

1 **Baseline T cell immune phenotypes predict virologic and disease control upon SARS-CoV**
2 **infection**

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4 Running Title: Baseline circulating immune predictors of SARS

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38

39 **Summary.** We used a screen of genetically diverse mice from the Collaborative Cross infected
40 with mouse-adapted SARS-CoV in combination with comprehensive pre-infection
41 immunophenotyping to identify baseline circulating immune correlates of severe virologic and

42 clinical outcomes upon SARS-CoV infection.

43

44 **Abstract**

45 The COVID-19 pandemic has revealed that infection with SARS-CoV-2 can result in a wide
46 range of clinical outcomes in humans, from asymptomatic or mild disease to severe disease that
47 can require mechanical ventilation. An incomplete understanding of immune correlates of
48 protection represents a major barrier to the design of vaccines and therapeutic approaches to
49 prevent infection or limit disease. This deficit is largely due to the lack of prospectively
50 collected, pre-infection samples from individuals that go on to become infected with SARS-CoV-
51 2. Here, we utilized data from a screen of genetically diverse mice from the Collaborative Cross
52 (CC) infected with SARS-CoV to determine whether circulating baseline T cell signatures are
53 associated with a lack of viral control and severe disease upon infection. SARS-CoV infection of
54 CC mice results in a variety of viral load trajectories and disease outcomes. Further, early control
55 of virus in the lung correlates with an increased abundance of activated CD4 and CD8 T cells
56 and regulatory T cells prior to infections across strains. A basal propensity of T cells to express
57 IFN γ and IL17 over TNF α also correlated with early viral control. Overall, a dysregulated, pro-
58 inflammatory signature of circulating T cells at baseline was associated with severe disease upon
59 infection. While future studies of human samples prior to infection with SARS-CoV-2 are
60 required, our studies in mice with SARS-CoV serve as proof of concept that circulating T cell
61 signatures at baseline can predict clinical and virologic outcomes upon SARS-CoV infection.
62 Identification of basal immune predictors in humans could allow for identification of individuals
63 at highest risk of severe clinical and virologic outcomes upon infection, who may thus most
64 benefit from available clinical interventions to restrict infection and disease.

65

66 Key words: SARS-CoV; immune correlates of disease; Collaborative Cross

67 **Introduction**

68 The SARS-CoV-2 pandemic has led to a massive number of infections worldwide, with
69 an unprecedented combined toll in terms of mortality, long-term health conditions, and economic
70 turmoil (Dong et al., 2020). While large-scale efforts to develop protective vaccines are
71 underway, the human immune response to natural infection and identification of immune
72 correlates of disease outcome and protection is still in process. These efforts are likely to help
73 guide such vaccine efforts, as an understanding of the natural immune correlates of protection
74 from disease could assist in the rational design of prophylactic or therapeutic vaccines against
75 SARS-CoV-2, as well as potential immunotherapeutic strategies. Multiple studies have
76 demonstrated that following infection with SARS-CoV-2, individuals can present with mild or
77 asymptomatic disease, though a subset of patients experience severe disease that often requires
78 hospitalization and ventilation. Thus, some of the first studies of the human immune response to
79 SARS-CoV-2 infection have examined changes in immune cell populations in peripheral blood
80 from patients with severe disease as compared to healthy controls. Such studies of patients with
81 severe COVID-19 have identified the existence of SARS-CoV-2-specific CD4 and CD8 T cells
82 (Grifoni et al., 2020; Mateus et al., 2020; Weiskopf et al., 2020), as well as an interferon-
83 stimulated gene signature (Wilk et al., 2020), and various changes in immune cell dynamics
84 (Lucas et al., 2020; Mathew et al., 2020; Wilk et al., 2020). Notably, most studies have reported
85 dysregulated and/or inflammatory responses in patients with severe COVID-19, including
86 decreases in regulatory T cells (Qin et al., 2020), increased neutrophil counts (Lucas et al., 2020;
87 Qin et al., 2020; Wilk et al., 2020) and increases in pro-inflammatory cytokines such as IL-6 and
88 TNF (Blanco-Melo et al., 2020; Lucas et al., 2020; Qin et al., 2020), thereby suggesting that a
89 dysregulated state of inflammation is associated with severe COVID-19. However, what is thus

90 far lacking is a study of prospectively collected, pre-infection samples that would serve to
91 identify if there are immune correlates of protection from infection and/or from severe disease
92 upon infection with SARS-CoV-2. Because most studies have been conducted after individuals
93 had been infected with SARS-CoV-2, it is unclear if the identified immune signatures are
94 predictive of severe disease or a manifestation of severe disease.

95 Previous studies of immunity to other coronaviruses have also contributed to our
96 understanding of what to expect from SARS-CoV-2 in terms of immunity (Sariol and Perlman,
97 2020). Specifically, studies of samples from survivors of MERS-CoV infection have determined
98 that the development of CD4+ and CD8+ T cell responses occurs in humans (Zhao et al., 2017),
99 and studies of SARS-CoV and MERS-CoV infection in mice have demonstrated that protection
100 is mediated by airway memory CD4+ T cells (Zhao et al., 2016). Given this published evidence
101 from human infection with SARS-CoV-2 plus these studies of other CoVs demonstrating that T
102 cells are likely to be involved in immunity to CoV infections, we reasoned that it is possible that
103 T cells could play a role in the initial stages of infection, and thus a pre-infection assessment of
104 the T cell phenotype could reveal novel predictors of severe virologic and clinical outcomes
105 upon infection. Further, given that a dysregulated, pro-inflammatory state is associated with
106 severe COVID-19, we hypothesized that such a signature prior to infection might be predictive
107 of disease outcome upon infection.

108 Immune correlates in humans are normally difficult to identify as they require a
109 prospective, longitudinal study of immune responses in infected individuals pre- and post-
110 infection. Animal models, on the other hand, have many advantages, such as the ease of study of
111 immunity at pre- and post-infection timepoints, as well as experimental control over most
112 variables including timing of infection, infection dose, host genetics, diet, and infection route.

