Discussion**

438 More than a year into the COVID-19 pandemic, numerous studies of peripheral blood 439 from individuals infected with SARS-CoV-2 have revealed that a hyper-inflammatory 440 and dysregulated immunotype is characteristic of COVID-19 patients compared to 441 healthy donors. In attempts to identify unique aspects of anti-SARS-CoV-2 immunity 442 that could underlie disease presentation and severity, a comparison with other common 443 respiratory virus infections is required. However, there have only been a limited number 444 of studies comparing immune phenotypes generated after SARS-CoV-2 infection to other respiratory viral infections^{6,28,68}. It was first demonstrated by Blanco-Melo et al that 445 446 compared to other respiratory viral infections, including human parainfluenza virus 3 447 and RSV, SARS-CoV-2 elicits a blunted early type I and type III interferon response in *vitro* and in animal models⁶. Through an scRNAseg study of PBMCs from individuals 448 449 with COVID-19 or severe influenza, another group demonstrated that cells from COVID-450 19 patients had a predominantly IL-1 β and TNF inflammatory signature, whereas Flu patients had an increased interferon-stimulated gene (ISG) response⁶⁸, thereby 451 452 uncovering differential pro-inflammatory pathways elicited by distinct respiratory viral 453 infections. Finally, a recent study comparing immune responses in patients with severe 454 influenza or COVID-19 found that the latter exhibited similar lymphocyte counts but 455 fewer monocytes and reduced HLA-DR expression on monocyte subsets as compared 456 to Flu patients²⁸. To extend these studies, we designed a study to comprehensively 457 examine serum cytokines and chemokines as well as the immunotypes of myeloid cells, 458 NK cells, T cells, and Treqs in the peripheral blood of patients hospitalized with Flu or 459 RSV compared to SARS-CoV-2 or healthy controls. Importantly, we used high-

460	parameter flow cytometry coupled with both unbiased computational analysis
461	approaches as well as traditional manual gating to perform a comprehensive
462	examination of many immune cell subsets as well as complex phenotypes. We
463	reasoned that comparison of immune phenotypes between patients hospitalized with
464	COVID-19 versus other severe respiratory virus infections could potentially reveal
465	common immunotherapeutic strategies that can thus be leveraged in the battle against
466	SARS-CoV-2 and future pandemic viruses. For example, knowledge of immune-
467	targeting therapeutic strategies to treat SARS-CoV-2 could potentially be applied to the
468	next pandemic respiratory virus, which may be Flu or another CoV.
469	Analysis of our cohort demonstrates that most of the previously identified
470	alterations in peripheral immune populations during SARS-CoV-2 infection are not a
471	distinguishing features of the anti-SARS-CoV-2 immune response, but rather indicate a
472	more common immune landscape associated with respiratory viruses in general. We
473	have identified a general respiratory virus-induced immune signature across three
474	different respiratory viral infections compared to healthy donors (Figure 3A-D).
475	However, applying an unsupervised phenotype discovery analysis (FAUST) revealed
476	previously undescribed alterations of Tregs with various complex phenotypes in SARS-
477	CoV-2 patients compared to those with Flu or RSV (Figure 4). More specifically, we
478	detected a reduced frequency of effector memory phenotype (CD45RA-CCR7-) Tregs
479	co-expressing various markers of activation, including ICOS, CD27, CD28, and HLA-DR
480	present in the blood of patients with SARS-CoV-2 compared to Flu or RSV (Figure 4B-
481	C). This could reflect a reduction in activated Tregs able to migrate to the peripheral
482	tissues including the lung, whereby they could participate in restraining

