

1 Structurally and functionally distinct early antibody responses predict COVID-19 disease
2 trajectory and mRNA vaccine response

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61 Abstract

62 A damaging inflammatory response is strongly implicated in the pathogenesis of severe COVID-
63 19 but mechanisms contributing to this response are unclear. In two prospective cohorts, early
64 non-neutralizing, afucosylated, anti-SARS-CoV-2 IgG predicted progression from mild, to more
65 severe COVID-19. In contrast to the antibody structures that predicted disease progression,
66 antibodies that were elicited by mRNA SARS-CoV-2 vaccines were low in Fc afucosylation and
67 enriched in sialylation, both modifications that reduce the inflammatory potential of IgG. To
68 study the biology afucosylated IgG immune complexes, we developed an *in vivo* model which
69 revealed that human IgG-Fc γ R interactions can regulate inflammation in the lung. Afucosylated
70 IgG immune complexes induced inflammatory cytokine production and robust infiltration of the
71 lung by immune cells. By contrast, vaccine elicited IgG did not promote an inflammatory lung
72 response. Here, we show that IgG-Fc γ R interactions can regulate inflammation in the lung and
73 define distinct lung activities associated with the IgG that predict severe COVID-19 and
74 protection against SARS-CoV-2.

75

76 One Sentence Summary: Divergent early antibody responses predict COVID-19 disease
77 trajectory and mRNA vaccine response and are functionally distinct *in vivo*.

78

79 The minority of people who develop severe COVID-19 during SARS-CoV-2 infection mount an
80 inflammatory response that is strongly implicated in disease pathogenesis (1-3). The extreme
81 inflammatory phenotype in the lungs of severe COVID-19 patients is clear from autopsy studies,
82 but mechanisms contributing to this response are not well understood (4-7). IgG antibodies

83 mediate cellular functions that are central in directing the course of disease during many viral
84 infections. Aside from neutralizing activity, IgG antibodies that bind to virus particles or viral
85 antigens can form immune complexes (ICs) that may have a profound impact on disease
86 pathogenesis, especially with regard to inflammation. This is observed in some autoimmune and
87 infectious diseases where persistent ICs drive a hyperinflammatory response that damages host
88 tissues (8). A clear mechanism underlying modulation of inflammation by antibodies is via IgG
89 interactions with activating and inhibitory Fc gamma receptors (FcγRs) on myeloid cells, which
90 are central regulators of the inflammatory response. We and others have previously found that
91 patients with severe COVID-19 produce a high level of afucosylated IgG antibodies that trigger
92 inflammatory responses in primary monocytes (9-11). This response was dependent on Fc
93 afucosylation, a modification that enhances affinity of monomeric IgG for the activating FcγR,
94 CD16a, by approximately 10-fold (12, 13).

95
96 Because IgG ICs can promote disease sequelae in some infections, the link between severe
97 COVID-19 and afucosylated IgG suggests that this antibody type may have a role in the
98 inflammatory pathogenesis of severe disease. To explore this, we first studied whether
99 afucosylated antibody production was a consequence of, or an antecedent to, the development of
100 more severe COVID-19. In two independent cohorts, assessed during an initial period of mild
101 symptoms, we found that the absence of early neutralizing antibodies, together with an increased
102 abundance of afucosylated IgG, predicted rapid progression to more severe disease. Elevated
103 frequencies of monocytes expressing the receptor for afucosylated IgG, CD16a, also predicted
104 more severe outcomes. To study the effect of afucosylated antibody signaling in the lungs, we
105 developed a novel model system in which human ICs of defined composition are intratracheally
106 administered to mice that express human FcγRs (14). Molecular and cellular changes that were
107 triggered in the lung by distinct antibody signaling pathways can then be assessed by
108 characterization of broncho alveolar lavage (BAL) fluid collected after IC administration. This
109 model provides a physiologically relevant system to study antibody effector responses in the

110 lung. We observed that afucosylated ICs triggered robust immune cell activation, infiltration into
111 the lungs, and proinflammatory cytokine production that was CD16a-dependent. In contrast to
112 natural infection, SARS-CoV-2 mRNA vaccination elicited IgG antibodies that were both highly
113 fucosylated and sialylated. Immune complexes formed from the mRNA vaccine-elicited IgG did
114 not trigger the cellular infiltration and the cytokines/chemokines that were associated with
115 afucosylated IgG *in vivo*. Overall, these findings demonstrate that early production of non-
116 neutralizing, afucosylated IgG1 was predictive of COVID-19 symptom progression; these
117 antibodies were structurally and functionally distinct from IgG1 elicited by mRNA SARS-CoV-2
118 vaccination.

119

120

121 Results

122 Study cohorts

123 To study the early antibody features that correlated with different disease outcomes in COVID-
124 19, we characterized IgG from two longitudinal cohorts of COVID-19 outpatients from Stanford
125 Hospital Center (n=109 Cohort 1 at enrollment; n=69 Cohort 2). While these samples were
126 collected from interventional clinical studies, we present data only from the placebo arm of both
127 studies; thus, our findings are not impacted by the experimental treatments trialed in either study.
128 Participants in both studies were enrolled early in infection, within three days of a positive
129 SARS-CoV-2 PCR test. All subjects presented with mild COVID-19 and had mild symptoms at
130 the time of enrollment, as determined by a physicians assessment (15). While uncomplicated
131 resolution of mild disease occurred in the majority of subjects, a subset of patients in each cohort
132 (n=8 in Cohort 1; n=7 in Cohort 2) developed worsening symptoms in the hours or days
133 following enrollment. These subjects were evaluated in the emergency department and some
134 required hospitalization; one subject succumbed to disease. We term these patients with distinct

135 disease trajectories as “progressors” (Tables S1, S2, S3) or “non-progressors”. Progressors and
136 non-progressors from Cohort 1 did not significantly differ by the parameters of age, weight, or
137 sex. Progressors from Cohort 2 also did not differ based on weight or sex but were older
138 compared to non-progressors (Table S1).

139

140 Low early neutralizing IgG levels in progressors

141 The availability of samples from the date of enrollment in both studies (here termed “day 0”),
142 when all subjects had mild disease, enabled our analysis of early antibody responses that
143 correlated with distinct disease trajectories. We first defined the evolution of the neutralizing
144 antibody response following SARS-CoV-2 infections using a pseudotyped vesicular stomatitis
145 virus neutralization assay. The fifty percent pseudoviral neutralizing antibody titers (pNT₅₀) were
146 calculated for day 0, day 5, day 28, month 7, and month 10 for all subjects in the placebo arm of
147 Cohort 1 from whom samples were available. Samples from study participants who received a
148 SARS-CoV-2 vaccine within the study period were not evaluated. In most subjects, levels of
149 neutralizing antibodies showed a significant increase over time, peaking by day 28. Once
150 initiated, the antibody response was durable and persisted in most people until 7 months post-
151 enrollment, after which there was a general decrease in neutralization by month 10 (Fig. 1A,
152 S1A). This analysis of Cohort 1 revealed that although there was considerable heterogeneity in
153 early neutralizing responses, those participants who would progress to more severe disease had
154 uniformly very low or no detectible neutralizing antibodies at the study day 0/enrollment time
155 point (Fig. 1B). Cohort 2 showed somewhat less heterogeneity in early neutralizing responses,
156 but as with Cohort 1, neutralizing antibodies were not detected on day 0 in any of the progressors

157 (Fig. 1B). These data were broadly consistent with studies showing a correlation between early
158 neutralizing antibody responses and outcomes in COVID-19 (16-19).

159

160 We initially reasoned that the absence of early neutralizing antibodies in progressors might have
161 been due to earlier sampling of participants who were on a more severe disease trajectory. To
162 evaluate this, we compared the number of symptomatic days prior to study enrollment in
163 progressors and non-progressors. This revealed that there was no significant difference in the
164 mean or median duration of symptoms prior to enrollment (Table S1). Thus, the kinetics of
165 sampling did not explain this observation. Despite the absence of early neutralizing responses,
166 SARS-CoV-2 spike-reactive IgG was clearly present in all progressors (Fig. 1C). While early
167 neutralizing responses were not detected, progressors from whom longitudinal samples were
168 available generally mounted neutralizing antibody responses by the later study timepoints (Fig.
169 S1B).

170

171 Elevated early production of afucosylated IgG in progressors

172 We next asked whether there were qualitative differences in the Fc structures of the IgG in
173 progressors and non-progressors. As we had previously observed elevated anti-SARS-CoV-2 Fc
174 afucosylation in hospitalized patients compared to outpatients (9), we sought to clarify whether
175 these antibodies were produced in response to severe disease or whether they might precede the
176 development of severe symptoms. To study this, we evaluated Fc glycosylation on antibodies
177 present at study enrollment when all subjects had mild symptoms. Indeed, at study enrollment
178 the progressors in both cohorts were already distinguished by elevated levels of afucosylated
179 IgG1, comparable to the levels observed in a cohort of hospitalized COVID-19 patients in the

180 Mount Sinai Health System (Fig. 1D, E, Table S1) (20). The abundance of afucosylated IgG1 in
181 COVID-19 outpatients was not different across timepoints that were separated by approximately
182 200 days (Fig. S1C). These data show that production of afucosylated IgG preceded the onset of
183 severe symptoms and afucosylated antibodies were maintained over time.

184

185 We next sought to investigate the basis of differences in antibody fucosylation. We hypothesized
186 that differences in expression of the relevant glycosyltransferase, α -1,6-fucosyltransferase
187 (FUT8), by antibody-secreting cells, might play a role. To investigate this, we assessed FUT8
188 protein levels in peripheral blood mononuclear cells (PBMCs) from progressors and non-
189 progressors (Fig. S2A). At the time of this experiment, only PBMCs from Cohort 2 were
190 available from the enrollment timepoint. Because we have previously observed a sex-based
191 difference in antibody afucosylation (9), an equivalent number of sex-matched non-progressors
192 were selected for this analysis. We observed no other correlations between demographic features
193 and IgG afucosylation in either cohort (Fig. S1D). Consistent with the elevated production of
194 afucosylated IgG by progressors, CD19⁺ B cells and plasmablasts from progressors expressed
195 less FUT8 than cells from non-progressors upon enrollment (Fig. 1F). FUT8 expression within
196 total PBMCs was comparable between groups, as was the distribution of B cell subsets,
197 suggesting that FUT8 expression is regulated at the effector cell level (Fig. S2A, S2B, S2C). Of
198 note, plasmablast expression of FUT8 correlated with IgG1 Fc afucosylation, supporting the
199 hypothesis that IgG afucosylation is regulated at least in part by the expression level of FUT8
200 (Fig. 1G).

201

202 Early non-neutralizing, afucosylated anti-spike IgG predict worsening symptoms in COVID-19
203 outpatients

204 To determine whether the combination of low/no neutralizing antibodies and elevated IgG Fc
205 afucosylation was a predictor of worsening disease trajectory in mild COVID-19 patients, we
206 next trained and evaluated a logistic regression model by using day 0 neutralization titers and
207 afucosylated IgG frequency as input features from Cohort 1. Individually, both early
208 neutralization titers and Fc afucosylation had low to modest predictive power to separate
209 progressors and non-progressors, while combining the two features could separate progressors
210 from non-progressors with higher predictive accuracy (Fig. 1H). Subsequently, the Cohort 1 data
211 was used as the training set and the performance of the model was evaluated on an independent
212 test dataset (Cohort 2). As shown, the combined features could discriminate divergent disease
213 outcomes with area under the receiver operating characteristic (ROC) curve (AUC) of 0.81 (Fig.
214 1I). Thus, early production of reactive, afucosylated antibodies and poor serum neutralizing
215 activity predicted progression from mild COVID-19 to more severe outcomes.