113 Therefore, we have used the Collaborative Cross (CC), a population of genetically diverse,
114 recombinant inbred mouse strains, to investigate whether pre-infectious immune predictors were
115 related to SARS-CoV disease. CC strains are derived from eight founder mouse strains that
116 include five classical inbred strains and three wild-derived strains using a funnel breeding
117 strategy followed by inbreeding (Churchill et al., 2004; Collaborative Cross, 2012; Keane et al.,
118 2011; Roberts et al., 2007b). It is well-documented that the CC can be used to model the
119 diversity in human immune responses and disease outcomes that are not present in standard
120 inbred mouse models (Brinkmeyer-Langford et al., 2017; Elbahesh and Schughart, 2016; Ferris
121 et al., 2013; Graham et al., 2018; Graham et al., 2016; Graham et al., 2015; Gralinski et al., 2015;
122 Kollmus et al., 2018; Leist and Baric, 2018; Rasmussen et al., 2014). We have previously shown
123 that the CC is a superior model for the vast diversity in T cell phenotypes present in the human
124 population (Graham et al., 2017b), and also used a screen of F1 mice derived from CC crosses
125 (CC recombinant intercross, CC-RIX) infected with three different RNA viruses (H1N1
126 influenza A virus, SARS-CoV, and West Nile virus) to reveal novel baseline immune correlates
127 that are associated with protection from death upon infection from all of these three viruses
128 (Graham et al., 2020). Here, we focus our analysis on specific circulating, pre-infection immune
129 phenotypes that associate with different virologic and clinical outcomes upon SARS-CoV
130 infection, including uncontrolled virus replication in the lung, weight loss, and death. We find
131 evidence to support the notion that a circulating dysregulated and inflammatory
132 immunophenotype prior to infection is associated with severe virologic and clinical disease
133 outcomes upon infection with SARS-CoV. While further testing in animal models and humans is
134 required, our data are consistent with the notion that a test of circulating immune signatures
135 could be used to predict infection outcomes and thereby identify patients at highest risk of high

136 rates of shedding and disease upon infection that would most benefit from targeted therapeutic
137 interventions.

138

139 **Methods**

140

141 *Mice*

142 CC mice were obtained from the Systems Genetics Core Facility at the University of North
143 Carolina-Chapel Hill (UNC) (Welsh et al., 2012). As reported previously (Graham et al., 2020),
144 between 2012 and 2017, F1 hybrid mice derived from intercrossing CC strains (CC-RIX) were
145 generated for this research study at UNC in an SPF facility based on the following principles: (1)
146 Each CC strain used in an F1 cross had to have been certified distributable (Welsh et al., 2012);
147 (2) The UNC Systems Genetics Core Facility was able to provide sufficient breeding animals for
148 our program to generate N=100 CC-RIX animals in a target three month window; (3) Each CC-
149 RIX had to have one parent with an *H2B^b* haplotype (from either the C57BL/6J or 129S1/SvImJ
150 founder strains), and one parent with a haplotype from the other six CC founder strains; (4) Each
151 CC had to be used at least once (preferably twice) as a dam, and once (preferably twice) as a sire
152 in the relevant CC-RIX; (5) Lastly, we included two CC-RIX multiple times across the five years
153 of this program to specifically assess and control for batch and seasonal effects. The use of CC-
154 RIX allowed us to explore more lines than the more limited number of available RI strains, and
155 additionally, CC-RIX lines were bred to ensure that lines were heterozygous at the H-2b locus,
156 having one copy of the H-2b haplotype and one copy of the other various haplotypes. This
157 design was selected such that we could examine antigen-specific T-cell responses for our parallel
158 studies of immunogenetics of virus infection, while concurrently maintaining genetic variation
159 throughout the rest of the genome.

160 Six to eight week old F1 hybrid (RIX) male mice were transferred from UNC to the
161 University of Washington and housed directly in a BSL-2+ laboratory within an SPF barrier

162 facility. Concurrently, F1 hybrid female mice were transferred internally to UNC to a BSL-3
163 facility for SARS-CoV infection. Male 8-10 week old mice were used for all baseline immune
164 experiments, with 3-6 mice per experimental group. All animal experiments were approved by
165 the UW or UNC IACUC. The Office of Laboratory Animal Welfare of NIH approved UNC
166 (#A3410-01) and the UW (#A3464-01), and this study was carried out in strict compliance with
167 the PHS Policy on Humane Care and Use of Laboratory Animals.

168

169 *Virus and Infection*

170 Mouse adapted SARS-CoV MA15 (Roberts et al., 2007a) was propagated and titered on Vero
171 cells as previously described (Gralinski et al., 2015; Gralinski et al., 2018). For virus
172 quantification from infected mice, plaque assays were performed on lung (post-caval lobe) tissue
173 homogenates as previously described (Gralinski et al., 2017). Mice were intranasally infected
174 with 5×10^3 PFU of SARS-CoV MA15 and measured daily for weight loss. Mice exhibiting
175 extreme weight loss or signs of clinical disease were observed three times a day and euthanized
176 if necessary based on humane endpoints. The virus inoculum dose was selected to result in a
177 range of susceptibility phenotypes in the 8 founder strains. Previous studies were performed on a
178 C57BL/6 background, so this dose was then tested in the founder strains to ensure a range of
179 susceptibility, mortality, and immune responses. We aimed to maximize phenotypic diversity
180 while still maintaining sufficient survival such that we could assess immune phenotypes at
181 various times post-infection.

182

183 *Flow cytometry*

184 Splens were prepared for flow cytometry staining as previously described (Graham et al.,
185 2017a; Graham et al., 2017b; Graham et al., 2016; Graham et al., 2015). All antibodies were
186 tested using cells from the 8 CC founder strains to confirm that antibody clones were compatible
187 with the CC mice prior to being used for testing.

188

189 *Statistical analysis*

190 When comparing groups, Mann-Whitney tests were conducted, with p-values <0.05 considered
191 significant. Error bars are +/- SD. Linear regression analysis was performed using GraphPad
192 Prism software.

193

194 **Results**

195 *Infection of genetically diverse mice with SARS-CoV results in a variety of viral load*
196 *trajectories.*

197 As part of a screen of genetically diverse mice from the CC for clinical outcomes and
198 immune phenotypes following SARS-CoV MA15 infection, 18-28 mice each from over 100
199 different CC-RIX lines were infected with SARS-CoV MA15, followed by monitoring for
200 survival and weight loss up to 28 days post-infection. In addition, lung viral loads were measured
201 at days 2 and 4 post-infection using separate cohorts of mice. Infection of CC-RIX mice with
202 SARS-CoV MA15 resulted in wide range of average lung viral loads at 2 days post-infection,
203 ranging from below the limit of detection to 4.75×10^7 PFU (**Figure 1A**). Furthermore, while the
204 vast majority of CC-RIX lines experienced a decrease in average viral loads from day 2 to day 4
205 post-infection, the amount of decrease varied considerably (**Figure 1B**). In order to investigate
206 the immune correlates of early viral control upon infection, we examined selected lines with
207 extreme phenotypes for further examination. As shown in Figure 1A, lines with an average lung
208 viral load of less than 10^5 at day 2 post-infection (N=8) were considered to be “low titer”, and
209 lines with an average lung viral load of greater than 10^7 at day 2 post-infection (N=24) were
210 considered to be “high titer” for further analysis (**Figure 1C** and **Supplementary Table 1**).