483 immunopathology and limiting ARDS. In contrast, we identified a unique population of 484 blood Tregs with a central memory phenotype (CD45RA CCR7⁺) co-expressing CD27, 485 CD28, Ki67 and HLA-DR that was present at a significantly increased frequency in 486 SARS-CoV-2 patients compared to those with Flu or RSV (Figure 4B-C). We speculate 487 that these Tregs represent a circulating population of activated suppressive cells that 488 may participate in restraining the inflammatory response in the context of COVID-19. 489 However, whether or not this is of benefit to the host in the context of disease is an 490 open question. Thus, additional studies are required to determine if Treg-modulating 491 therapies could be of benefit in limiting COVID-19 severity. We recently demonstrated 492 that in a mouse model of SARS-CoV, an elevated steady-state, pre-infection frequency of Tregs correlates with protection from high viral loads and disease upon infection⁶⁹, 493 494 thereby contributing to the notion that Tregs could play a protective role in limiting 495 disease. However, examination of prospectively collected pre-COVID-19 pandemic 496 samples from humans that went on to become infected would be required to establish 497 whether or not Treg abundance is predictive of viral loads or disease severity upon 498 SARS-CoV-2 infection. Recent evidence suggests that the airways of patients with severe COVID-19 have reduced Treg frequencies compared to healthy airways²⁷. 499 500 leading us to speculate that there may be a defective trafficking of Tregs from the 501 circulation into the respiratory tract in the context of COVID-19, thus contributing to lung 502 immunopathogenesis. We hypothesize that this may be due to the increased levels of 503 CXCL10 and CXCL9 found in peripheral blood (Figures 5B and 5D) that may retain 504 CXCR3⁺ Treg in the periphery and prevent them from entering the airways via a 505 chemokine gradient. In addition, the reduced frequency of effector memory phenotype

506 Treg present in the blood of patients infected with SARS-CoV-2 compared to Flu and 507 RSV may indicate that Treg able to migrate to tissue sites may be diminished in the 508 context of SARS-CoV-2. Thus, while additional studies of the mucosal immune 509 response to SARS-CoV-2 are warranted, we speculate that immunotherapies designed 510 to attract Treg out of the circulation and into the respiratory tract could be beneficial in 511 limiting disease. Of note, there are several ongoing clinical trials that target various 512 chemokine receptors, including CCR2 and CCR5, in an effort to minimize immune-513 mediated lung tissue damage (NCT04435522 and NCT04500418). 514 Our study has some limitations, first of which is our exclusive focus on peripheral 515 blood immune responses rather than tissue-specific responses. In addition, our cohort 516 includes patient sample collection from variable times post-symptom onset, from zero to 517 47 days. This variability could clearly impact the types of immune phenotypes detected. 518 as could variability in viral loads and durability of viral shedding, for which we are 519 lacking data from the majority of patients due to scarcity of testing in the early days of 520 the pandemic. Finally, while we were powered to uncover unique aspects of the 521 circulating Treg phenotypes of patients with SARS-CoV-2 compared to Flu or RSV, our 522 relatively small N (Table 1) may have precluded identification of other distinguishing 523 immune phenotypes.

In sum, our study based on high dimensional flow cytometry data combined with several analysis methods reveals a largely similar immune landscape of patients hospitalized with respiratory virus infections, including SARS-CoV-2. This is further supported by our analysis of 71 soluble cytokines and chemokines in the blood of patients with SARS-CoV-2, Flu, or RSV. The recent identification of novel SARS-CoV-2

variants that may increase transmission and alter vaccine efficacy⁷⁰ underscores the 529 530 need for continued development of treatment strategies specifically for severe COVID-531 19 disease course. Thus, we speculate that the overlapping immune landscapes in 532 SARS-CoV-2, Flu, and RSV infections could be leveraged to identify and hasten 533 common treatment strategies that could be leveraged for the response to the next 534 pandemic respiratory virus. Surprisingly, we identified that SARS-CoV-2 patients with 535 the most critical disease presented with unique alterations in the Treg compartment. 536 including an increase in a population of CD45RA⁻CCR7⁺Ki67⁺HLA-DR⁺ Tregs within the 537 circulation compared to patients with Flu or RSV, and an increase in CXCR3⁺ Tregs in 538 the blood of patients with COVID-19, thus leading us to predict that Treg-targeting 539 therapies could be useful in limiting disease associated with SARS-CoV-2. Additional 540 studies of Treas present in the respiratory tract of COVID-19 patients, as well as 541 investigations into immune-therapeutic approaches to target multiple respiratory virus 542 infections will be useful in identifying additional therapeutic avenues that can curtail viral 543 infection-mediated severe lung disease, including disease induced by future pandemic 544 viruses.