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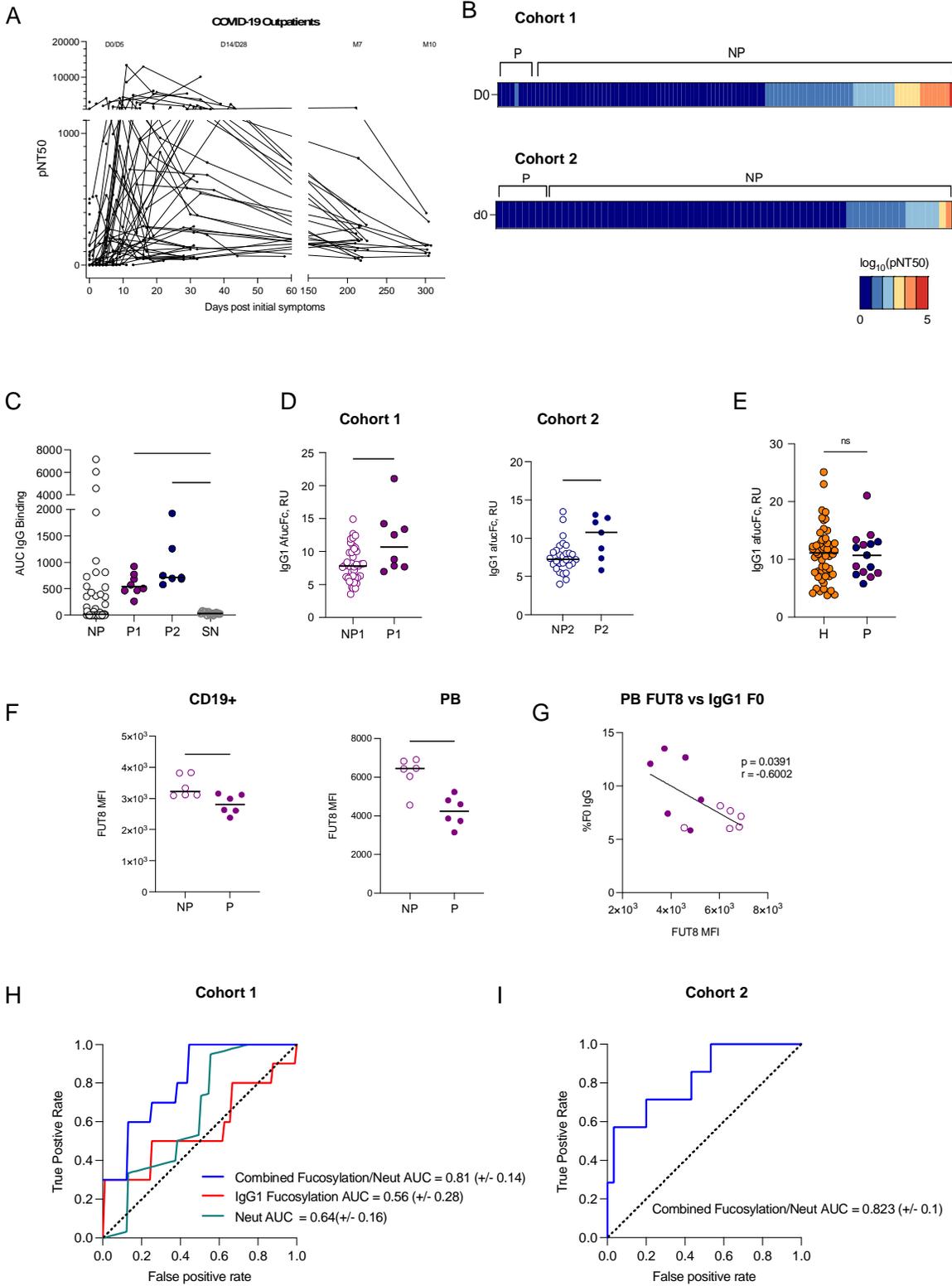


Figure 1. Low early neutralizing titers and elevated Fc afucosylation predict disease progression.

(A) The kinetics of neutralizing antibody response over time in Cohort 1. Half-maximal SARS-CoV-2 pseudovirus neutralizing titers (pNT₅₀) at each study time point, graphed based on days of symptoms for each participant. Samples were collected at study day 0 (D0 enrollment; n=101), 5 (D5; n=50), 14 (D14; n=33), 28 (D28; n=43), month 7 (M7; n=24) and month 10 (M10; n=9). (B) Heatmap of pNT₅₀ data in progressors (P) (Cohort 1 n=8, Cohort 2 n=7) and non-progressors (NP) at enrollment timepoint (D0). (C) SARS-CoV-2 spike-binding IgG (AUC) of Cohort 1 progressors (P1, solid purple), Cohort 2 progressors (P2, solid blue), random subset of non-progressors, and historic seronegative (SN) sera. (D) IgG1 Fc afucosylation levels of progressors and non-progressors at enrollment timepoint (D0) of Cohort 1 (purple; progressors=P1, non-progressors=NP1), Cohort 2 progressors (blue; progressors=P2, non-progressors=NP2). (E) IgG1 Fc afucosylation levels in COVID-19 patients who were hospitalized (H, orange) (n=52) and combined outpatient progressors (P, Cohort 1 progressors: purple), Cohort 2 progressors: blue) (n=15). (F) α -1,6-Fucosyltransferase 8 (FUT8) median fluorescence intensity in total CD19+ B cells and in plasmablasts (PB) from progressors (n=6) relative to sex-matched non-progressors (n=6). (G) Correlation in matched samples: plasmablast expression of FUT8 and the abundance of IgG1 afucosylation. Solid and open circles represent data points from progressors and non-progressors, respectively. (H) Mean receiver operating characteristic (ROC) response and the area under the curve (AUC) with its standard deviation obtained using a logistic regression model using neutralization titers and IgG1 afucosylation levels. (I) Receiver operating characteristic (ROC) response and the area under the curve (AUC) with standard deviation obtained by testing logistic regression model on an independent Cohort 2. Median values are depicted in C-F with a solid black line. P values in (C) were calculated using Brown-Forsythe and Welch ANOVA test with Dunnett T3 correction, in (D-E) were calculated using Wilcoxon rank-sum test and in (F) using unpaired Student's test. *P < 0.05; **P < 0.01; ***P < 0.001; ****P < 0.0001. Pearson's correlation coefficient (r = -0.6002, p = 0.0391,) was computed in (G).

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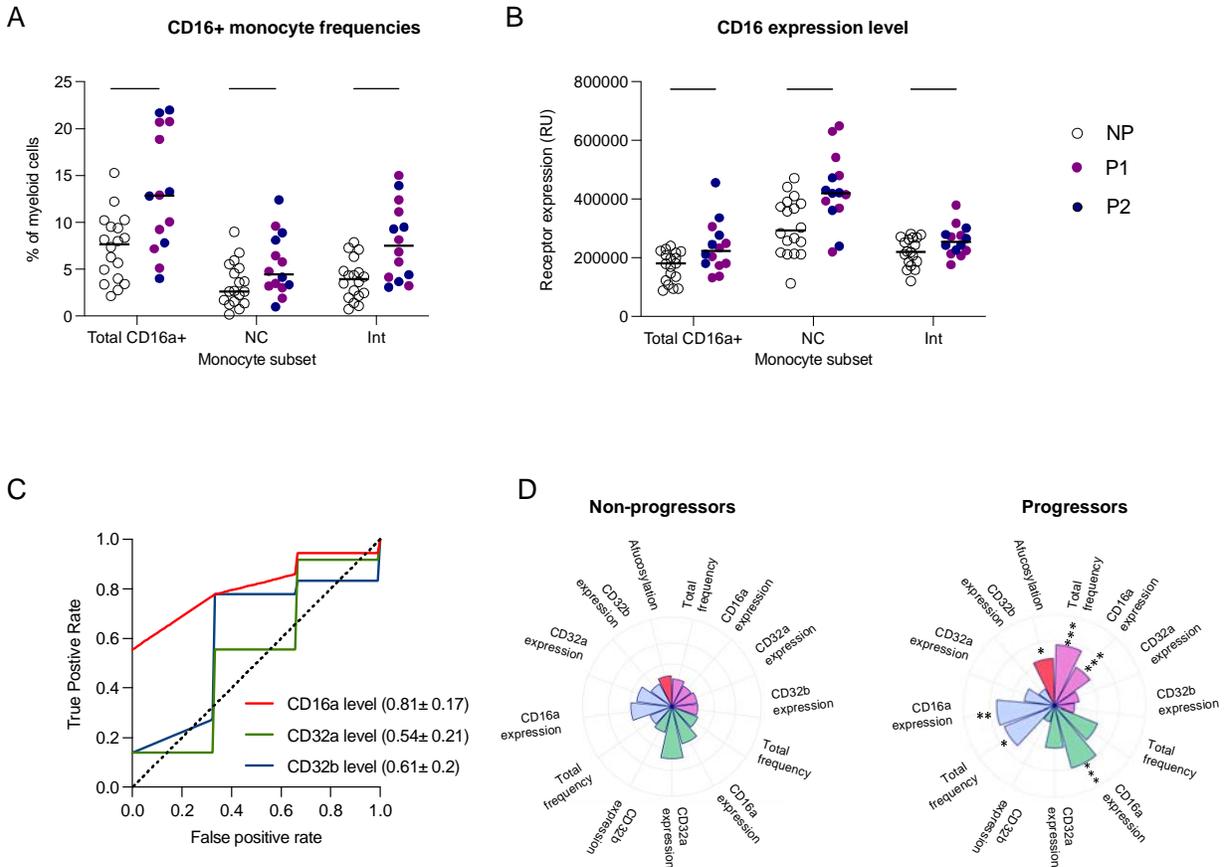
220 The receptor for afucosylated IgG1, CD16a, is enriched in the myeloid compartment of
221 progressors

222 In addition to afucosylated antibody production, a hallmark of patients with severe COVID-19 is
223 inflammatory myeloid cell infiltration into the lung and excessive inflammatory cytokine
224 production (2, 21, 22). These cells express the low affinity Fc γ Rs CD32a (activating), CD32b
225 (inhibitory) and, on some subsets, CD16a (activating). These low affinity Fc γ Rs are engaged

226 through avidity-based interactions when ICs are formed during infection. Depending on the
227 magnitude of activating or inhibitory signal received upon engagement, an effector cell will
228 respond with a proportional level of inflammatory activity (9). Considering that severe COVID-
229 19 is often characterized by an aberrant effector cell activation state (1, 23-25), we next sought to
230 define the expression of activating and inhibitory Fc γ Rs on peripheral monocytes from
231 progressors and non-progressors that might counterbalance or compound an enrichment of
232 afucosylated IgG.

233

234 To study this, available PBMC samples collected at study enrollment were assessed for the
235 frequency of CD16a-expressing monocyte subsets as well as their expression of all low affinity
236 Fc γ Rs (Fig. S3A). Notably, we found that progressors had significantly increased frequencies of
237 total CD16a⁺ monocytes, CD16a⁺ CD14⁻ non-classical monocytes, and CD16a⁺ CD14⁺
238 intermediate monocytes within the peripheral CD11c⁺ HLA-DR⁺ myeloid cell compartment
239 compared to non-progressors upon study enrollment (Fig. 2A) (26-28). Further, quantitative
240 expression analysis of CD16a within these immune cell subsets revealed higher levels of CD16a
241 on cells from progressors, while other low affinity Fc γ Rs (CD32a/b) were not differentially
242 expressed (Fig. 2B, Fig. S3B). Taken together, early CD16a expression within the peripheral
243 myeloid cell compartment predicted the development of more severe symptoms in COVID-19
244 outpatients (Fig. 2C,D).