211
212 *Early viral control in the lung correlates with distinct T cell phenotypes and inflammatory*
213 *potential.*

214 In order to determine baseline immune signatures that correlate with progression to high
215 viral load upon infection, we examined the frequency of different populations and phenotypes of
216 T cells within the spleen (as a proxy for the circulation) at steady state by assessment of a second

217 cohort of age-matched mice from each of these CC-RIX lines (**Figure 1C** and **Supplementary**
218 **Table 1**). CC-RIX mice with superior virologic containment at day 2 post-infection had a higher
219 mean frequency of CD44⁺ CD4 and CD8 T cells in the spleen prior to infection (**Figures 2A-B**),
220 in addition to an increased proportion of CD4 T cells that express Ki67 (**Figure 2C**), which
221 signals recent proliferation. Along with this increase in the frequency of CD44⁺ memory T cells,
222 mice from CC-RIX lines with low viral titers at day 2 post-infection had a significantly increased
223 frequency of baseline splenic Foxp3⁺ regulatory T cells (Treg) (**Figure 2D**). Furthermore, mice
224 from these lines had an increased frequency of Tregs that are CD44⁺ (**Figure 2E**) and that are
225 CD73⁺ (**Figure 2F**). In addition to these significant findings, we assessed a variety of activation
226 markers on conventional CD4 and CD8 T cells as well as Tregs at steady state, many of which
227 are not different between the two groups (**Figures 2G-H**). Finally, there is a statistically
228 significant positive correlation between the frequency of regulatory T cells and CD44⁺ CD4⁺,
229 CD44⁺ CD8⁺, and Ki67⁺ CD4⁺ T cells independent of SARS-COV MA15 viral outcomes
230 (**Figures 2I-K**). Together, these data suggest that mice that are better able to contain virus
231 replication early following infection have a higher baseline circulating frequency of both
232 memory T cells as well as regulatory T cells in the spleen.

233 Next, we assessed the ability of T cells to express cytokines at steady state by stimulating
234 baseline splenocytes polyclonally using an *ex vivo* intracellular cytokine stimulation assay. Mice
235 from CC-RIX lines that had a low lung viral titer at day 2 post-infection had an increased
236 frequency of baseline splenic CD8 T cells that could express IFN γ (**Figure 3A**) as well as IL-17
237 (**Figure 3B**). Additionally, an increased frequency of steady-state splenic CD4 T cells that
238 express IL-17 upon polyclonal stimulation was found in mice from CC-RIX lines with low lung
239 viral loads at day 2 post-infection (**Figure 3C**). Upon examination of T cells expressing a

240 combination of TNFa and IFNg, we found that mice from lines with superior early virologic
241 control had an increased frequency of CD8 T cells that were TNFa-IFNg+ (**Figure 3D**) and a
242 decreased frequency that were TNFa+IFNg- (**Figure 3E**). Similarly, mice from lines with high
243 viral titers at day 2 post-infection had an increased fraction of baseline circulating CD4 T cells
244 that express TNFa (**Figure 3F**), as well as an increased fraction of CD4 T cells that are
245 TNFa+IFNg- (**Figure 3G**). Taken together, our results suggest that early viral control upon
246 infection with SARS-CoV MA15 correlates with a pre-infection increased frequency of
247 circulating T cells with a potential to express IFNg or IL17 rather than TNFa (**Figure 3H**). This
248 latter finding is consistent with previous studies of SARS-CoV that found TNFa to play a
249 detrimental role in tissue damage after infection (McDermott et al., 2016), and therefore may
250 serve as a biomarker for individuals who may be at higher risk of high viral loads upon CoV
251 infections. Notably, there is a significant positive correlation between the frequency of splenic
252 Tregs at baseline and the expression of IL-17 by CD4 or CD8 T cells, and a negative correlation
253 between baseline frequency of Tregs in the spleen and TNFa expression by CD4 or CD8 T cells
254 (**Figure 3I**), further underscoring the potential immunoprotective signature linked with baseline
255 Treg frequency.

256

257 *Circulating T cell phenotypes at steady state predict protection from high titers and disease upon*
258 *SARS-CoV MA15 infection*

259 To identify possible baseline immune predictors of both severe virologic and disease
260 outcomes upon infection, we classified CC-RIX lines with extreme phenotypes based on both
261 lung viral loads at days 2 and 4 post-infection, as well as weight loss and mortality. Lines were
262 categorized as “low infection and disease” (LID), which had 0-5% weight loss upon infection, no

263 death, day 2 average lung viral titers of $<10^5$ and average day 4 lung viral titers of $<10^4$ (N=5
264 lines). Conversely, N=4 lines were categorized as “high infection and disease” (HID) if they
265 experienced greater than 15% weight loss and death, as well as average lung viral titers at day 2
266 post-infection of $>10^6$ and average lung viral titers at day 4 post-infection of $>10^5$ (**Figure 4A**
267 and **Supplemental Table 1**). Upon examination of splenic baseline T cell phenotypes in mice
268 from these 9 CC-RIX lines, we found a significantly elevated CD4:CD8 T cell ratio in mice from
269 lines that experienced low infection and disease compared to those that had high infection and
270 disease (**Figure 4B**). Similar to what we found when considering day 2 post-infection viral titers
271 alone, we found that a higher frequency of circulating CD44⁺ CD8 T cells at baseline correlated
272 with protection from high infection and disease (**Figure 4C**), whereas a lower frequency of
273 CCR5⁺ or CD25⁺ CD4 T cells correlated with protection from high viral loads and disease
274 (**Figures 4D-E**). In addition to conventional T cells, we also assessed the ability of circulating
275 Treg frequency and phenotype to predict viral load and disease outcomes upon SARS-CoV
276 MA15 infection. An increased baseline frequency of circulating Tregs was present in mice from
277 LID CC-RIX lines (**Figure 4F**). Mice from CC-RIX lines with low infection and disease had a
278 reduced frequency of Tregs expressing CD25 or CCR5 (**Figures 4G-H**), but an increased
279 frequency of Tregs expressing CD73 (**Figure 4I**). Thus, it is possible that Treg migration
280 patterns and/or mechanisms of suppression may influence the virologic and clinical outcomes
281 upon SARS-CoV infection.

282 Finally, we assessed the potential of T cells to express cytokines at baseline. Mice from
283 CC-RIX lines with low infection and disease had increased expression of IFN γ upon polyclonal
284 *ex vivo* stimulation (**Figure 4J**), as well as increased co-expression of both IFN γ and TNF α
285 (**Figure 4K**). Additionally, mice from CC-RIX lines with low lung viral loads and low disease

286 upon infection also had an increased circulating fraction of splenic CD8 and CD4 T cells that
287 express IL-17 upon stimulation (**Figures 4L-M**). Altogether, our findings suggest a distinct
288 circulating T cell signature at steady-state that is associated with severe virologic and clinical
289 outcomes upon SARS-CoV infection (**Figures 4O-P**).