545

546

547 Methods

548 Sample Collection

549 Study Population

550 Study samples were collected as part of the prospective longitudinal cohort study 551 HAARVI (Hospitalized or Ambulatory Adults with Respiratory Viral Infections) in Seattle, 552 Washington. Individuals 18 years or older were eligible for inclusion and were recruited 553 from two groups: inpatients with laboratory confirmed respiratory viral infection, and 554 healthy controls. Inpatients were hospitalized at Harborview Medical Center, University 555 of Washington Medical Center, or Northwest Hospital and identified through a laboratory 556 alert system. A cohort of healthy individuals were enrolled in this study and were 557 recruited through email and flyer advertising. They were considered eligible if they had 558 no history of laboratory confirmed SARS-CoV-2 infection and had not presented with ILI 559 (influenza-like illness) in the last 30 days.

Participants or their legally authorized representatives completed informed 560 561 consent. Sociodemographic and clinical data were collected from electronic chart review and from participants via a data collection questionnaire (Project REDCap)⁷¹ at the time 562 of enrollment. The questionnaire collected data on the nature and duration of 563 564 symptoms, medical comorbidities, and care-seeking behavior. Based on these data, 565 individuals were classified by disease severity utilizing an eight-point ordinal clinical assessment scale ⁷². For our study, a clinical assessment score of 1 (death) or 2 566 567 (intubation, ECMO) was categorized as critical COVID-19. A score of 3 (non-invasive ventilation or high flow O2 device) or 4 (required supplemental O2) was categorized as 568 569 severe COVID-19. Finally, a score or 5 (not-requiring supplemental O2) or 6 (no longer

570 requires ongoing medical care) was categorized as Moderate COVID-19. There were 571 no participants with a clinical assessment score of 7 or 8 because our cohort solely 572 consisted of hospitalized patients. All SARS-CoV-2 patient samples were collected 573 after March 1, 2020. All Flu and RSV patient samples were collected between 2017 574 and 2019 during Flu season.

575

576 Ethics

577 The studies were approved by the University of Washington Human Subjects 578 Institutional Review Board, IRB numbers STUDY00000959 and STUDY00002929.

579

580 Sample Processing

581 Participant samples obtained before March 1, 2020 were collected in Mononuclear Cell 582 Processing (CPT, BD) and serum tubes and immediately transferred to the University of 583 Washington. Whole blood in serum tubes was allowed to clot by incubating for at least 1 584 hour at room temperature then centrifuged at 700xg for 15 minutes, aliquoted, and 585 stored at -20°C. CPT tubes were incubated for 2 hours at room temperature before 586 centrifuging at 2000xg for 40 minutes. Purified PBMCs were transferred to a 15mL 587 conical tube, washed twice with PBS, resuspended in Recovery Freezing Medium 588 (Thermo Fisher Scientific, Waltham, MA), and stored in liquid nitrogen until use. 589 Participant samples obtained after March 1, 2020 were collected in acid citrate dextrose 590 and serum-separating tubes (SST, BD) and immediately transferred to the University of 591 Washington. Whole blood in SST tubes was allowed to clot by incubating for at least 1 592 hour at room temperature then centrifuged at 700xg for 10 minutes, aliguoted, and

stored at -20°C. Peripheral blood mononuclear cells (PBMC) were isolated by densitygradient centrifugation using Histopaque (Sigma-Aldrich, St. Louis, MO). After washing,
purified PBMC were resuspended in 90% heat-inactivated fetal bovine serum (FBS)
(Sigma-Aldrich, St. Louis, MO) with 10% dimethyl sulfoxide (DMSO) (Sigma-Aldrich, St.
Louis, MO) cryopreservation media and stored in liquid nitrogen until use. All samples
were frozen within six hours of collection time.

599

600 Flow Cytometry

For flow cytometric analysis, good practices were followed as outlined in the guidelines 601 for use of flow cytometry ⁷³. Directly following thawing, cells were incubated with Fc-602 603 blocking reagent (BioLegend Trustain FcX, #422302) and fixable UV Blue Live/Dead 604 reagent (ThermoFisher, #L34961) in PBS (Gibco, #14190250) for 15 minutes at room 605 temperature. After this, cells were incubated for 20 minutes at room temperature with 50 606 µl total volume of antibody master mix freshly prepared in Brilliant staining buffer (BD 607 Bioscience, #563794), followed by two washes. All antibodies were titrated and used at 608 optimal dilution, and staining procedures were performed in 96-well round-bottom 609 plates. A detailed list of the main panels used, including Fluorochromes and final 610 dilutions of all antibodies is provided in **Supplemental Table 1**.