245

Figure 2. Elevated CD16a signaling potential in myeloid compartment in progressors.

Enrollment time point PBMCs were characterized in progressors (n=14) and a randomly selected subset of non-progressors (n=18). Solid purple and blue circles represent data points from progressors within Cohort 1 and Cohort 2, respectively whereas open circles represent data points from non-progressors. The median values have been depicted with a black line. **(A)** Total CD16a+ monocyte, CD16a+ CD14- non-classical monocyte (NC), and CD16a+ CD14+ intermediate monocyte (Int) frequencies as percents of total CD11c+ HLA-DR+ CD3- CD19- CD56- myeloid cells are shown. **(B)** CD16a expression levels on total CD16a+, non-classical, and intermediate monocyte populations. **(C)** Mean ROC response and the area under the curve (AUC) with its standard deviation obtained using random forest classifier with 6-fold cross validation in 2 outpatient cohorts using FcγR expression levels on myeloid cells. **(D)** Radar plots summarizing the various features of IgG1-CD16a signaling axis in progressors and non-progressors. Significant differences between the two groups are indicated with asterisks in the radar plot for progressors. P values in (A-B) were calculated using unpaired t-tests. (*P < .05, **P < .01, ***P < .001, ****P < 0.0001).

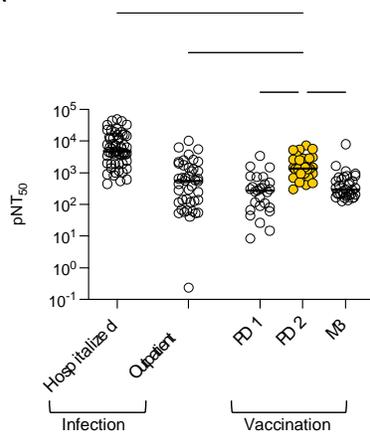
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247 mRNA vaccination elicits the production of neutralizing IgG with glycoforms that are distinct
248 from those elicited by infection
249 We next sought to compare the quality of antibodies produced after SARS-CoV-2 mRNA
250 vaccination and infection. To do so, we studied the antibodies elicited after 1 and 2 doses of the
251 Pfizer BNT162b2 SARS-CoV-2 mRNA vaccine in a group of healthy SARS-CoV-2-naïve adults
252 (Stanford adult vaccine cohort, n=29) (Table S4). Neutralizing titers increased between the post-
253 primary vaccination timepoint (21 days post-dose 1 (PD1)) and the post-boost timepoint (21 days
254 post-dose 2 (PD2)). In all, two doses of mRNA SARS-CoV-2 vaccine elicited robust neutralizing
255 antibody responses that were elevated over peak outpatient neutralizing titers (day 28 shown)
256 (Fig. 3A). Over time after vaccination, the distribution of anti-spike IgG subclasses shifted to a
257 more dominant proportion of IgG1 antibodies (Fig. 3B).

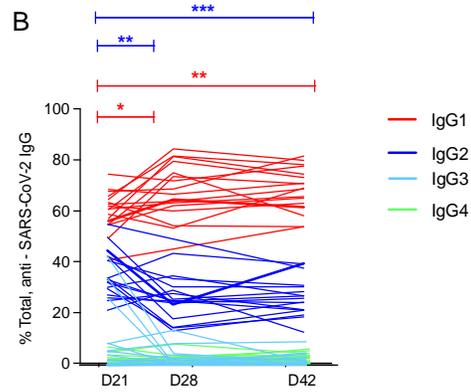
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259 We next characterized Fc glycoforms of anti-spike IgG to determine whether infection- and
260 mRNA vaccine-elicited IgG were distinct in this respect (10). For this analysis, IgG from day 28
261 of the outpatient COVID-19 study (from non-progressors) were compared to samples drawn
262 from vaccine recipients on day 28 post-primary vaccination (7 days post-boost). Additionally, we
263 compared these groups to IgG from the hospitalized COVID-19 cohort (Mount Sinai). Levels of
264 IgG1 Fc afucosylation were similar between the outpatient and vaccine-elicited IgG (Fig. 3C)
265 and both groups were significantly reduced in afucosylation relative to hospitalized patients.
266 Interestingly, vaccination-induced IgG was significantly enriched in Fc sialylation over both
267 outpatient and hospitalized COVID-19, suggesting differential regulation of Fc sialylation by
268 mRNA vaccination and infection, though we cannot exclude a contribution from demographic
269 features that were not matched between cohorts. The relative homogeneity of Fc glycosylation in

270 response to mRNA vaccination contrasted with the heterogeneity observed in natural infection,
271 as well as with our previous observations after seasonal influenza virus vaccination, suggesting
272 differences in the response that may be based on the context of antigen encounter, antigen
273 experience, or different vaccine platforms (29). Vaccine-elicited Fc afucosylation and sialylation
274 were relatively stable over time, similar to the stability observed after natural infection (Fig. 3D,
275 Fig. S1C). Thus, SARS-CoV-2 infection and mRNA vaccination both elicited high neutralizing
276 titers, but distinct and stable levels of IgG1 Fc afucosylation and sialylation.

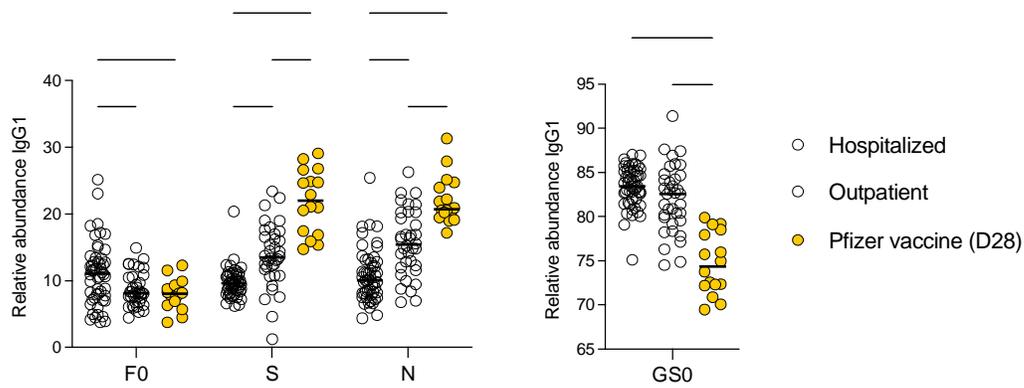
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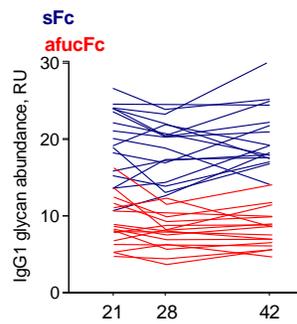
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Figure 3. mRNA vaccination elicits high neutralizing antibody titers with Fc glycoforms distinct from both infection-induced phenotypes. (A) The half-maximal SARS-CoV-2 pseudovirus neutralizing titers (pNT₅₀) in healthy adults following mRNA vaccination (yellow n=29) or in COVID-19 outpatients on study day 28 (blue n=42). PD1: post-dose 1, PD2: post-dose 2, M3: month 3. (B) Longitudinal analysis of IgG subclasses on day 21, 28 or 42 post-primary vaccination (n=17). (C) SARS-CoV2 IgG1 Fc posttranslational modifications in hospitalized COVID-19 patients (n=52), COVID-19 outpatients (day 28 n=36) and in subjects who received the mRNA SARS-CoV-2 vaccine (day 28 post primary vaccination, n=17). F0: afucosylation, S: sialylation, N: bisection, GS0: galactosylation. The median values have been depicted with a black line. (D) Longitudinal analysis of anti-SARS-CoV-2 IgG1 Fc afucosylation (afucFc, red line) and sialylation (sFc, blue line) on day 21, 28 or 42 post-primary vaccination. P values in (A) were calculated using Kruskal Wallis test with Dunn's correction, (B) using mixed effect analysis with Geissser-Greenhouse and Tukey's corrections, (C) two-way ANOVA and one-way ANOVA with Tukey's correction. *P < 0.05; **P < 0.01; ***P < 0.001; ****P < 0.0001.

279

280

281 Afucosylated immune complexes trigger inflammation in the lung *in vivo*

282 To study the functional relevance of the differential glycosylation of mRNA- and infection-

283 elicited IgG, we established an *in vivo* experimental model designed specifically to enable

284 dissection of human antibody signaling outcomes in the lung, in the absence of any additional

285 effects imposed by infection. In this model, pre-formed human IgG ICs, simulating what would

286 be formed during an infection, are delivered to lungs of mice that express human, instead of

287 murine, FcγRs, with cell-specific distribution that mimics the human system (14). Polyclonal

288 IgG pools were generated from purified serum IgG. Pools were from patients with elevated (pool

289 1, >20%) or normal levels (pool 2, <10%) of afucosylated IgG or from sera of mRNA-vaccinated

290 adults (pool 3). Pools 1 and 2 did not significantly differ in other glycan modifications, and all 3

291 pools exhibited comparable distribution of IgG subclasses, though we acknowledge that pool 3

292 trends toward a lower IgG1 and higher IgG2 content (Fig. S4A, S4B). All IgG pools were
293 standardized for binding to SARS-CoV-2 spike (Fig. S4C). Mice were intratracheally
294 administered ICs composed of the anti-SARS-CoV-2 IgG and trimeric SARS-CoV-2 spike
295 protein. Four hours following IC administration, contents of BAL fluid were analyzed for
296 immune cells and soluble factors. This system provided a context in which to specifically study
297 how modulation of IgG Fc-Fc γ R interactions impacts the immune response in the lung.

298

299 BAL fluid collected from the lungs of mice that were treated with afucosylated ICs (pool 1) had
300 significantly elevated frequencies of neutrophils and monocytes over BAL fluid from mice
301 treated with fucosylated ICs (pool 2) or mRNA-vaccine elicited ICs (pool 3) (Fig. 4A, Fig. S5).
302 BAL fluid from mice that received afucosylated ICs was also distinguished from all other
303 experimental conditions by increased concentrations of proinflammatory cytokines and
304 chemokines. TNF α , IL-6, CCL3, CCL4, CXCL1, and CXCL10 were significantly and uniquely
305 upregulated while no difference was observed in levels of the immunoregulatory or
306 immunosuppressive cytokine IL-10 (Fig. 4B). Collectively, these findings functionally
307 distinguish afucosylated IgG, characteristic of severe COVID-19, from the highly sialylated and
308 fucosylated, vaccine-elicited antibody glycoforms *in vivo*.

309

310 We next assessed the Fc γ R dependence of the immune response to afucosylated ICs. Mice
311 specifically lacking expression of CD16a (CD16a $^{-/-}$), but expressing all other human Fc γ Rs, did
312 not exhibit a similar inflammatory response to afucosylated ICs as mice expressing the complete
313 human repertoire (WT) (Fig. 4C, D). This showed that the inflammatory potential of
314 afucosylated IgG1 was almost entirely dependent on the presence of CD16a-expressing immune

315 effector cells. Because CXCL1 and CCL3 are known neutrophil chemoattractants, we next asked
316 whether these molecules mediated the neutrophil influx after afucosylated IC administration.
317 Indeed, pre-administration of blocking monoclonal antibodies against the chemokines CXCL1 or
318 CCL3 led to a significant reduction in neutrophil recruitment (Fig. 4E) (30, 31). Together, these
319 findings support a mechanism in which afucosylated ICs in the lung trigger CD16a-dependent
320 production of chemokines which promote subsequent influx of innate immune cells.