290

291 *Dysregulated circulating T cell phenotypes at steady state are associated with disease in the*
292 *setting of high viral loads upon SARS-CoV MA15 infection*

293 To further improve our understanding of why some individuals experience severe illness
294 and disease upon infection while others do not, we wished to further investigate immune
295 correlates of protection from disease when viral loads were normalized. Thus, to identify
296 possible baseline immune predictors of disease upon infection with a high early lung viral load,
297 we differently classified CC-RIX lines with extreme phenotypes based on both lung viral loads at
298 days 2 and 4 post-infection, as well as weight loss and mortality. Lines were categorized as “no
299 disease high titer” (NDHT), which had 0-5% weight loss upon infection and no death despite day
300 2 average lung viral titers of $>10^7$ and average day 4 lung viral titers of $>10^5$ (N=3 lines) and
301 “disease high titer” (DHT; N=3 lines) if they experienced greater than 15% weight loss and
302 death, as well as average lung viral titers at day 2 post-infection of $>10^7$ and average lung viral
303 titers at day 4 post-infection of $>10^5$ (**Supplemental Table 1**). Thus, there were no differences in
304 average viral loads between groups (**Figure 5A**), and we could assess how baseline T cell
305 phenotypes correlated with eventual disease upon similar levels of infection. We found that there
306 was a significantly elevated CD4:CD8 T cell ratio in mice from lines that experienced no disease
307 in the context of high viral loads compared to those that showed signs of disease (**Figure 5B**).
308 However, upon examination of the phenotype of these CD4 T cells, we found that a decreased

309 baseline frequency of CD25+ or CCR5+ circulating CD4 T cells was associated with protection
310 from disease (**Figure 5C-D**). In addition, mice from CC-RIX lines that were protected from
311 disease in a setting of high viral loads had a reduced fraction of Tregs that expressed CD25 or
312 CTLA-4 (**Figures 5E-F**). Finally, mice from lines that were protected from disease had baseline
313 circulating CD8 T cells that were more likely to express both TNF α and IFN γ upon polyclonal
314 stimulation (**Figure 5G**), thereby indicating that this could be a predictor of protection from
315 disease upon infection. In sum, our findings suggest a baseline circulating signature of T cell
316 dysfunction is associated with severe clinical outcomes upon SARS-CoV infection with high
317 levels of early virus replication (**Figures 5H-J**).

318

319

320 **Discussion**

321 The COVID-19 pandemic poses enormous challenges to global healthcare systems, as
322 healthcare workers struggle to find adequate personal protective equipment (PPE) with which to
323 shield themselves as they attempt to treat patients with a single FDA-authorized drug for
324 emergency use, remdesivir (Pruijssers et al., 2020; Sheahan et al., 2017), and without access to a
325 protective vaccine. While the latter are under rapid development, it is clear that as new treatment
326 and prevention strategies are developed, there will likely be an inadequate supply available for
327 all those in need. This underscores the need to be able to identify individuals at highest risk of
328 infection and disease to be able to best triage protective PPE as well as newly developed
329 treatment and prevention strategies, including vaccines. Further, the concept of “super-
330 spreaders”, or rare individuals with a unique capacity to infect a large number of individuals
331 (Goyal et al., 2020), suggests that virologic control and identification of individuals who may be
332 most prone to high viral loads may be critical to limit and/or halt the spread of SARS-CoV-2.
333 While many immune correlates of severe disease upon infection with SARS-CoV-2 have been
334 recently identified in humans, to date these studies involve analysis of already infected
335 individuals who present with mild or severe illness, as compared to healthy controls. Therefore,
336 it is difficult to determine whether immune signatures from these individuals are predictive, or
337 rather represent symptoms associated with specific disease states.

338 In the absence of prospectively collected, pre-SARS-CoV-2 infection human samples that
339 could be used for a case-control analysis to allow for identification of predictive immune
340 signatures of COVID-19 virologic and clinical outcomes, we utilized a mouse model system to
341 identify baseline, circulating T cell signatures that predict severe infection and disease outcomes
342 upon SARS-CoV infection. Use of the CC mouse model population enabled the study of a

343 diversity of virologic and disease outcomes upon infection with SARS-CoV, as the genetic
344 diversity inherent to the model better replicates the genetic diversity in the human population,
345 and thus contributes to diverse phenotypes, including immunophenotypes and disease
346 phenotypes pre- and post- infection. The use of the mouse-adapted SARS-CoV MA15, while not
347 the same as SARS-CoV-2, at the very least allowed us to perform proof-of-concept studies
348 demonstrating that baseline T cell phenotypes can predict infection and disease outcomes
349 following coronavirus infections, though future studies of both mice as well as human samples
350 using SARS-CoV-2 are required to validate our findings for COVID-19.

351 In our previous study, we used data from our screen of CC mice to identify more
352 universal immune correlates of mortality following infection with influenza, SARS-CoV, and
353 WNV (Graham et al., 2020). The protective signature included an increased level of basal T-cell
354 activation that was associated with protection, which we also found here to be associated with
355 protection from severe virologic and clinical outcomes following SARS-CoV infection (**Figures**
356 **2, 4, & 5**). As CD44 is a T cell marker associated with antigen experience or a memory
357 phenotype, it is possible that these memory T cells could undergo rapid bystander activation via
358 the innate immune response following CoV infection, and thus play a critical early role in a
359 protective response. The presence of these CD44⁺ T cells may indicate true, conventional
360 memory T cells that resulted from previous microbial exposures in the murine specific pathogen-
361 free (SPF) colony. Alternatively, such cells could also be unconventional memory cells that
362 possess a memory phenotype despite not having encountered cognate antigen (Jameson, 2005;
363 Le Campion et al., 2002; Min et al., 2003; Schuler et al., 2004; Surh and Sprent, 2005).
364 Nevertheless, CD44⁺ T cells of either origin could participate in early viral control through
365 bystander-mediated activity and thus confer a protective advantage through rapid viral

366 containment before the virus-specific T cell response has been generated (Chu et al., 2013). Such
367 activity is consistent with previous work demonstrating that unconventional memory T cells can
368 aid in protection against pathogens including *Listeria monocytogenes* and influenza virus
369 (Lanzer et al., 2018; Lee et al., 2013; Sosinowski et al., 2013).

370 It stands to reason that such an active innate-like T cell response would need to be subject
371 to immunoregulation in order to limit activity and prevent excess collateral damage. Also in our
372 previous study, we found that an increased frequency of Tregs correlated with protection from
373 death following each of the three infections (influenza A virus, West Nile virus, and SARS-CoV)
374 (Graham et al., 2020). Our results presented herein further support that an increased basal
375 frequency of Tregs in the circulation correlates with protection both from early SARS-CoV viral
376 replication, as well as from disease upon infection (**Figures 2 and 4**). In the context of multiple
377 viral infections, we and others have found that Tregs are critical to orchestrate proper anti-viral
378 immune responses (Lanteri et al., 2009; Lund et al., 2008; Pattacini et al., 2016; Ruckwardt et al.,
379 2009; Soerens et al., 2016), while it has also been found that Tregs in the context of infections,
380 including respiratory infections such as RSV and influenza, can assist in protecting the host from
381 excessive immunopathology (Belkaid and Tarbell, 2009; Brincks et al., 2013; Lee et al., 2010;
382 Loebbermann et al., 2012; Richert-Spuhler and Lund, 2015; Smigiel et al., 2014). Thus, our
383 results here further support the concept that balance between anti-viral immunity and
384 immunoregulation is essential to spare the host from both unrestricted viral replication as well as
385 severe disease after infection. We predict that Tregs play this dual role in the context SARS-CoV
386 infection as well, wherein their increased abundance at steady state (**Figures 2D and 4F**) is
387 advantageous in terms of allowing for the generation of an appropriately focused anti-viral
388 immune response, while variable expression of particular homing and activation markers allows

389 for an appropriately tuned suppressive response. While a complete characterization of Tregs after
390 infection would help to reveal the dynamics of an appropriate Treg response in the context of
391 SARS-CoV infection, we do not have this data from our screen, and so further studies are needed
392 to fully assess Treg phenotype and function in both mice and humans after SARS-CoV and
393 SARS-CoV-2.