The stained cells were fixed with 4% PFA (Cytofix/Cytoperm, BD Biosciences) for 20 minutes at room temperature, washed, resuspended in FACS buffer and stored at 4°C in the dark until acquisition. For panels with intranuclear staining, the cells were fixed with intranuclear transcription factor staining kit (eBioscience Foxp3/Transcription

Factor Staining Buffer Set, Thermo Fisher #00-5532-00) following manufacturers'protocols.

617 Single-stained controls were prepared with every experiment using antibody capture 618 beads diluted in FACS buffer (BD Biosciences anti-mouse, #552843, anti-rat, #552844, and Miltenvi anti-REA. #130-1040693). Beads (ArC[™] Amine Reactive Compensation 619 620 Bead Kit, Themo Fisher #A10346) or cells were used for Live/Dead single-stained 621 control, and treated exactly the same as the samples (including fixation procedures). All 622 samples were acquired using a FACSymphony A5 (BD Biosciences), equipped with 30 623 detectors and 355nm (65mW), 405nm (200mW), 488nm (200mW), 532nm (200mW) and 628nm (200mW) lasers and FACSDiva acquisition software (BD Biosciences). 624 Detector voltages were optimized using a modified voltage titration approach ⁷⁴ and 625 626 standardized from day to day using MFI target values and 6-peak Ultra Rainbow Beads (Spherotec, # URCP-38-2K)⁷⁵. After acquisition, data was exported in FCS 3.1 format 627 628 and analyzed using FlowJo (version 10.7.x, BD Biosciences). Doublets were excluded 629 by FSC-A vs FSC-H gating.

630 Importantly, as the samples were stained and acquired in two different batches, each experiment was conducted along with a technical control: a cryopreserved vial of 631 632 PBMC collected via leukapheresis from one single healthy donor. This method is 633 valuable in order to ensure that the variability of expression of the different markers is 634 neither due to variability on the instrument side nor staining-related and allows to 635 compare data from biological samples stained on different days. For samples acquired on different experiment days, files were exported as compensated data and analyzed 636 637 combined together in a new workspace. Gates were kept the same across all samples

638 except where changes in the density distribution clearly indicated the need for 639 adjustment.

640

641 Cytokine and Chemokine Measurements

- 642 Patient serum aliquots were stored at −80□°C. Serum samples were shipped to Eve
- Technologies (Calgary, Alberta, Canada) on dry ice, and levels of cytokines and
- 644 chemokines were measured using the Human Cytokine Array/Chemokine Array 71-403
- 645 Plex Panel (HD71). All samples were measured upon the first thaw.
- 646

647 Statistical Analysis

- 648 After testing the normal distribution of our data using the D'Agostino & Person test,
- 649 statistical analyses were performed using either an ordinary one-way ANOVA
- 650 (parametric test) or Kruskal Wallis test (nonparametric test) using the GraphPad
- 651 Software. Data are expressed as mean ± SD. Significant P values were annotated as

652 follows. * P < 0.05; ** P < 0.01; *** P < 0.001; **** P < 0.0001.

653

654 **FAUST Analysis**

FAUST was used to discover and annotate phenotypes in the 4 tested panels. Manual
gating was first used in order to define on which cell type FAUST should be run. FAUST
was applied to live cells for the APC panel; live, CD3⁺ cells for the T cell panel; live,
CD3⁺ CD4⁺ CD25⁺ CD127⁻ for the Treg panel; and live, CD14⁻ CD19⁻ CD3⁻ CD127⁻ for
the NK panel. After incorporating expert information about the panel design, FAUST

- selected markers to be used for annotation and discovery of phenotypes. The markers
- identified for the different panels were the following:
- 662 **APC panel**: CD1c, CD5, CD11b, CD11c, CD14, CD16, CD32, CD38, CD46. CD85k,
- 663 CD86, CD88, CD123, CD141, CD163, CD301, CX3CR1, FcER1, PD-L1 and Sirpa
- 664 **T cell panel:** BTLA, CCR7, CD4, CD8, CD25, CD27, CD28, CD38, CD45RA, CD127,
- 665 CD161, Granzyme B, HLA-DR, ICOS, Ki67, MR1-tet, TCRgd, Tim3
- ⁶⁶⁶ Treg cell panel: CCR5, CCR7, CD39, CD101, CTLA-4, CXCR3, GITR, KI67, Tbet,
- 667 TCF-1