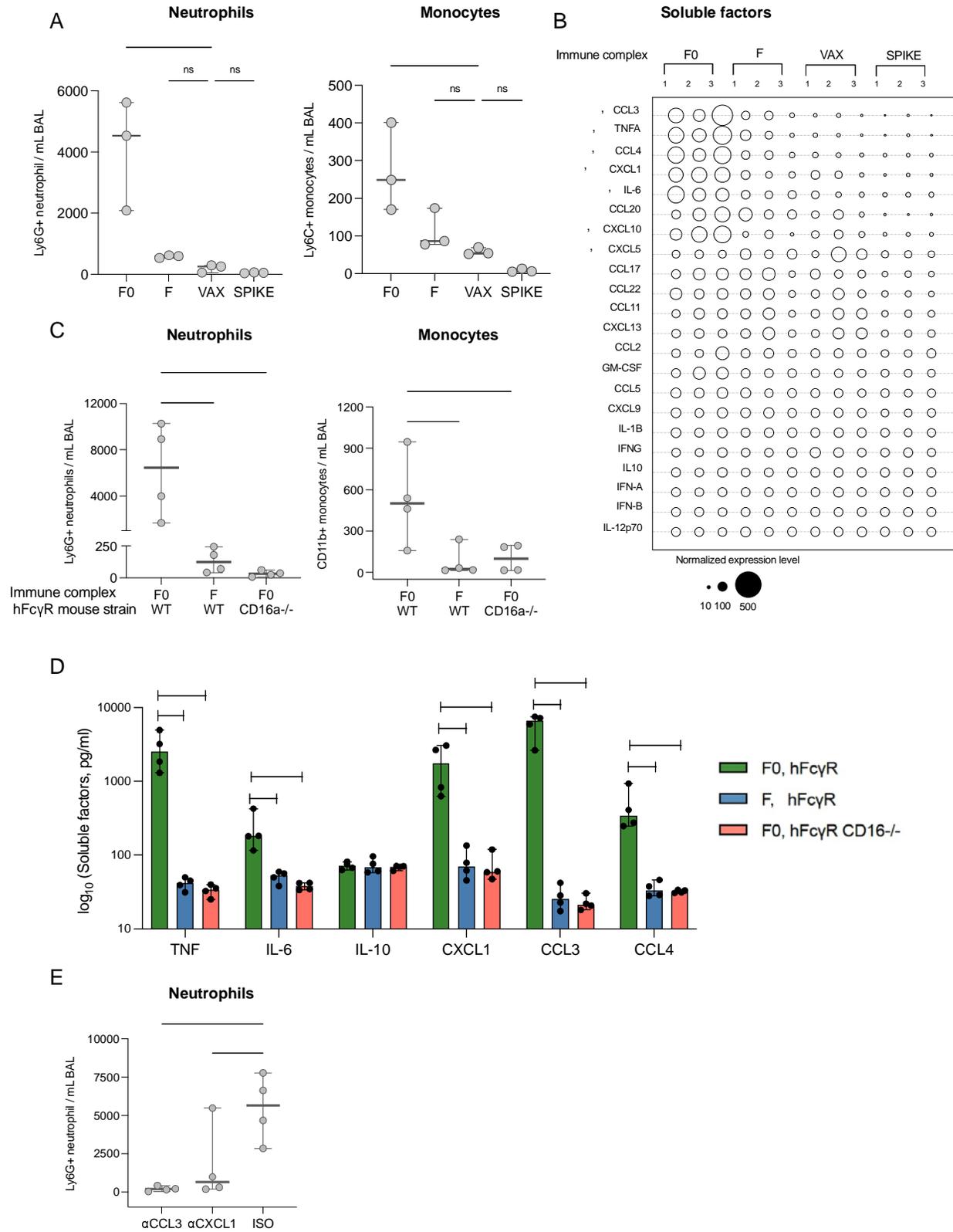


Figure 4. Afucosylated IgG immune complexes promote cell infiltration and proinflammatory cytokine production *in vivo*. (A) Immune cells measured in the bronchoalveolar lavage (BAL) fluid of human Fc γ receptor mice (hFc γ R) that were treated with either afucosylated (F0, pool 1), normally fucosylated (F, pool 2), vaccine-induced (VAX, pool 3) immune complexes or spike alone, by intratracheal administration. (B) Cytokine/chemokine levels in the BAL of the various groups of mice. The size of the bubble represents normalized cytokine and chemokine levels. p values are indicated for each soluble factor (blue: F0 vs F, red: F0 vs VAX). (C) Immune cell subsets, (D) cytokines (TNF, IL-6, IL-10) and chemokines (CXCL1, CCL3, CCL4) quantitated in the bronchoalveolar lavage (BAL) fluid of hFc γ R or hFc γ R mice with a specific deletion in CD16a (CD16a^{-/-}) that received afucosylated (F0, pool 1) or normally fucosylated (F, pool 2) immune complexes by intratracheal administration. In (A) and (C) neutrophils were defined as Ly6G⁺ CD11b⁺ CD2⁻ CD3⁻ B220⁻ cells and total monocytes defined as CD11b⁺ Ly6G⁻ MERTK⁻ MHC IA/IE⁻ CD2⁻ CD3⁻ B220⁻ cells. (E) Frequency of Ly6G⁺ CD11b⁺ CD2⁻ CD3⁻ B220⁻ neutrophils in BAL fluid of hFc γ R mice that were pre-treated with chemokine neutralizing mAbs (α CXCL1 and α CCL3) or isotype control followed by administration of afucosylated immune complexes. The median and the 95% confidence interval have been depicted in each graph with solid lines. P values in (A-D) were calculated using one-way ANOVA with Dunnett's correction using n=3 mice per group for A and B and n=4 mice per group for C-E. Data in A-E are representative of at least two independent experiments. *P < 0.05; **P < 0.01; ***P < 0.001; ****P < 0.0001.

322

323 Discussion

324 Prognostic biomarkers and treatments that may halt the progression to severe COVID-19 are
325 urgently needed to prevent mortality associated with this disease. To identify new avenues of
326 treatment, mechanisms underlying the distinct trajectories in COVID-19 must be clarified. Here,
327 we show that early antibody quality and the expression of cognate Fc γ Rs on peripheral
328 monocytes may be used to anticipate distinct COVID-19 trajectories, including progression to
329 more severe outcomes. Overall, mild COVID-19 patients who experienced a worsening disease
330 trajectory were characterized by the absence of an early robust neutralizing antibody response
331 with elevations in both afucosylated anti-spike IgG and the CD16a receptor on myeloid cells.
332 The IgG elicited by SARS-CoV-2 infection was heterogenous in Fc glycosylation relative to IgG
333 generated in response to SARS-CoV-2 mRNA vaccination. Vaccine-elicited IgG exhibited high
334 neutralization and low afucosylation, along with other significant differences in Fc glycoforms.

335 The early inflammatory response to ICs in the lung was a function of the abundance of IgG1
336 afucosylation and CD16 expression.

337

338 Our data support a model in which the combination of a lack of early SARS-CoV-2
339 neutralization and an enhanced afucosylated IgG-CD16a signaling axis contribute to the
340 inflammatory phenotype of severe COVID-19. We propose that this may be one mechanism
341 contributing to the hyperinflammatory response in severe COVID-19. Determining how various
342 immune aberrancies, including those described here and others such as elevated IL-6 or an
343 impaired renin-angiotensin system might contribute to the pathogenesis of severe COVID-19
344 will require the development of new animal models (2, 24, 32, 33). To examine whether
345 afucosylated ICs can augment the inflammatory milieu in the lungs, we established a model to
346 specifically evaluate the impact of human IgG signaling on the pulmonary inflammatory
347 response. This model advances our ability to evaluate human IgG antibodies in a functional
348 dimension, beyond what *in vitro* approaches can reveal. We show that the afucosylated
349 IgG/CD16a signaling axis can result in a complete remodeling of the inflammatory lung milieu.
350 Of note, the increased frequency of neutrophils and monocytes observed within the lungs of mice
351 that received afucosylated ICs mirrors what has been observed in some severe COVID-19
352 patients (4, 21, 34, 35). Tissue-resident alveolar macrophages likely serve as an initial effector of
353 afucosylated IC activity in this model as they are the predominant innate immune cell population
354 within the lung, express high levels of CD16a, and can produce many of the observed soluble
355 factors (11). This *in vivo* model is not a model of COVID-19 pathogenesis; rather, it enables a
356 more targeted investigation of how distinct human antibody repertoires activate effector cells and
357 the complex molecular changes involved in those interactions specifically within the lung.

358 Animal models that more accurately reflect the immunophenotype of patients at highest risk for
359 mortality in COVID-19 are needed to truly study the pathogenesis of this disease.

360

361 While we did not observe a significant correlation between IgG afucosylation and the
362 demographic features studied here, it is known that IgG post-translational modifications are
363 associated with specific patient characteristics including sex and age (36). Thus, differences in
364 demographics between our cohorts may have contributed to our findings. How IgG glycosylation
365 is regulated is not fully understood, but numerous studies support a role for both heritable and
366 non-heritable influences (29, 37-41). We believe that the data in our current manuscript are the
367 first to support a direct role for plasmablast FUT8 expression as a determinant of IgG
368 afucosylation. Defining specific regulatory pathways of IgG glycosylation will be important for
369 modulating the *in vivo* activities of IgG to improve human disease outcomes.

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376 Materials and Methods

377

378 Clinical cohorts and samples

379 Characterization of these samples at Stanford was performed under a protocol approved by the
380 Institutional Review Board of Stanford University (protocol #55718).

381 Stanford Lambda cohort (Cohort 1):

382 120 participants were enrolled in a phase 2 randomized controlled trial of Peginterferon Lambda-
383 1a beginning April 25, 2020 (Lambda, NCT04331899). Inclusion/exclusion criteria and the study
384 protocol for the trial have been published(15). Briefly, adults aged 18-75 years with an FDA
385 emergency use authorized reverse transcription-polymerase chain reaction (RT-PCR) positive for
386 SARS-CoV-2 within 72 hours prior to enrollment were eligible for study participation. Exclusion
387 criteria included hospitalization, respiratory rate >20 breaths per minute, room air oxygen
388 saturation <94%, pregnancy or breastfeeding, decompensated liver disease, recent use of
389 investigational and/or immunomodulatory agents for treatment of COVID-19, and prespecified
390 lab abnormalities. All participants gave written informed consent, and all study procedures were
391 approved by the Institutional Review Board of Stanford University (IRB-55619). Participants
392 were randomized to receive a single subcutaneous injection of Lambda or saline placebo.
393 Peripheral blood was collected at enrollment, day 5, and day 28 post enrollment. A subset of
394 participants (n=80) returned for long-term follow-up visits 4-, 7-, and 10-months post
395 enrollment, with peripheral blood obtained. Longitudinal samples from the 56 SARS-CoV-2-
396 infected outpatients who were in the placebo arm of the broader Lambda study were obtained
397 and assessed here.