394 Finally, in both our previous study as well as this focused study of SARS-CoV, we found
395 that a restricted pro-inflammatory potential of T cells is correlated with protection from mortality
396 upon infection with each of the three viruses (Graham et al., 2020) as well as severe virologic
397 outcomes upon SARS-CoV infection (**Figures 3-5**). Specifically, we demonstrate that pre-
398 infection ability of T cells to express the pro-inflammatory cytokine TNF correlated with more
399 severe virologic outcomes (**Figures 3E-G**), as has been demonstrated as well for SARS-CoV and
400 COVID-19 (Blanco-Melo et al., 2020; Lucas et al., 2020; McDermott et al., 2016; Qin et al.,
401 2020). On the other hand, the presence of circulating T cells at steady-state with the potential to
402 express IFN γ or IL-17 is associated with protection from both early and high lung viral loads
403 (**Figures 3A-D and 4J-M**) as well as disease (**Figures 4J-M and Figure 5G**). IFN γ is well
404 known as a potent anti-viral cytokine, and so it is not a surprise that this cytokine could play a
405 role in SARS-CoV restriction, and though the potential role of IL-17 is less clear.

406 Overall, the results from our study demonstrate that baseline T cell phenotypes can
407 predict early virologic and clinical outcomes upon infection with SARS-coronaviruses. While it
408 is clear that additional mechanistic and human studies are needed to validate these findings for
409 extrapolation to COVID-19, this study also serves to highlight the complexity of inflammation,
410 which can at the same time be protective and detrimental to the host. We hypothesize that
411 particular T cell immunophenotypes or signatures may be critical to promoting rapid immunity

412 upon infection and limiting immune-mediated collateral damage, and further predict that
413 bystander-activated T cells may play a powerful role in the early innate immune response to
414 SARS-CoV. However, as COVID-19 is associated with more inflammatory responses than
415 SARS, the correlates of disease and protection for SARS-CoV-2 may differ from those of SARS-
416 CoV. Thus, future studies include using select CC strains with extreme baseline immune
417 phenotypes to validate our findings with SARS-CoV MA15 as well as mouse-adapted SARS-
418 CoV-2 (Dinnon et al., 2020). Alternatively, usage of transient depletion systems, such as the
419 Foxp3^{DTR} mouse model (Kim et al., 2007), would enable targeted elimination of all or some
420 Foxp3⁺ Tregs prior to infection with SARS-CoV or SARS-CoV-2 in order to directly test the
421 role of Tregs in SARS-CoV virologic and clinical outcomes. Nevertheless, our data presented
422 herein support the concept that levels of inflammation prior to coronavirus infection may impact
423 post-infection virologic and clinical disease states.

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429

430 **Author Contributions**

431 DRM, SKM, MTF, FPMV, MTH, RSB, and JML designed the research studies; JBG, JLS, SRL,
432 VDM, LEG, and AS conducted experiments and acquired and analyzed data; SJ and MAM
433 performed data cleaning and integration; and JBG and JML wrote the first draft of the
434 manuscript. All authors read the manuscript and contributed editorial suggestions.

435

436 **Declaration of Interests**

437 The authors declare no competing interests.

438

Supplemental Table 1. CC F1 lines in infection and disease categories			
RIX Line	d2 Viral Load	D4 Viral Load	Group
CC042xCC019	0	847	Low titer
CC030xCC061	33	333	Low titer
CC018xCC065	683	N/A	Low titer
CC030xCC023	700	0	Low titer
CC052xCC014	6333	233	Low titer
CC012xCC032	46333	233	Low titer
CC032xCC013	46667	67	Low titer
CC011xCC032	91500	0	Low titer
CC019xCC004	10200000	27000	High titer
CC068xCC043	10350000	105750	High titer
CC006xCC039	10366667	211000	High titer
CC057xCC052	11193333	28000	High titer
CC062xCC046	11333333	114667	High titer
CC029xCC071	12166667	577500	High titer
CC060xCC037	13200000	14470	High titer
CC041xCC016	14100000	120700	High titer
CC028xCC024	14650000	2966667	High titer
CC065xCC010	14683333	330667	High titer
CC001xCC055	14800000	N/A	High titer
CC013xCC041	15366667	172500	High titer
CC074xCC058	16800000	128667	High titer
CC004xCC011	16816667	1003333	High titer
CC026xCC034	17500000	175667	High titer
CC061xCC025	18200000	192667	High titer
CC016xCC038	18666667	116000	High titer
CC056xCC033	20333333	300033	High titer
CC033xCC046	21000000	409667	High titer
CC025xCC028	23166667	640333	High titer
CC042xCC025	23666667	N/A	High titer
CC015xCC059	26000000	80000	High titer
CC055xCC006	37333367	N/A	High titer
CC055xCC028	47566667	33	High titer
CC018xCC065	683	8400	LID
CC032xCC013	46667	67	LID
CC030xCC023	700	0	LID
CC030xCC023	33	333	LID
CC052xCC014	6333	233	LID
CC001xCC074	3686667	688833	HID
CC074xCC058	16800000	128667	HID
CC025xCC028	23166667	640333	HID
CC061xCC025	18200000	192667	HID
CC013xCC041	15366667	172500	NDHT
CC016xCC038	18666667	116000	NDHT
CC033xCC046	21000000	409667	NDHT
CC074xCC058	16800000	128667	DHT
CC025xCC028	23166667	640333	DHT
CC061xCC025	18200000	192667	DHT

440 **Figure Legends**

441

442 **Figure 1. SARS-CoV MA15 infection of genetically diverse mice results in a variety of viral**

443 **load trajectories.** Age-matched female CC-RIX were infected intranasally with SARS-CoV

444 MA15. (A) Average viral loads in the lung at day 2 post-infection are shown for each CC-RIX

445 line. Red dotted line indicates titers above 10^7 PFU, and blue dotted line indicates viral titers

446 below 10^5 PFU. (B) Average viral loads in the lung at day 2 post-infection and at day 4 post-

447 infection for each CC-RIX line. (C) The day 2 post-infection average lung viral loads are shown

448 for selected CC-RIX lines are with extreme phenotypes: low or high viral titers. Lines with an

449 average lung viral load of less than 10^5 at day 2 post-infection (N=8) were considered to be “low

450 titer”, and lines with an average lung viral load of greater than 10^7 at day 2 post-infection (N=24)

451 were considered to be “high titer” for further analysis.