668 **NK cell panel**: CD2, CD16, CD38, CD56, CD57, CD69, Granzyme B, NKG2A, NKG2C,

- 669 Ki67.
- Then, within a given panel, a binomial generalized linear mixed-effects model (GLMM)
- 671 with a subject-level random effect was used to test for association between counts of
- the discovered phenotypes and COVID-19 patients relative to Flu and RSV patients.
- The severity of the COVID-19 disease was also tested in comparison to the other
- groups of the cohort (i.e., when the moderate COVID-19 patients were tested in
- 675 comparison to Flu and RSV patients, the severe and critical COVID-19 patients were
- removed from the analysis). The entire collection of tested hypotheses was then
- adjusted using the Bonferroni adjustment. Within a given panel, discovered FAUST
- 678 phenotypes with a Bonferroni adjusted p-values under 0.05 were selected.
- 679

680 FlowSOM, UMAP, and Heatmap Generation

- 681 Pipelines outlined in the Spectre R package were used to generate UMAP and
- ⁶⁸² FlowSOM clusters ^{29,30,76}. In FlowJo from the APC Panel, cells were gated by time

683 (Time, FSC-A), cell size (SSC-A, FSC-A), singlets (FSC-H, FSC-A), and live (SSC-A, 684 Dead). Each sample was then downsampled to 20,000 events if able and then exported 685 as CSV files for the channel values of all parameters. Channel values in R were 686 transformed by ArcSinH using a cofactor of 1000. Batches were normalized based on a reference sample run on both days using CytoNorm⁷⁶. For clustering with FlowSOM and 687 688 dimensionality reduction with UMAP, only lineages markers CD3, CD19, HLADR, CD56, 689 CD14, CD88, CD16, CD11c, CD123, CD141, FcER1, CD5, and CD163 were used. 690 FlowSOM was initiated on default parameters where the number of clusters was 691 automatically generated and produced 5. Clusters were then re-annotated to four 692 labeling NK cells, T cells, B cells, and Lin- HLA-DR +/- cells. A UMAP was generated 693 with default parameters on 40,000 events from downsampling 10,000 events per study 694 group (healthy, RSV, FLU, and Sars-CoV2) so as to be equally represented. A heatmap 695 was generated representing the median fluorescent intensity of the lineage markers 696 normalized between 0 and 1 for the annotated clusters. 697

698

699 Acknowledgements

- 700 We thank the members of the Lund and Prlic labs for helpful discussions, the HAARVI
- study team, and the patients and healthy donors for providing samples.

702 Figure Legends

703

Table 1. Demographic and clinical information for study patient cohorts.

705

706 Figure 1. Deep immunological profiling of a unique cohort of patients reveals 707 circulating immune profiles between respiratory infections. A) Overview of the 708 cohort. The number in each box indicates the number of donors per group. Criteria of 709 inclusion are depicted in Table 1. Among the SARS-CoV-2 patients, 4 died from 710 COVID-19. B-D) Previously frozen PBMCs isolated from each group of the cohort were 711 stained using the APC panel (See Supplemental Table 1). B) FlowSOM was used to 712 visualize the main immune cell populations found in the PBMCs from healthy donors or 713 infected patients. C) Heatmaps generated by FlowSOM and used to identify the main 714 immune population. (D-E) (D) Manual gating used to assess the frequencies of the main 715 immune subsets, (E) bar graphs showing these frequencies for each group of our 716 cohort. All data include at least 9 patients per group (Table 1) and are represented as mean ± SD. Statistical analyses were performed using Kruskal-Wallis test. * P < 0.05; ** 717 718 P < 0.01.