398 Stanford Favipiravir Cohort (Cohort 2):

399 149 participants were enrolled in a phase 2 randomized controlled trial of Favipiravir beginning
400 July 12, 2020 (NCT04346628). Inclusion/exclusion criteria and the study protocol for the trial
401 are publicly available. Briefly, adults aged 18 – 80 years old were enrolled within 72 hours of a
402 positive NAAT for SARS-CoV-2. Upon enrollment, participants were mildly symptomatic with
403 no evidence of respiratory distress. Participants were randomized to receive favipiravir or

404 placebo. Participants were followed for 28 days, with study visits on days 1, 5, 10, 14, 21 and 28.
405 At each study visit, clinical assessment was performed and oropharyngeal swabs and blood
406 samples were collected. Samples collected upon enrollment from the 69 SARS-CoV-2-infected
407 outpatients who were in the placebo arm of the broader Favipiravir study were obtained and
408 assessed here.

409 Mount Sinai Cohort (Hospitalized COVID-19 patients):

410 Fifty-two samples were obtained from hospitalized COVID-19 patients enrolled in the Mount
411 Sinai Health System (MSHS) collected by the Mount Sinai COVID-19 biobank²². The median
412 age was 65 years old with a range from 33 - 98 years old. There are 31 males and 21 females in
413 the study. 13 patients succumbed to disease.

414 Stanford Adult vaccine cohort:

415 Fifty-seven healthy volunteers were enrolled in the study approved by Stanford University
416 Institutional Review Board (IRB 8629). The median age was 36 years old with a range from 19 -
417 79 years old. There are 28 males and 29 females in the study. There are 27 White participants, 23
418 Asian participants, 4 Black participants, 1 Native American participant, and 2 other participants.

419

420 Cell lines. Human embryonic kidney (HEK) 293T (American Type Culture Collection, ATCC;
421 CRL-3216) and Vero (ATCC; CCL-81) cells were grown and maintained in 1X Dulbecco's
422 Modified Eagle Medium (DMEM; ThermoFisher Scientific) supplemented with 10% fetal
423 bovine serum (FBS).

424

425 Cloning, expression, and protein purification. The His₆-tagged SARS-CoV-2 RBD and full-
426 length SARS-CoV-2 spike protein were purified in house as previously described.³ Briefly, both

427 the constructs were transiently transfected into Expi293F cells (Thermo Fisher Scientific) and
428 proteins purified from culture supernatants Ni-nitriloacetic acid (NTA) resin (GE HealthCare).
429
430 Generation of SARS-CoV-2 pseudoparticles. To generate vesicular stomatitis virus (VSV)
431 pseudotyped with the S of SARS-CoV-2, we first constructed an expression plasmid encoding
432 the Wuhan S. We did this by modifying a pCAGGS mammalian expression vector encoding the
433 full-length Wuhan S and deleting its last 18 amino acids of the cytoplasmic domain, which we
434 call pCAGGS-S Δ 18. This reagent was produced under HHSN272201400008C and obtained
435 through BEI Resources, NIAID, NIH: Vector pCAGGS containing the SARS-related
436 coronavirus 2, Wuhan S, NR52310. To generate VSV pseudotyped with SARS-CoV-2 S, we
437 first coated 6-well plates with 0.5 μ g/mL poly-D-lysine (ThermoFisher, Cat. No. A3890401) for
438 1 to 2 hours at room temperature (RT). After poly-D-lysine treatment, plates were washed three
439 times with sterile water and then seeded with 1.5e6 cells of HEK 293T per well. After 24 hours
440 (h), cells were transfected with 1 μ g of pCAGGS-S Δ 18 per well using Lipofectamine 2000
441 transfection reagent (ThermoFisher, Cat. No., 11668019). 48 h after transfection, the cells were
442 washed once with 1X phosphate buffered saline (PBS), and were infected with VSV- Δ G-
443 GFP/nanoluciferase (a generous gift from Matthias J. Schnell) at a multiplicity of infection of 2
444 to 3 in a 300 μ L volume. Cells were infected for an hour with intermittent rocking every 15
445 minutes. After infection, the inoculum was carefully removed, and the cell monolayer was
446 washed three times with 1X PBS to remove residual VSV- Δ G-GFP/nanoluciferase. Two mL of
447 infection media (2% FBS, 1% glutamine, 1% sodium pyruvate in 1X DMEM) was added to each
448 well. At 24 h post-infection, the supernatants from all the wells were combined, centrifuged (600
449 g for 10 min, 4°C), and stored at -80°C until use.

450

451 Neutralization assays. Vero cells were seeded at 5×10^5 cells per well in 50 μL aliquots in half area
452 Greiner 96-well plates (Greiner Bio-One; Cat. No. 675090) 24 h prior to performing the
453 neutralization assay. On separate U-bottom plates, patient plasma was plated in duplicates and
454 serially 5-fold diluted in infection media (2% FBS, 1% glutamine, 1% sodium pyruvate in 1X
455 DMEM) for a final volume of 28 μL per well. We also included ‘virus only’ and ‘media only’
456 controls. Twenty-five microliters of SARS-CoV-2 pseudo-typed VSV particles (containing 500
457 to 1500 fluorescent forming units) were added to the wells on the dilution plate, not including the
458 “virus-free” column of wells and incubated at 37°C for 1 hour. Prior to infection, Vero cells were
459 washed twice with 1X PBS and then 50 μL of the incubated pseudo-typed particles and patient
460 plasma mixture was then transferred from the U-bottom 96-well dilution plates onto the Vero
461 cells and placed into an incubator at 37°C and 5% CO_2 . At 24 h post-incubation, the number of
462 GFP-expressing cells indicating viral infection were quantified using a Celigo Image Cytometer.
463 We first calculate percent infection based on our ‘virus only’ controls and then calculate percent
464 inhibition by subtracting the percent infection from 100. A non-linear curve and the half-
465 maximal neutralization titer (pNT_{50}) were generated using GraphPad Prism.

466

467 ELISA. ELISA was performed following a modified version of a protocol described previously³.
468 Briefly, 96 Well Half-Area microplates (Corning (Millipore Sigma)) plates were coated with
469 antigens at $2\mu\text{g}/\text{ml}$ in PBS for 1h at room temperature (RT). Next, the plates were blocked for an
470 hour with 3% non-fat milk in PBS with 0.1% Tween 20 (PBST). All serum samples from
471 patients with COVID-19, and the negative controls were heated at 56°C for 1h, aliquoted and
472 stored at -80°C . Sera were diluted fivefold starting at 1:50 in 1% non-fat milk in PBST. $25\mu\text{L}$ of

473 the diluted sera was added to each well and incubated for 2h at RT. Following primary
474 incubation with the sera, 25 μ l of 1:5000 diluted horse radish peroxidase (HRP) conjugated anti-
475 Human IgG secondary antibody (Southern Biotech) was added and incubated for 1h at RT. The
476 plates were developed by adding 25 μ l/well of the chromogenic substrate 3,3',5,5'-
477 tetramethylbenzidine (TMB) solution (Millipore Sigma). The reaction was stopped with 0.2N
478 sulphuric acid (Sigma) and absorbance was measured at 450nm (SPECTRAMax iD3, Molecular
479 Devices). The plates were washed 5 times with PBST between each step and an additional wash
480 with PBS was done before developing the plates. All data were normalized between the same
481 positive and negative controls and the binding AUC has been reported.

482

483 IgG Fc glycan analysis. Methods for relative quantification of Fc glycans and IgG subclasses
484 have been previously described^{20,23}. Briefly, IgG were isolated from serum by protein G
485 purification. Antigen-specific IgG were isolated on NHS agarose resin (ThermoFisher; 26196)
486 coupled to the protein of interest. Following tryptic digestion of purified IgG bound to antigen-
487 coated beads, nanoLC-MS/MS analysis for characterization of glycosylation sites was performed
488 on an UltiMate3000 nanoLC (Dionex) coupled with a hybrid triple quadrupole linear ion trap
489 mass spectrometer, the 4000 Q Trap (SCIEX). MS data acquisition was performed using Analyst
490 1.6.1 software (SCIEX) for precursor ion scan triggered information dependent acquisition
491 (IDA) analysis for initial discovery-based identification.

492

493 For quantitative analysis of the glycoforms at the N297 site of IgG1, multiple-reaction
494 monitoring (MRM) analysis for selected target glycopeptides and their glycoforms was applied
495 using the nanoLC-4000 Q Trap platform to the samples which had been digested with trypsin.

496 The m/z of 4-charged ions for all different glycoforms as Q1 and the fragment ion at m/z 366.1
497 as Q3 for each of transition pairs were used for MRM assays. A native IgG tryptic peptide (131-
498 GTLVTVSSASTK-142) with Q1/Q3 transition pair of, 575.9⁺²/780.4 was used as a reference
499 peptide for normalization. IgG subclass distribution was quantitatively determined by nanoLC-
500 MRM analysis of tryptic peptides following removal of glycans from purified IgG with PNGase
501 F. Here the m/z value of fragment ions for monitoring transition pairs was always larger than that
502 of their precursor ions with multiple charges to enhance the selectivity for unmodified targeted
503 peptides and the reference peptide. All raw MRM data was processed using MultiQuant 2.1.1
504 (SCIEX). All MRM peak areas were automatically integrated and inspected manually. In the
505 case where the automatic peak integration by MultiQuant failed, manual integration was
506 performed using the MultiQuant software.

507

508 Immune cell phenotyping and FcγR quantification. Cryopreserved human PBMCs collected
509 upon enrollment on study day 0 were rapidly thawed, washed, and blocked with Human TruStain
510 FcX (BioLegend) to reduce nonspecific binding. Cells were then stained for viability with
511 Live/Dead Fixable Staining Kit (ThermoFisher) as well as the following antibodies: anti-CD3
512 (clone OKT3), anti-CD11c (clone S-HCL-3), anti-CD14 (clone M5E2), anti-CD16 (clone 3G8),
513 anti-CD19 (clone SJ25C1), anti-CD21 (Bu32), anti-CD27 (clone O323), anti-CD32
514 (STEMCELL Technologies; clone IV.3), anti-CD32B/C (clone S18005H), anti-CD38 (clone
515 S17015A), anti-CD56 (clone 5.1H11), anti-CD138 (clone IA6-2), anti-FucT-VIII (Santa Cruz
516 Biotechnologies; clone B-10), anti-HLA-DR (clone L243) purchased from BioLegend unless
517 noted otherwise. After staining, cells were fixed and acquired using an Attune NxT flow
518 cytometer (Invitrogen). In the case of intracellular anti-FucT-VIII staining, cells were further

519 permeabilized using Intracellular Staining Permeabilization Wash Buffer (BioLegend) prior to
520 acquisition by flow cytometry. Bulk myeloid cells were defined as viable CD3⁻ CD19⁻ CD56⁻
521 CD11c⁺ HLA-DR⁺ cells, while CD16a⁺ monocytes within this population were additionally
522 positive for CD16a (Fig S3). Within CD16a⁺ monocytes, non-classical (NC) monocytes were
523 CD16a⁺ CD14⁻ while intermediate (int) monocytes were CD16a⁺ CD14⁺. Leukocyte expression
524 of FcγRs was quantified by measuring the median fluorescence intensity (MFI) of a particular
525 FcγR and comparing it to the MFI of stained Quantum™ Simply Cellular microsphere beads
526 (Bangs Laboratories) of known and discrete antibody-binding capacities. Total CD19⁺ B cells
527 were similarly assessed from within viable PBMCs. Plasmablasts were further defined as CD19⁺
528 CD27⁺ CD38⁺⁺. Memory B cells were defined as CD19⁺ CD27⁺ IgD⁻, double negative (DN) B
529 cells were CD19⁺ CD27⁻ IgD⁻, and naïve B cells were CD19⁺ CD27⁻ IgD⁺.