452

453 **Figure 2. Early virologic control correlates with increased baseline circulating frequency of**

454 **activated T cells and regulatory T cells.** Age-matched female CC-RIX were infected

455 intranasally with SARS-CoV MA15 and lung viral loads at day 2 post-infection were used to

456 select CC-RIX lines with extreme phenotypes: “Low 2d Titer” or “High 2d Titer”, as indicated in

457 Figure 1. Mice from a second cohort of 3-6 age-matched male mice of these selected lines were

458 euthanized and splenic cells analyzed by flow cytometry staining to determine the % of CD4 T

459 cells that are CD44+ (A), the % of CD8 T cells that are CD44+ (B), the % of CD4 T cells that

460 are Ki67+ (C), the % of CD4 T cells that are Foxp3+ Tregs (D), the % of Tregs that are CD44+

461 (E), and the % of Tregs that are CD73+ (F). Statistical significance was determined by Mann-

462 Whitney test. Heat maps were made to compare the average percent of the indicated cell

463 populations for conventional T cells (G) and for regulatory T cells (H). No statistical significance
464 ($p > 0.05$ by Mann-Whitney test) was found for any comparisons except those indicated in Figures
465 2A-F. The correlation between the baseline splenic frequency of Tregs (% Foxp3+ of CD4 T
466 cells) and (I) % of CD4 T cells that are CD44+, (J) % of CD8 T cells that are CD44+, or (K) %
467 of CD4 T cells that are Ki67+ are shown with linear regressions for mice from all CC-RIX lines
468 with low or high day 2 titer.

469

470 **Figure 3. Early viral control upon infection correlates with baseline T cells with a potential**
471 **to express IFN γ or IL17 rather than TNF.** Age-matched female CC-RIX were infected
472 intranasally with SARS-CoV MA15 and lung viral loads at day 2 post-infection were used to
473 select CC-RIX lines with extreme phenotypes: “Low 2d Titer” or “High 2d Titer”, as indicated in
474 Figure 1. Mice from a second cohort of 3-6 age-matched male mice of these selected lines were
475 euthanized and splenic cells were treated with anti-CD3/CD28 for intracellular cytokine staining
476 assessment of (A) %IFN γ + of CD8 T cells, (B) %IL-17+ of CD8 T cells, (C) %IL-17+ of CD4 T
477 cells, (D) %TNF-IFN γ + of CD8 T cells, (E) %TNF+IFN γ - of CD8 T cells, (F) %TNF+ of CD4
478 T cells, and (G) %TNF+IFN γ - of CD4 T cells. Statistical significance was determined by Mann-
479 Whitney test. (H) Heat maps were made to compare the average percent of the indicated cell
480 populations. No statistical significance ($p > 0.05$ by Mann-Whitney test) was found for any
481 comparisons except those indicated in Figures 3A-G. (I) The correlation between the baseline
482 splenic frequency of Tregs (% Foxp3+ of CD4 T cells) and % of CD8 T cells that are IL-17+, %
483 of CD4 T cells that are IL-17+, % of CD8 T cells that are TNF+IFN γ -, % of CD4 T cells that are
484 TNF+, and the % of CD4 T cells that are TNF+IFN γ - are shown with linear regressions for mice
485 from all CC-RIX lines with low or high day 2 titer.

486

487 **Figure 4. Baseline activated CD8 T cells and Tregs correlate with severe virologic and**
488 **disease outcomes upon SARS-CoV infection.** Age-matched female CC-RIX were infected
489 intranasally with SARS-CoV MA15 and mice were monitored for death, weight loss, and lung
490 viral loads. To identify possible baseline immune predictors of both viral replication as well as
491 disease upon infection, we classified CC-RIX lines with extreme phenotypes based on both lung
492 viral loads at days 2 and 4 post-infection, as well as weight loss and mortality. Lines were
493 categorized as “low infection and disease” (LID), which had 0-5% weight loss upon infection, no
494 death, day 2 average lung viral titers of $<10^5$ and average day 4 lung viral titers of $<10^4$ (N=5
495 lines). Conversely, N=4 lines were categorized as “high infection and disease” (HID) if they
496 experienced greater than 15% weight loss and death, as well as average lung viral titers at day 2
497 post-infection of $>10^6$ and average lung viral titers at day 4 post-infection of $>10^5$. Lung viral
498 titers from these 9 CC-RIX lines are shown for days 2 and 4 post-infection (A). Mice from a
499 second cohort of 3-6 age-matched male mice of these selected 9 lines were euthanized and
500 splenic cells analyzed by flow cytometry staining to determine the CD4:CD8 ratio (B), % of
501 CD8 T cells that are CD44+ (C), % of CD4 T cells that are CCR5+ (D), % of CD4 T cells that
502 are CD25+ (E), % of CD4 T cells that are Foxp3+ Treg (F), % of Tregs that are CD25+ (G), %
503 of Tregs that are CCR5+ (H), and % of Tregs that are CD73+ (I). In addition, splenic cells were
504 treated with anti-CD3/CD28 for intracellular cytokine staining assessment of (J) %IFN γ + of
505 CD8 T cells, (K) %TNF+IFN γ + of CD8 T cells, (L) %IL-18+ of CD8 T cells, and (M) %IL-17+
506 of CD4 T cells. Statistical significance was determined by Mann-Whitney test. (N-P) Heat maps
507 were made to compare the average percent of the indicated cell populations. No statistical

508 significance ($p > 0.05$ by Mann-Whitney test) was found for any comparisons except those
509 indicated in Figures 4B-M.

510

511 **Figure 5. A dysregulated circulating baseline T cell phenotype is associated with severe**
512 **disease in the setting of high viral loads upon infection.** Age-matched female CC-RIX were
513 infected intranasally with SARS-CoV MA15 and mice were monitored for death, weight loss,
514 and lung viral loads. To identify possible baseline immune predictors of disease upon infection
515 with a high early lung viral load, we classified CC-RIX lines with extreme phenotypes based on
516 both lung viral loads at days 2 and 4 post-infection, as well as weight loss and mortality. Lines
517 were categorized as “no disease high titer” (NDHT), which had 0-5% weight loss upon infection
518 and no death despite day 2 average lung viral titers of $>10^7$ and average day 4 lung viral titers of
519 $>10^5$ (N=3 lines) and “disease high titer” (DHT; N=3 lines) if they experienced greater than 15%
520 weight loss and death, as well as average lung viral titers at day 2 post-infection of $>10^7$ and
521 average lung viral titers at day 4 post-infection of $>10^5$. Lung viral titers from these 6 CC-RIX
522 lines are shown for days 2 and 4 post-infection (A). Mice from a second cohort of 3-6 age-
523 matched male mice of these selected 6 lines were euthanized and splenic cells analyzed by flow
524 cytometry staining to determine the CD4:CD8 ratio (B), % of CD4 T cells that are CD25+ (C),
525 % of CD8 T cells that are CCR5+ (D), % of Tregs that are CD25+ (E), and % of Tregs that are
526 CTLA-4+ (F). In addition, splenic cells were treated with anti-CD3/CD28 for intracellular
527 cytokine staining assessment of (G) % TNF+IFN γ + of CD8 T cells. Statistical significance was
528 determined by Mann-Whitney test. (H-J) Heat maps were made to compare the average percent
529 of the indicated cell populations. No statistical significance ($p > 0.05$ by Mann-Whitney test) was
530 found for any comparisons except those indicated in Figures 5B-G.