719

Figure 2. A decreased frequency of dendritic cell subsets is common across respiratory infections compared to healthy donors. Previously frozen PBMCs isolated from each group of the cohort were stained using 4 high parameter flow cytometry panels. Manual gating was used to estimate the frequencies of **A**) the monocyte family (Supplemental Figure 1A), **B**) the DC family (Supplemental figure 1A),

725 **C)** the NK cell family (Supplemental Figure 1B), and, **D)** the T cell family (Supplemental 726 Figure 1C), for each group of the cohort. All data include at least 9 patients per group 727 (Table 1) and are represented as mean \pm SD. Depending on the distribution of our data, 728 statistical analyses were performed using either one-way ANOVA or Kruskal Wallis test. 729 * P < 0.05; ** P < 0.01; *** P < 0.001, **** P <0.0001.

730

731 Figure 3. Immune cell phenotypic changes are consistent with a respiratory virus 732 signature. (A-D) Heatmaps representing the expression pattern for all the indicated 733 molecules within the main subsets of A) the monocyte family, B) the DC family, C) the 734 NK cell family and, D) the T cell family for each group of the cohort. Gating strategy of 735 the different subsets can be found under each heatmap (also see Supplemental Figure 736 1) and numbers inside boxes represent the mean of frequency for each marker among 737 the specific subsets. Depending on the distribution of our data, statistical analyses were 738 performed using either one-way ANOVA or Kruskal Wallis test. Asterix inside the boxes 739 is indicative of a significant difference compared to the healthy donors' group and can 740 include a p-value from 0.05 to 0.0001.

741

742 Figure 4. Unsupervised analysis reveals a SARS-CoV-2-specific signature

including complex Treg phenotypes. A) FAUST analysis was used to discover
complex phenotypes in the APC, NK and T cell panels. The multiple comparisons were
adjusted using the Bonferroni correction and the numbers in the table are showing the
number of identified phenotypes that are significantly different for SARS-CoV-2 infected
patients compared to the Flu and RSV infected patients for each panel, with Bonferroni

748 adjusted p-values under 0.05 considered significant. B) Example of three Treg 749 phenotypes identified by FAUST within the T cell panel as shown in **Supplemental** 750
Table 2. Bar graphs display the frequency of the phenotype for each group of the cohort
 751 among live, CD3⁺ cells. Data are represented as mean ± SD. Statistical analyses displayed were performed using Kruskal Wallis test. * P < 0.05: ** P < 0.01. *** P < 752 753 0.001. C) Representative flow plots showing the expression pattern of Ki67⁺ HLA-DR⁺ 754 cells among either CCR7⁻ICOS⁺ or CCR7⁺, live, CD3⁺CD4⁺CD25⁺CD127⁻CD27⁺CD28⁺ 755 among the different groups of the cohort. Manual gating was performed using the T cell 756 panel.

757

758 Figure 5. Pro-inflammatory cytokines and chemokines are increased during 759 respiratory infections compared to healthy donors. (A-B) Violin plots showing the 760 A) cytokine and B) chemokine concentrations in the serum for healthy donors (n=25), 761 patients infected by Flu (n=3), RSV (n=10) and SARS-CoV-2 (n=22) (C-D) SARS-CoV-2 762 infected patients were grouped based on the severity of the disease (see Table 1) and 763 Violin plots are showing the C) cytokine and D) chemokine concentrations in the serum 764 for healthy donors as well as moderate COVID-19 (n=5), severe COVID-19 (n=11) and 765 critical COVID-19 (n=6). All data are represented as mean \pm SD. Depending on the 766 distribution of our data, statistical analyses were performed using either one-way ANOVA or Kruskal Wallis test. * P < 0.05; ** P < 0.01; *** P < 0.001, **** P < 0.0001. 767

768

769 Figure 6. Markers of cellular activation among NK and T cells are increased after

770 **COVID-19 to varying degrees.** SARS-CoV-2 infected patients were grouped based on

771 the severity of the disease and markers of cellular activation were analyzed among A) 772 CD56^{bright} CD16⁻ NK cells **B)** CD8⁺ T cells and **C)** CD4⁺T cells, for healthy donors as well as moderate COVID-19 (n=6), severe COVID-19 (n=12) and critical COVID-19 773 774 (n=6). All data are represented as mean \pm SD. Depending on the distribution of our 775 data, statistical analyses were performed using either one-way ANOVA or Kruskal Wallis test. * P < 0.05; ** P < 0.01; *** P < 0.001, **** P <0.0001. 776 777 778 Figure 7. Regulatory T cells in patients with critical COVID-19 disease are 779 increased in frequency and display a heightened activation signature. 780 **A.** Bar graphs showing (*left*) the frequency of Treg and (right) the MFI of Foxp3 among 781 parent for healthy donors and severity-based groups of COVID-19. B. Representative 782 histograms and quantification of the expression of activation and suppressive markers 783 within Treqs for healthy donors as well as moderate COVID-19 (n=6), severe COVID-19 784 (n=12) and critical COVID-19 (n=6). All data and are represented as mean \pm SD.