530

531 *In vivo* lung inflammation model. All *in vivo* experiments were performed in compliance with
532 federal laws and institutional guidelines and have been approved by the Stanford University
533 Institutional Animal Care and Use Committee. Polyclonal IgG was isolated from PCR-positive
534 SARS-CoV-2 patients' plasma samples, pooled based on the frequency of afucosylated anti-
535 RBD IgG1 (>20% or <10%). Similarly, plasma from all vaccinated patient samples were pooled
536 and IgG was purified. The purified IgG pools were incubated with SARS-CoV-2 spike trimer at
537 a 20:1 molar ratio overnight at 4°C. Immune complexes were intratracheally administered to 8–
538 12-week-old humanized FcγR or CD16a-deficient mice. Experimental groups were consistently
539 matched for sex and age. 4hr post-administration, mice were sacrificed and bronchoalveolar
540 lavage (BAL) was performed. Immune cells were isolated from within the BAL fluid and stained
541 with the following cell staining panel: Live/Dead Fixable Dye (ThermoFisher), anti-CD2

542 (BioLegend; clone RM2-5), anti-CD3 (BioLegend; clone 17A2), CD11b (BioLegend; clone
543 M1/70), anti-CD45 (BioLegend; clone I3/2.3), anti-human CD64 (BioLegend; clone 10.1), anti-
544 B220 (BioLegend), anti- anti-Ly6G (BioLegend; clone 1A8), anti-MERTK (BioLegend; clone
545 2B10C42), anti-MHC II (BioLegend; clone M5/114.15.2). Once stained, cells were fixed and
546 acquired via an Attune NxT flow cytometer (Invitrogen). Neutrophils were defined as viable
547 Ly6G+ CD11b+ CD3- B220- leukocytes. Monocytes were defined as viable CD11b+ Ly6G-
548 MERTK- MHC IA/IE- CD3- B220- leukocytes (Fig S6). Cell-free BAL fluid was stored at 4°C
549 and processed within 24hr to measure cytokine/chemokine content using a LEGENDplex bead
550 array kit (BioLegend).

551

552 *In vivo* blocking experiments. In chemokine-blockade experiments, mice received intraperitoneal
553 injections of 5mg/kg anti-CXCL1, anti-CCL3, or rat IgG2a isotype control (MAB453,
554 MAB4502, MAB006; R&D) 8hr prior to immune complex administration and immune complex
555 administration and BAL were performed as described above.

556

557 Data and Statistical analysis. The log₁₀+1 transformed half-maximal serum neutralization titers
558 (pNT50) were used to generate the heatmap.

559 Python version 3.8.5 was used for machine learning. The class progressor was mapped to 1 and
560 non-progressor was mapped to 0, making it a binary classification problem.

561 To determine whether the combination of low/no neutralizing antibodies and elevated IgG Fc
562 afucosylation was a predictor of worsening disease trajectory, a logistic regression model was
563 used. The model was trained using data from Cohort 1 (training set), and to obtain the best

564 hyperparameters, GridSearch cross-validation (cv) was performed. The model was tested using
565 an independent test set (Cohort 2) and the ROC AUC score was generated.

566 To generate ROC AUC scores from Fc γ Rs frequency and expression to distinguish progressors
567 and non-progressors, Random Forest Classifier was used. The input data was split using 6-fold
568 cross validation in which the classifier was trained on 5 folds of the data and tested on the
569 remaining part of the data. The ROC response for all these different datasets were used for
570 calculating the mean area under curve.

571 R Studio (version 1.2.1335) was used to perform the multivariate regression analyses and to
572 generate the radar plots and bubble plot using ggplot2 package. For the radar plots, each feature
573 was normalized across the entire dataset and the mean value within each cohort (progressor and
574 non-progressor) was plotted. For the bubble plot, cytokine and chemokine levels were
575 normalized between 0 and the average of all values across all the groups.

576 All other data were analyzed with GraphPad Prism 9.0 software.

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597

598 Author contributions:

599 SC, JG, GST, TTW designed the study and analyzed data. SC, JG, GST, TTW wrote the
600 manuscript with input from EMD, KCN, TUM, PJ, VM, and UA. SC, JG, BLS, GST, VM, SC,
601 MD, UA, AS, BY-LC, KQTT, CS, RS, SZ and XJ performed experiments. AC, STC, TG, FG,
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603 and PJ provided critical support and/or reagents.

604

605 Competing Interests: None

606

607 Supplemental information

608 Correspondence and requests for materials should be addressed to T.T.W

609

610 Data availability

611 All raw data are available in the manuscript or from the corresponding author on request.

612 References

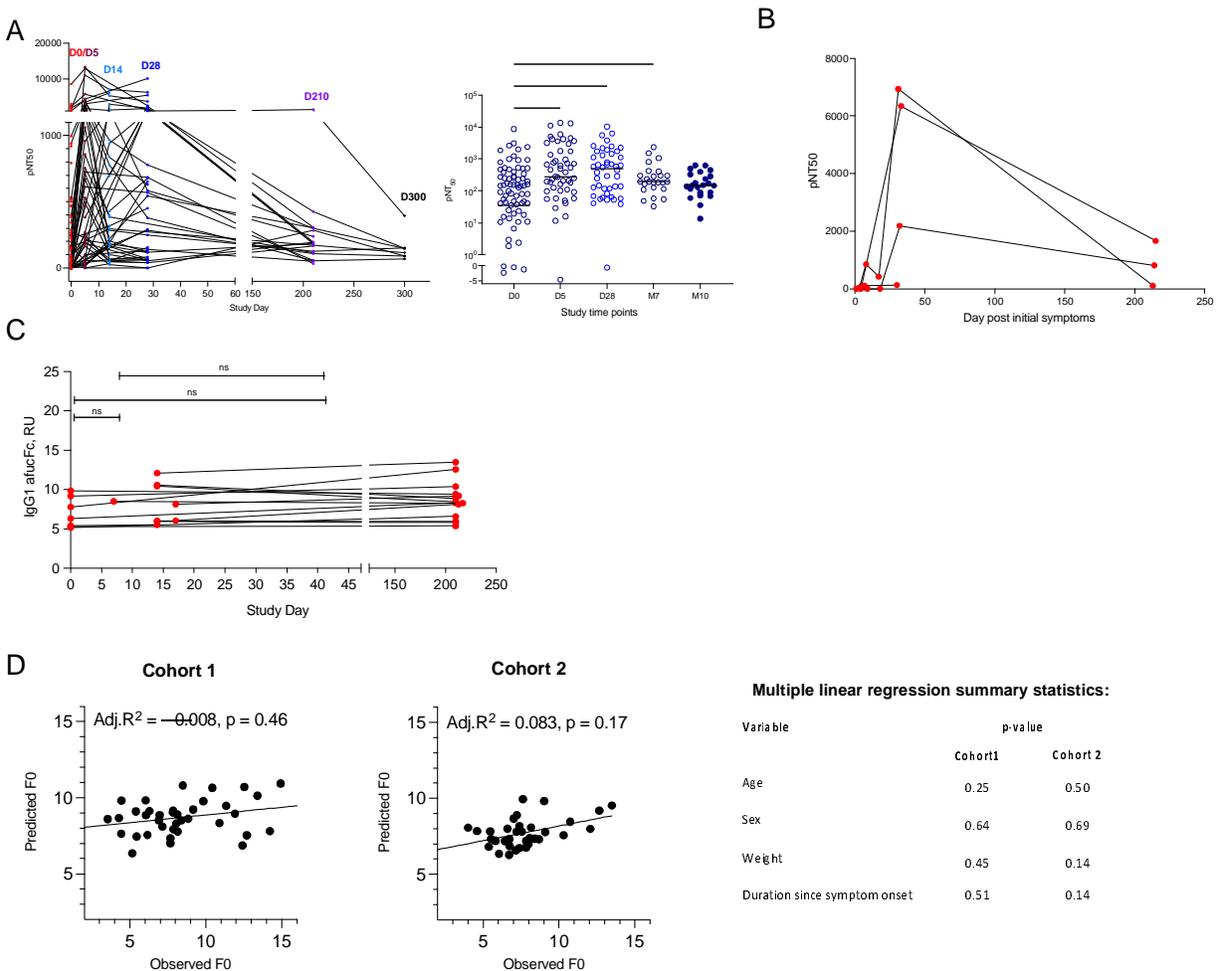
613

- 614 1. M. Z. Tay, C. M. Poh, L. Renia, P. A. MacAry, L. F. P. Ng, The trinity of COVID-19:
615 immunity, inflammation and intervention. *Nat Rev Immunol* 20, 363-374 (2020).
- 616 2. D. M. Del Valle *et al.*, An inflammatory cytokine signature predicts COVID-19 severity
617 and survival. *Nature medicine* 26, 1636-1643 (2020).
- 618 3. M. Merad, J. C. Martin, Pathological inflammation in patients with COVID-19: a key
619 role for monocytes and macrophages. *Nat Rev Immunol* 20, 355-362 (2020).
- 620 4. B. Schurink *et al.*, Viral presence and immunopathology in patients with lethal COVID-
621 19: a prospective autopsy cohort study. *Lancet Microbe* 1, e290-e299 (2020).
- 622 5. B. J. Barnes *et al.*, Targeting potential drivers of COVID-19: Neutrophil extracellular
623 traps. *J Exp Med* 217, (2020).
- 624 6. C. Wang *et al.*, Alveolar macrophage dysfunction and cytokine storm in the pathogenesis
625 of two severe COVID-19 patients. *EBioMedicine* 57, 102833 (2020).
- 626 7. C. Wang *et al.*, Imaging Mass Cytometric Analysis of Postmortem Tissues Reveals
627 Dysregulated Immune Cell and Cytokine Responses in Multiple Organs of COVID-19
628 Patients. *Front Microbiol* 11, 600989 (2020).
- 629 8. J. S. Warren, P. A. Ward, in *eLS*. pp. 1-9.
- 630 9. S. Chakraborty *et al.*, Proinflammatory IgG Fc structures in patients with severe COVID-
631 19. *Nature immunology* 22, 67-73 (2021).
- 632 10. M. D. Larsen *et al.*, Afucosylated IgG characterizes enveloped viral responses and
633 correlates with COVID-19 severity. *Science* 371, (2021).
- 634 11. W. Hoepel *et al.*, High titers and low fucosylation of early human anti-SARS-CoV-2 IgG
635 promote inflammation by alveolar macrophages. *Sci Transl Med* 13, (2021).
- 636 12. R. L. Shields *et al.*, Lack of fucose on human IgG1 N-linked oligosaccharide improves
637 binding to human FcγRIII and antibody-dependent cellular toxicity. *The Journal of*
638 *biological chemistry* 277, 26733-26740 (2002).
- 639 13. D. J. Falconer, G. P. Subedi, A. M. Marcella, A. W. Barb, Antibody Fucosylation Lowers
640 the FcγRIIIa/CD16a Affinity by Limiting the Conformations Sampled by the
641 N162-Glycan. *ACS Chem Biol* 13, 2179-2189 (2018).
- 642 14. P. Smith, D. J. DiLillo, S. Bournazos, F. Li, J. V. Ravetch, Mouse model recapitulating
643 human Fcγ receptor structural and functional diversity. *Proceedings of the National*
644 *Academy of Sciences of the United States of America* 109, 6181-6186 (2012).
- 645 15. P. Jagannathan *et al.*, Peginterferon Lambda-1a for treatment of outpatients with
646 uncomplicated COVID-19: a randomized placebo-controlled trial. *Nat Commun* 12, 1967
647 (2021).
- 648 16. C. Lucas *et al.*, Delayed production of neutralizing antibodies correlates with fatal
649 COVID-19. *Nature medicine*, (2021).
- 650 17. S. Dispinseri *et al.*, Neutralizing antibody responses to SARS-CoV-2 in symptomatic
651 COVID-19 is persistent and critical for survival. *Nat Commun* 12, 2670 (2021).