531

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Figure 1

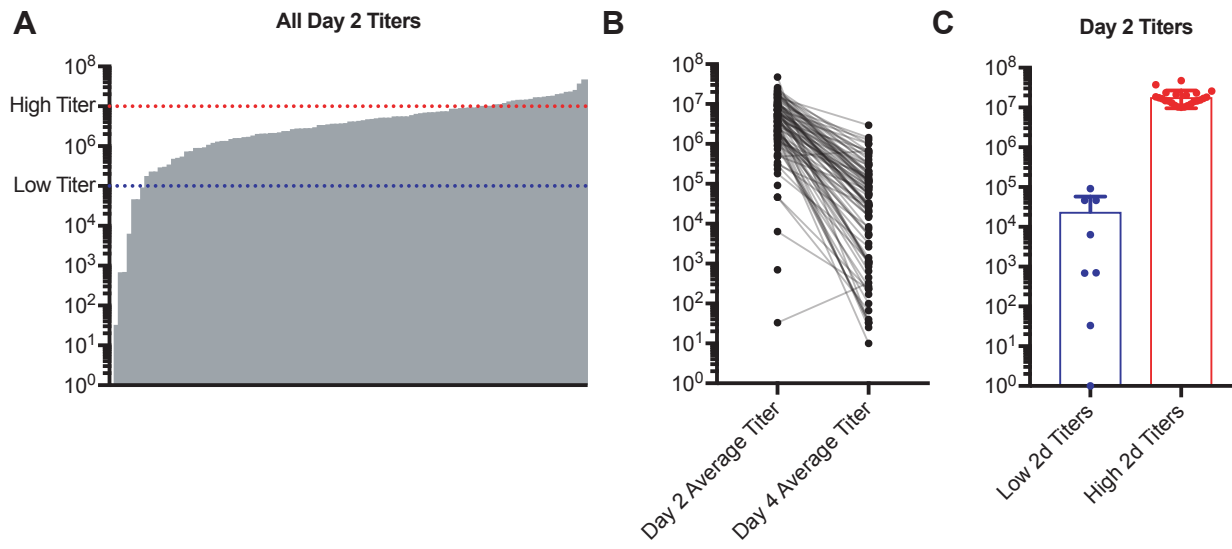


Figure 2