Depending on the distribution of our data, statistical analyses were performed using
either one-way ANOVA or Kruskal Wallis test. * P < 0.05; ** P < 0.01; *** P < 0.001, ****
P <0.0001.

788

Supplemental Figure 1. Gating strategies. Gating scheme used to identify A) the subsets of myeloid cells using the APC panel; B) the 2 NK cell subsets using the NK panel; and C) the T cell subsets using the Treg panel.

792

Supplemental Figure 2. Similar and specific patterns of phenotypical changes among immune cells. Heatmaps representing the frequency for all the indicated molecules within the main subsets of **A**) the monocyte family, **B**) the DC family, **C**) the NK cell family and, **D**) the T cell family. Gating strategy can be found in Supplemental Figure 1 and numbers inside boxes represent the mean of frequency for each marker among the specific subsets.

799

Supplemental Figure 3. Phenotypical changes in the Myeloid and NK cell 800 801 **populations across respiratory infections.** Bar graphs showing the mean frequency 802 of indicated makers within the A. the monocyte, B. the nonclassical monocyte, C. the DC subsets, **D**. the CD56^{bright} CD16^{neg} NK cells, **E.** CD56^{dim} CD16⁺ NK cells. Gating 803 804 strategy can be found in Supplemental Figure 1. All data include at least 9 patients per 805 group (Table 1) and are represented as mean \pm SD. Depending on the distribution of 806 our data, statistical analyses were performed using either one-way ANOVA or Kruskal Wallis test. * P < 0.05; ** P < 0.01; *** P < 0.001, **** P <0.0001. 807

808

Supplemental Figure 4. Phenotypical changes in T cell populations across respiratory infections. Bar graphs showing the mean frequency of indicated markers within the **A.** the CD8⁺ T cells, **B.** the CD4⁺ Tconv cells, **C.** the CD4⁺ Treg cells. Gating strategy of the different subsets can be found in Supplemental Figure 1. All data include at least 9 patients per group (Table 1) and are represented as mean \pm SD. Depending on the distribution of our data, statistical analyses were performed using either one-way ANOVA or Kruskal Wallis test. * P < 0.05; ** P < 0.01; *** P < 0.001, **** P <0.0001.

816

817 Supplemental Figure 5. Markers of activation on NK and T cells by days post-818 symptom onset to sample collection. SARS-CoV-2 infected patients were grouped 819 based on the reported days post-symptom onset to sample collection into four groups: 820 0-7 days, 8-14 days, 15-21 days, and 22 or greater days. The severity of COVID-19 821 disease is indicated by color of symbol. Markers of cellular activation were analyzed among A. CD56^{bright} CD16⁻ NK cells B. CD8⁺ T cells and C. CD4⁺T cells, for moderate 822 823 COVID-19 (n=6), severe COVID-19 (n=12) and critical COVID-19 (n=6). All data are 824 represented as mean ± SD. Depending on the distribution of our data, statistical analyses were performed using either one-way ANOVA or Kruskal Wallis test. * P < 825 0.05; ** P < 0.01; *** P < 0.001, **** P <0.0001. 826

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Graphical Abstract



Figure 1. Deep immunological profiling of a unique cohort of patients reveals shared circulating immune cell composition between respiratory infections.



Figure 2. A decreased frequency of dendritic cell subsets is common across respiratory infections compared to healthy donors.



Figure 3. Immune cell phenotypic changes are similar between respiratory infections resulting in a respiratory virus signature.