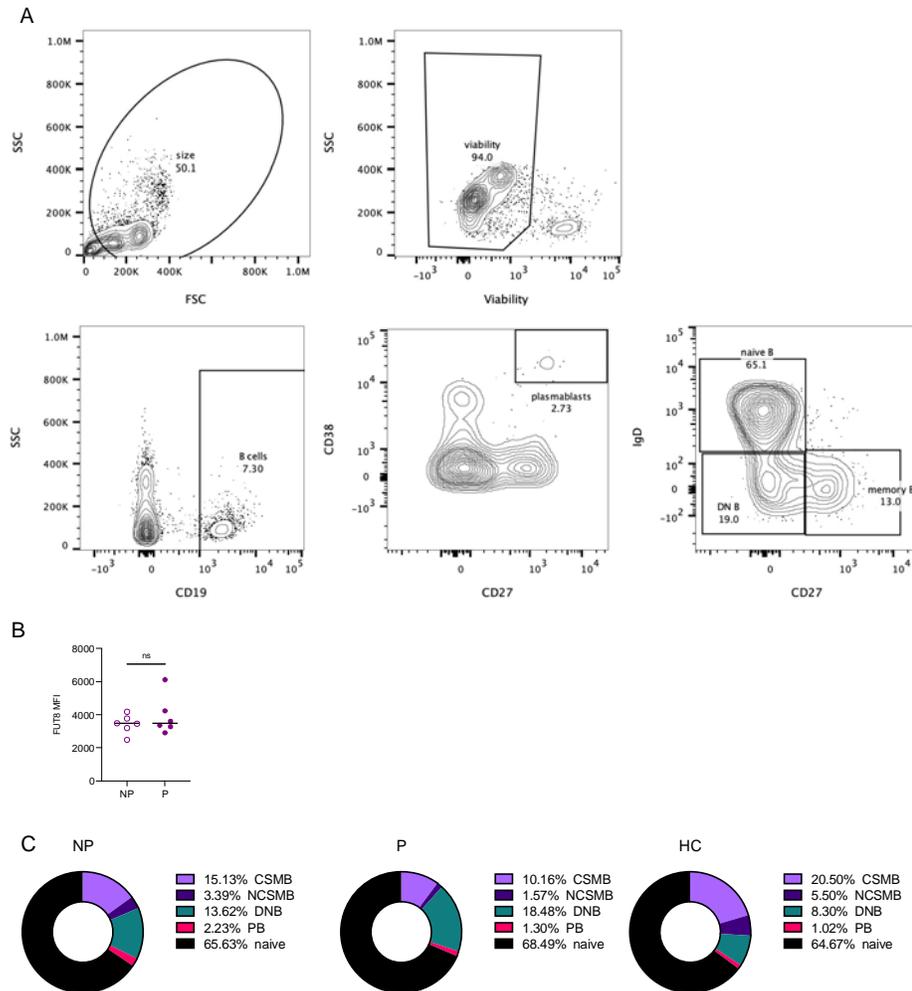
- 652 18. S. Feng *et al.*, Correlates of protection against symptomatic and asymptomatic SARS-
653 CoV-2 infection. *Nature medicine*, (2021).
- 654 19. D. S. Khoury *et al.*, Neutralizing antibody levels are highly predictive of immune
655 protection from symptomatic SARS-CoV-2 infection. *Nature medicine* 27, 1205-1211
656 (2021).
- 657 20. A. W. Charney *et al.*, Sampling the host response to SARS-CoV-2 in hospitals under
658 siege. *Nat Med* 26, 1157-1158 (2020).
- 659 21. M. Liao *et al.*, Single-cell landscape of bronchoalveolar immune cells in patients with
660 COVID-19. *Nature medicine* 26, 842-844 (2020).
- 661 22. A. F. Rendeiro *et al.*, The spatial landscape of lung pathology during COVID-19
662 progression. *Nature* 593, 564-569 (2021).
- 663 23. P. Brodin, Immune determinants of COVID-19 disease presentation and severity. *Nat*
664 *Med* 27, 28-33 (2021).
- 665 24. Z. Xu *et al.*, Pathological findings of COVID-19 associated with acute respiratory
666 distress syndrome. *Lancet Respir Med* 8, 420-422 (2020).
- 667 25. Z. Zhou *et al.*, Heightened Innate Immune Responses in the Respiratory Tract of COVID-
668 19 Patients. *Cell Host Microbe* 27, 883-890 e882 (2020).
- 669 26. L. Ziegler-Heitbrock *et al.*, Nomenclature of monocytes and dendritic cells in blood.
670 *Blood* 116, e74-80 (2010).
- 671 27. G. D. Thomas *et al.*, Human Blood Monocyte Subsets: A New Gating Strategy Defined
672 Using Cell Surface Markers Identified by Mass Cytometry. *Arterioscler Thromb Vasc*
673 *Biol* 37, 1548-1558 (2017).
- 674 28. T. S. Kapellos *et al.*, Human Monocyte Subsets and Phenotypes in Major Chronic
675 Inflammatory Diseases. *Front Immunol* 10, 2035 (2019).
- 676 29. T. T. Wang *et al.*, Anti-HA Glycoforms Drive B Cell Affinity Selection and Determine
677 Influenza Vaccine Efficacy. *Cell* 162, 160-169 (2015).
- 678 30. K. V. Sawant *et al.*, Chemokine CXCL1-Mediated Neutrophil Trafficking in the Lung:
679 Role of CXCR2 Activation. *J Innate Immun* 7, 647-658 (2015).
- 680 31. J. L. M. Dunn *et al.*, Blocking CXCL1-dependent neutrophil recruitment prevents
681 immune damage and reduces pulmonary bacterial infection after inhalation injury. *Am J*
682 *Physiol Lung Cell Mol Physiol* 314, L822-L834 (2018).
- 683 32. C. Lucas *et al.*, Longitudinal analyses reveal immunological misfiring in severe COVID-
684 19. *Nature* 584, 463-469 (2020).
- 685 33. T. S. Rodrigues *et al.*, Inflammasomes are activated in response to SARS-CoV-2
686 infection and are associated with COVID-19 severity in patients. *J Exp Med* 218, (2021).
- 687 34. C. Nathan, Neutrophils and COVID-19: Nots, NETs, and knots. *J Exp Med* 217, (2020).
- 688 35. I. Sanchez-Cerrillo *et al.*, COVID-19 severity associates with pulmonary redistribution of
689 CD1c+ DCs and inflammatory transitional and nonclassical monocytes. *The Journal of*
690 *clinical investigation* 130, 6290-6300 (2020).
- 691 36. T. T. Wang, IgG Fc Glycosylation in Human Immunity. *Current topics in microbiology*
692 *and immunology*, (2019).
- 693 37. G. Lauc *et al.*, Genomics meets glycomics-the first GWAS study of human N-Glycome
694 identifies HNF1alpha as a master regulator of plasma protein fucosylation. *PLoS Genet* 6,
695 e1001256 (2010).
- 696 38. J. Wang *et al.*, Fc-glycosylation of IgG1 is modulated by B-cell stimuli. *Mol Cell*
697 *Proteomics* 10, M110 004655 (2011).

- 698 39. G. Lauc *et al.*, Loci associated with N-glycosylation of human immunoglobulin G show
 699 pleiotropy with autoimmune diseases and haematological cancers. *PLoS Genet* 9,
 700 e1003225 (2013).
 701 40. L. Klaric *et al.*, Glycosylation of immunoglobulin G is regulated by a large network of
 702 genes pleiotropic with inflammatory diseases. *Sci Adv* 6, eaax0301 (2020).
 703 41. R. Pfeifle *et al.*, Regulation of autoantibody activity by the IL-23-TH17 axis determines
 704 the onset of autoimmune disease. *Nature immunology* 18, 104-113 (2017).
 Supplemental Figures