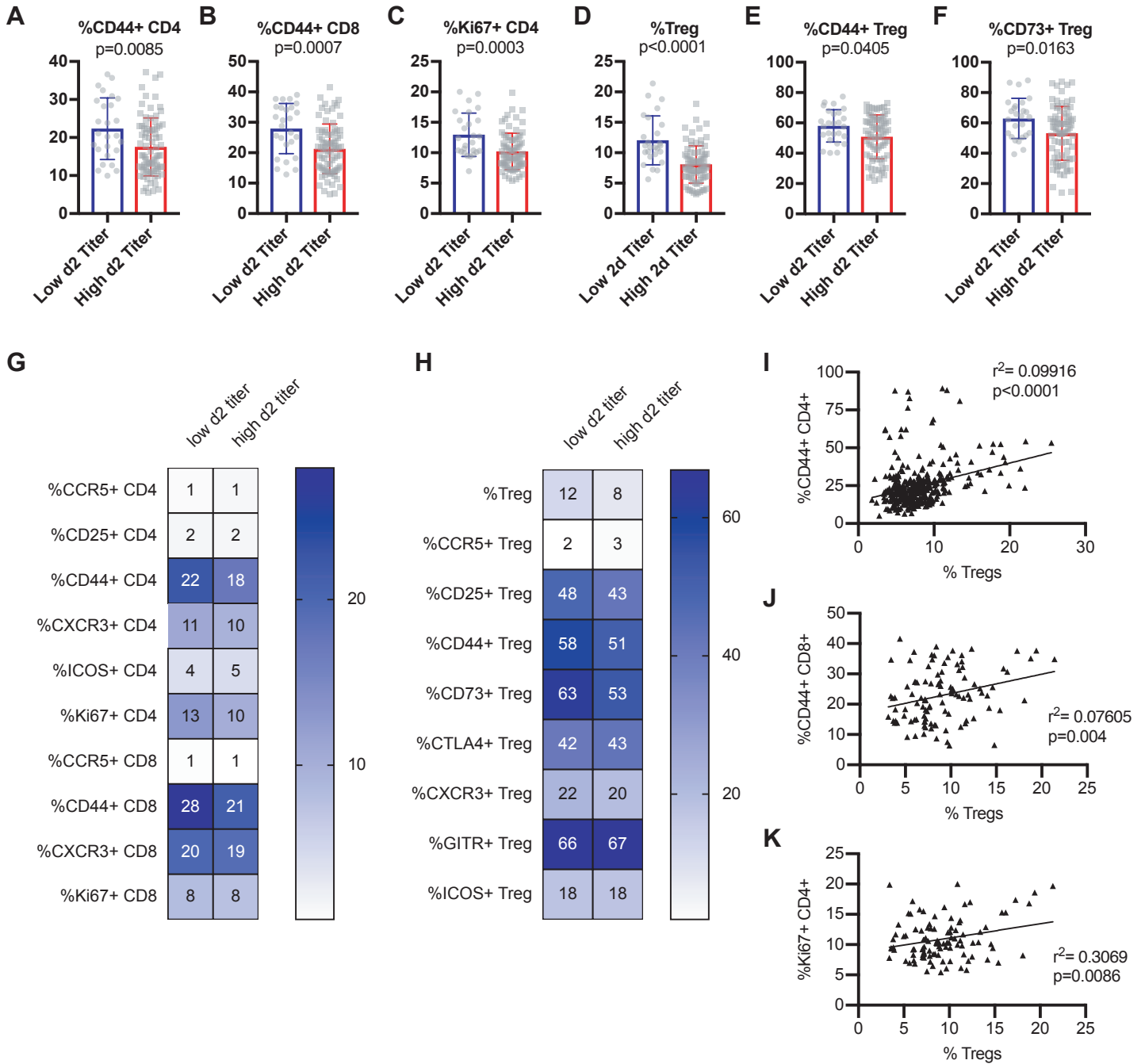


Figure 3

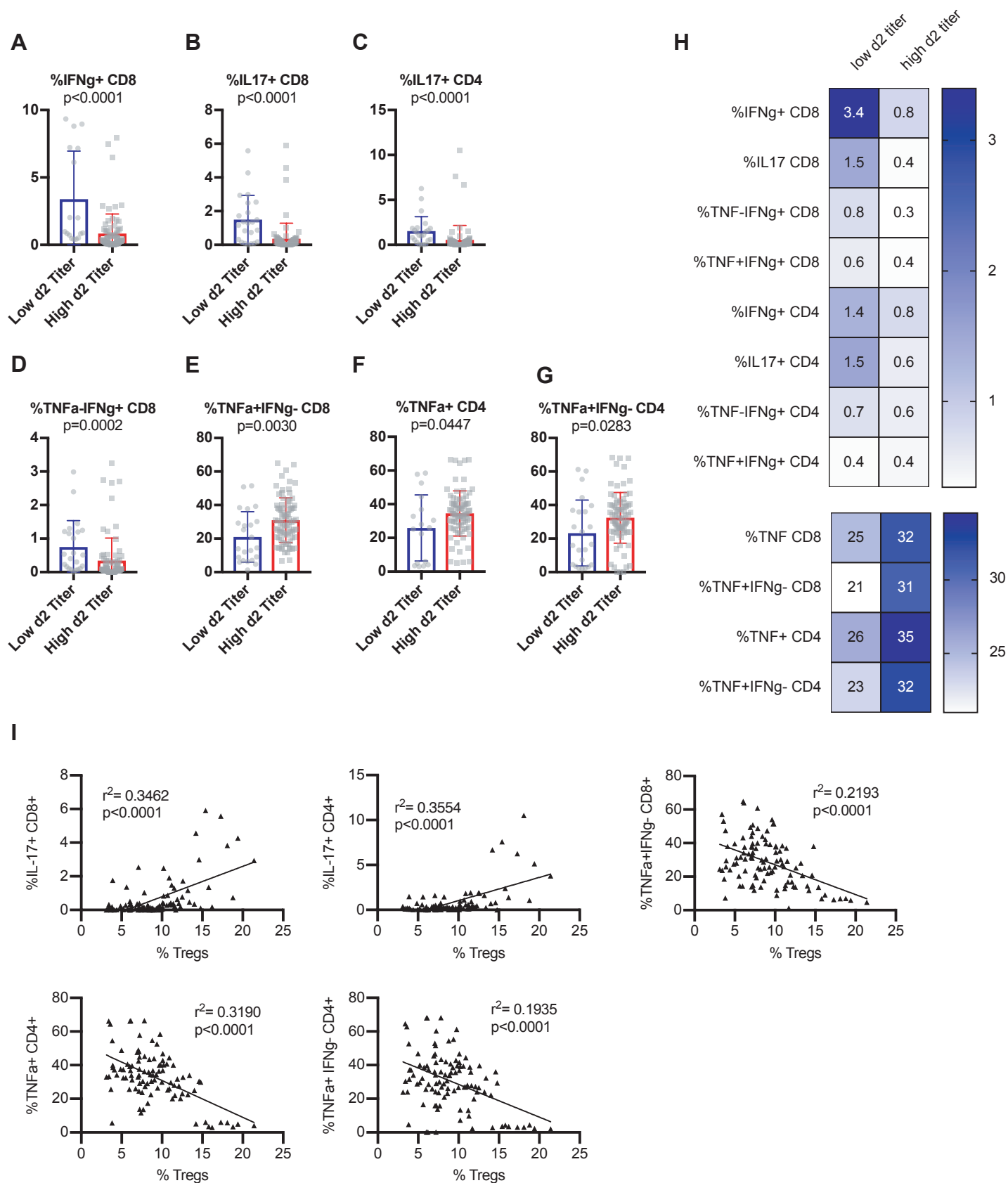


Figure 4

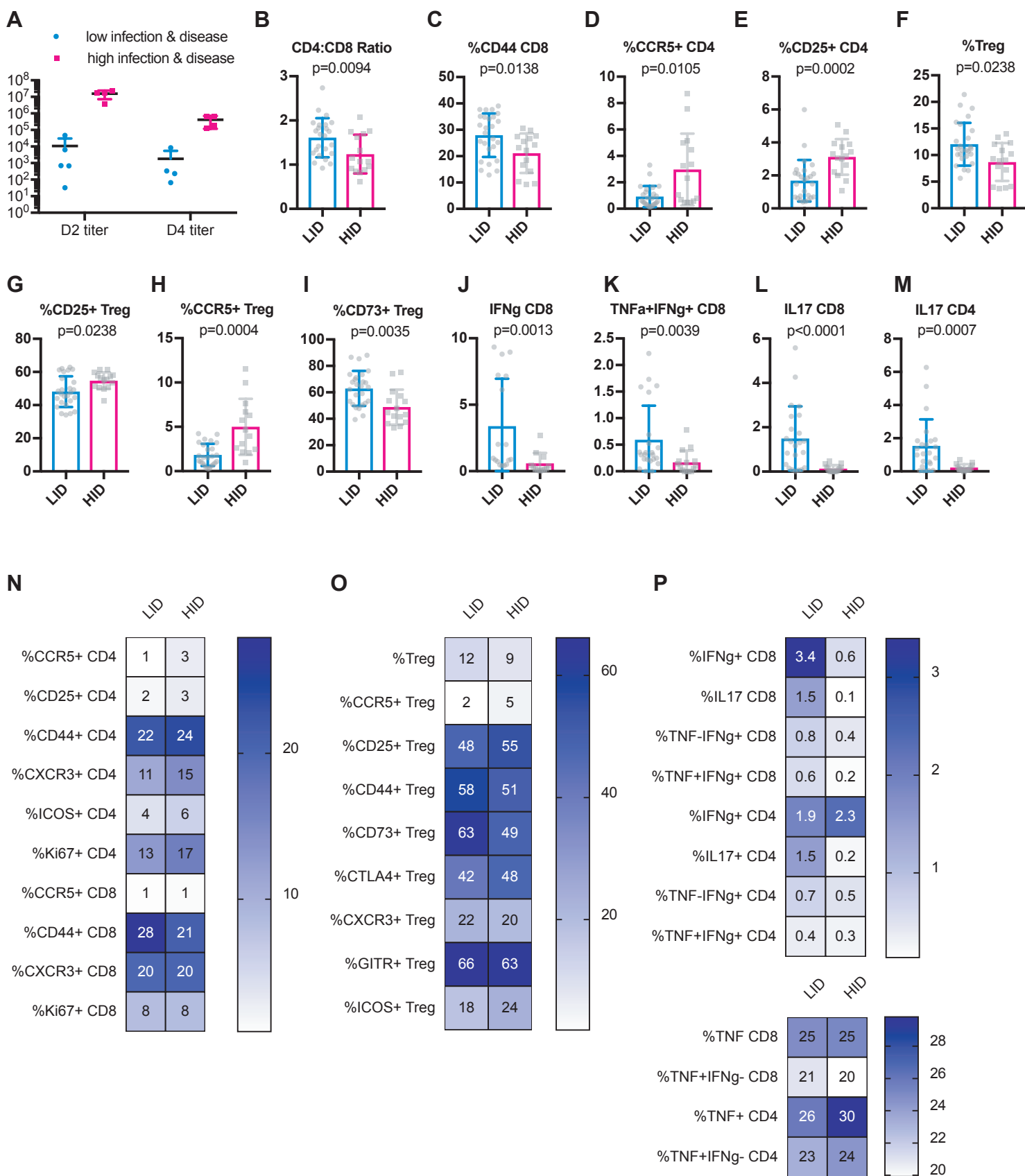


Figure 5