SARS-

B. T cell panel (57% comprise Treg subsets)

CD4⁺CD8⁻CD27⁺TCRgd⁻CD45RA⁻GrzmB⁻CD28⁺CD127⁻ BTLA⁻CD161⁻MR1-Tet⁻CD38⁻Tim3⁻CD25⁺



C. Among Live, CD3+CD4+CD25+CD127-CD27+CD28+



Figure 4. Unsupervised analysis reveals a SARS-CoV-2 specific signature including complex Treg phenotypes.



Figure 5. Pro-inflammatory cytokines and chemokines are increased during respiratory infections compared to healthy donors.



Figure 6. Markers of cellular activation are increased with COVID-19 severity.



Figure 7. Regulatory T cells in patients with critical COVID-19 disease are increased in frequency and display a heightened activation signature.

	Healthy Donors	Flu	RSV	SARS-CoV-2
Number of Patients	25	9	10	24
Age median, (range)	60, (33-79)	59, (36-70)	57.5, (38-71)	62, (23-88)
Sex (female/male)	(12/13)	(4/5)	(4/6)	(11/13)
Race n, (%)				
White	20 (80)	4 (44.4)	5 (50)	11 (45.9)
Black/African American	1 (4)	2 (22.3)	3 (30)	3 (12.5)
Native Hawaiian/Pacific Islander		1 (11)		1 (4.1)
American-Indian/Alaskan Native			2 (20)	
Hispanic	1 (4)	2 (22.3)		6 (25)
Asian	3 (12)			3 (12.5)
Days since symptom onset to	n.a.	7+, (0-7+)*	14, (2-21)	14.5, (2-47)
sample collection median, (range)				
Comorbidities n				
None	17	3	2	7
Diabetes mellitus	1	1		9
Hypertension	3			12
Chronic liver disease			4	2
Chronic kidney disease			2	5
Congestive heart failure		1	2	6
Cardiovascular disease		3	3	3
Asthma	3	3	2	2
COPD/emphysema	1	1	3	
Other chronic lung disease				3
Sleep apnea				7
Malignancy			2	3
ACTT Clinical Status Categories n	n.a.			
Not requiring supplemental O2 –		4	6	6
ongoing medical care				
Required supplemental O2		3	0	8
Non-invasive ventilation or high		1	1	4
flow O2 device				
Intubation, ECMO		1	3	2
Death		0	0	4
Outcome n, (%)	n.a.			
discharged		9, (100)	10, (100)	20, (83.3)
death		0 (0)	0 (0)	4, (16.7)

Table 1. Demographic and clinical information for study patient cohorts.

n.a. = not applicable for healthy donors

* Hospitalized Flu patients were given the option "a week or more" for symptom duration



Supplemental Figure 1. Gating strategies for immune cell populations.



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SAR5.COV?2

47.5

13.4

85.2

6.0

0.3

14.6

0.5

SARS.COV?2

70.3

90.9

974

8.8

42.7

57.0

94 4

62.5

10.3

66.8

78.5

80.1

16.2

Supplemental Figure 2. Phenotypical changes across respiratory infections.

А Monocytes



В **Non-Classical Monocytes**

Lin⁻HLA-DR⁺CD88⁺CD14⁻CD16⁺





cDC2



С **DC** subsets

cDC1 Lin-HLA-DR+CD88-CD11c+CD141+FcER1-







Lin-HLA-DR+CD88-CD11c+CD141-FcER1+CD5-CD163+CD14+



D CD56^{bright} CD16⁻NK cells

Live CD14⁻CD19⁻CD3⁻CD127⁻NKp46⁺HLA-DR^{+/-}CD56⁺CD16⁻ **CD38 CD69** HLA-DR







Ki67

100

80

60

40

20

80

60

40

20

Supplemental Figure 3. Phenotypical changes in Myeloid and NK Cell populations across respiratory infections.

Lin-HLA-DR+CD88-CD11c+CD141-FcER1+CD5+CD163-CD206



GranzymeB

1

100

**

Ŧ

CD11b

CD57

100

CD244

1



B CD4⁺ Tconv Cells

Α

Live Lymphocytes CD3+ CD4+ CD25- CD127+/-



C CD4⁺ Treg Cells

Live Lymphocytes CD3+ CD4+ CD25+ CD127- Foxp3+



Supplemental Figure 4. Phenotypical changes in T Cell populations across respiratory infections.





Supplemental Figure 5. Markers of activation on NK and T cells by days post symptom onset to sample collection.