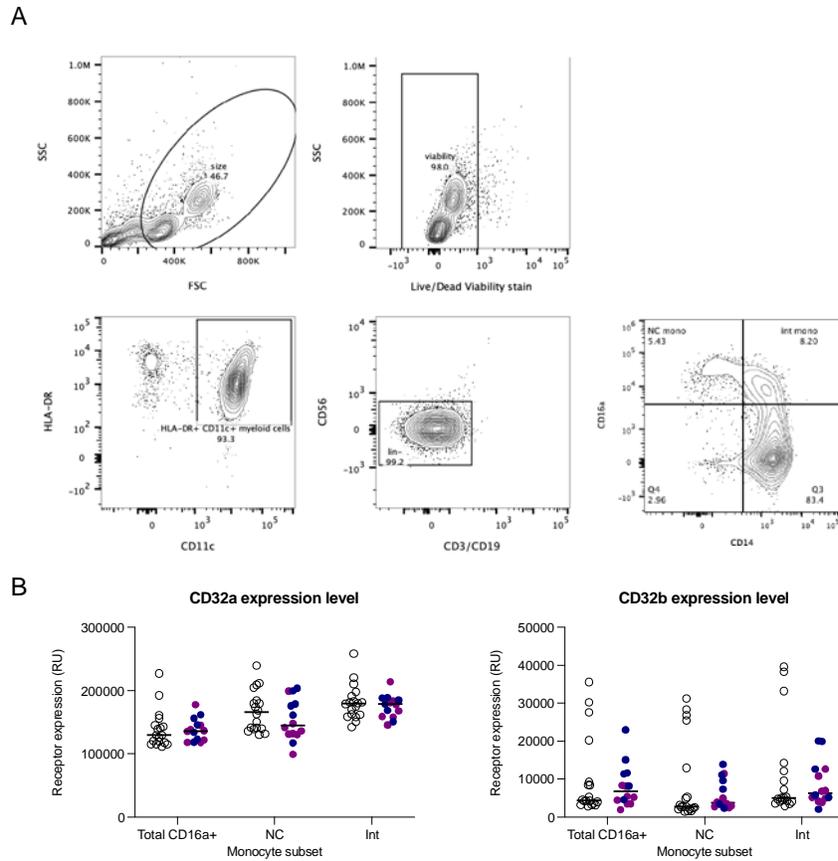
Figure S1



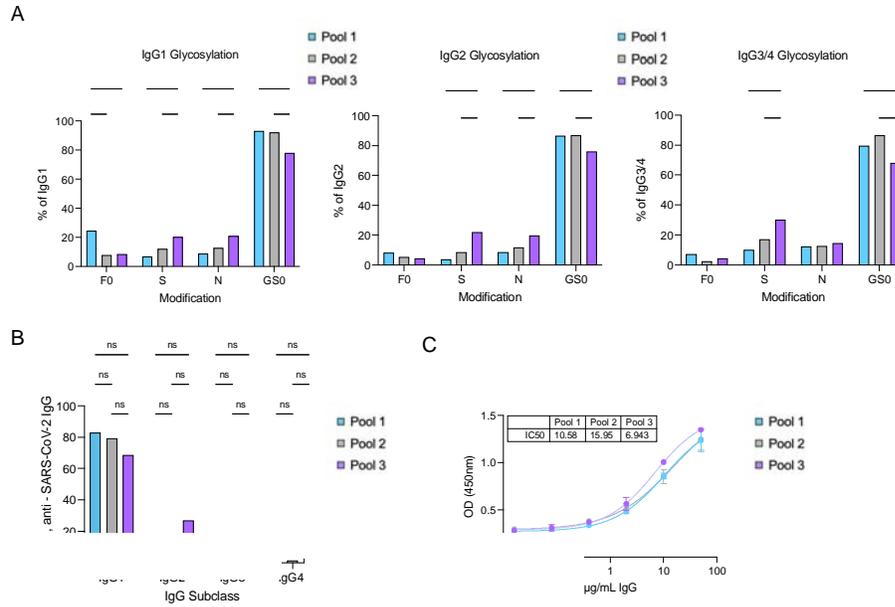
Supplemental Figure S1: (A) Half-maximal SARS-CoV-2 pseudovirus neutralizing titers (pNT₅₀) at each study time point. Left panel: graphed to match format of Figure 1A. Right panel: plotted to clearly show the median pNT₅₀ at each study time point. (B) The kinetics of neutralizing antibody response over time of progressors in Cohort 1. (C) Abundance of SARS-CoV-2 specific afucosylated IgG1 in Cohort 1 COVID-19 outpatients over time (n=19). (D) Multivariate regression analysis to test the contribution of age, sex, weight, or duration since COVID-19 onset on abundance of afucosylated anti-RBD IgG1 in two cohorts. *P < 0.05; **P < 0.01; ***P < 0.001; ****P < 0.0001



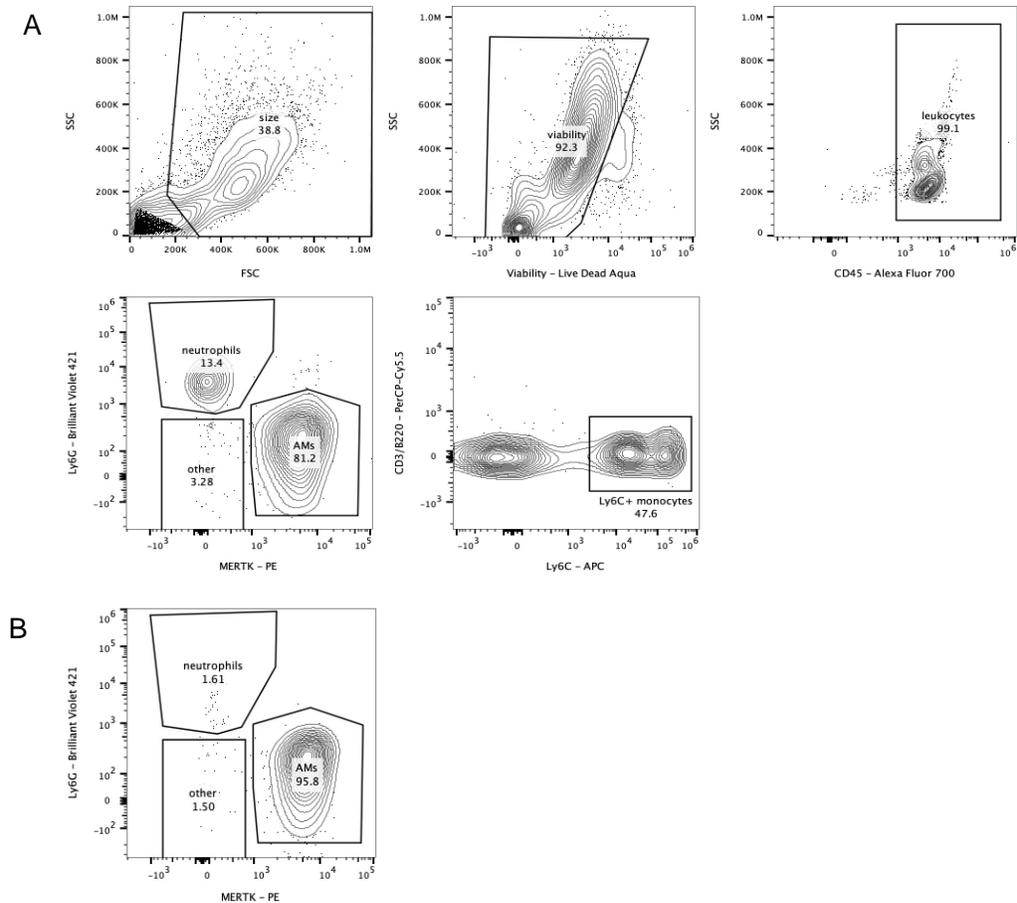
Supplemental Figure S2: (A) Gating strategy for B cell subsets. Total CD19⁺ B cells were assessed from within viable PBMCs. Plasmablasts were further defined as CD19⁺ CD27⁺ CD38⁺⁺. Memory B cells were defined as CD19⁺ CD27⁺ IgD⁻, double negative (DN) B cells were CD19⁺ CD27⁻ IgD⁻, and naïve B cells were CD19⁺ CD27⁻ IgD⁺. (B) FUT8 expression within total viable PBMCs in progressors (P; n=6) and sex-matched non-progressors (NP; n=6). (C) Distribution of B cell subsets (class switched memory B cells (CSMB), non-class switched memory B cells (NCSMB), CD27⁻ IgD⁻ double negative (DNB), plasmablast (PB), and naïve B cells in progressors (P; n = 6), non-progressors (NP, n = 6), and healthy controls (HC, n = 4). P value in (B) was calculated using unpaired Student's t test.



Supplemental Figure S3: (A) Gating strategy for day 0 monocyte subsets and Fc γ R expression. Bulk myeloid cells were defined as viable CD3- CD19- CD56- CD11c+ HLA-DR+ cells, while CD16a+ monocytes within this population were additionally positive for CD16a. Within CD16a+ monocytes, non-classical (NC) monocytes were CD16a+ CD14- while intermediate (int) monocytes were CD16a+ CD14+. **(B)** Fc γ R (CD32a and CD32b) expression levels on myeloid cell subsets. P values were determined by unpaired Student's test.



Supplemental Figure S4: (A) Glycan composition (F0-afucosylation, GS0-Galactosylation, S-Sialylation and N-Bisection) of IgG1, IgG2 and IgG3/4 of the individual purified patient IgG comprising polyclonal pool 1 (F0, F0>20%), pool 2 (F, F0<10%), and pool 3 (VAX) polyclonal pools. (B) IgG subclass distribution of the individual purified patient IgG comprising polyclonal pool 1, pool 2, and pool 3. (C) SARS-CoV-2 full length spike binding of polyclonal pool 1, pool 2, and pool 3. P values in (A-B) were calculated using two-way ANOVA with Šidák's correction. *P < 0.05; **P < 0.01; ***P < 0.001; ****P < 0.0001



Supplemental Figure S5. Gating strategy for immune cell infiltrates in mouse BAL. (A) Neutrophils were defined as viable Ly6G⁺ CD11b⁺ CD3⁻ B220⁻ leukocytes. Monocytes were defined as viable CD11b⁺ Ly6G⁻ MERTK⁻ MHC IA/IE⁻ CD3⁻ B220⁻ or Ly6C⁺ CD11b⁺ Ly6G⁻ MERTK⁻ MHC IA/IE⁻ CD3⁻ B220⁻ leukocytes. (B) Alveolar macrophage were magnetically sorted based on positive expression of MERTK. This sorting method consistently resulted in >90% purity as determined by flow cytometry.

Tables

Table S1. Demographics of the COVID-19 infection cohorts

Stanford Lambda cohort (Cohort 1)	Non-progressor (n=102)	Missing values	Progressor (n=8)	Missing values	p value
Age, years (median, 95%CI)	36 (32.8-38.2)	0	45 (34.4-55.7)	0	ns
Sex Female	45 (44.1%)	0	3 (38%)	0	ns
Race/Ethnicity		0		0	
Latinx	65 (63.7%)		5 (62.5%)		
White	29 (28.4%)		2 (25%)		
Asian	7 (6.9%)		0 (0%)		
Others	1(1%)		1 (12.5%)		
Weight (lbs) (median, 95% CI)	175 (168.1-181.9)	1	198.5 (148.8-248.2)	0	ns
Body mass index (BMI) (median, 95% CI)	27.2 (26.5-28.9)	3	28.8 (23.9-33.7)	0	ns
<25	25 (25.3%)		2 (25%)		
25-30	38 (38.4%)		3 (37.5%)		
>30	36 (36.4%)		3 (37.5%)		
Median days from symptoms onset to study enrollment	4	17	3.5	0	ns
Mean days from symptoms onset to study enrollment	5	17	3.6	0	ns
Median days from randomization to disease resolution	9	0	16	4	ns

Stanford Favipiravir Cohort (Cohort 2)	Non-progressor (n=67)	Missing values	Progressor (n=7)	Missing values	p value
Age, years (median, 95%CI)	40 (36.9-43.1)	0	52 (45.9-58)	0	**
Sex Female	35 (52.2%)	0	3 (42.9%)	0	ns
Race/Ethnicity		4		0	
Latinx	26 (38.8%)		5 (71.4%)		
White	27 (40.2%)		1 (14.3%)		
Asian	7 (10.4%)		0 (0%)		
Others	3(4.5%)		1 (14.3%)		
Weight (lbs) (median, 95% CI)	180 (170.4-189.6)	0	190 (146.5-233.4)	0	ns
Body mass index (BMI) (median, 95% CI)	28.3 (26.8-29.7)	0	30.8 (24.7-37)	0	ns
<25	20 (29.9%)		2 (28.6%)		
25-30	21 (31.3%)		1 (14.3%)		
>30	26(38.8%)		4 (57.1%)		
Median days from symptoms onset to study enrollment	5	3	5	0	ns
Mean days from symptoms onset to study enrollment	5.7	3	6.4	0	ns
Median days from randomization to disease resolution	11	0	16	0	ns

Mount Sinai Cohort	Hospitalized (n=52)
Age, years (median, 95%CI)	65(60.6-69.4)
Sex Female	21(40.4%)
Race/Ethnicity	
Latinx	13 (25%)
White	7 (13.5%)
Asian	3 (5.8%)
Others	29 (55.8%)
Weight (lbs) (median, 95% CI)	N/A
Body mass index (BMI) (median, 95% CI)	26.79(24.6-29.01)
<25	15(28.8%)
25-30	21(40.4%)
>30	16(30.8%)
Median days of sample time point post hospitalization (95% CI)	4(2.87-5.13)

P values were calculated by comparing features between the progressors and non-progressors using unpaired t-tests with Welch's correction or Fisher's t-test.

Table S2. Description of progressors from Cohort 1

Age	Sex	Days of symptoms prior to enrollment	Days to Hospitalization/ED visit post assessment of mild COVID-19
25	Female	3	0; progressive symptoms leading to hospitalization within 24-hours.
58	Male	4	5; progressively worsening respiratory symptoms. Referred to ED by study-associated physician on study day 5.
44	Female	3	1; progressively worsening respiratory symptoms.
34	Male	2	13; worsening symptoms.
47	Male	5	3; two ED visits within first 3 days for worsening respiratory symptoms.
59	Female	7	0; progressive symptoms leading to hospitalization within 24-hours.
28	Male	4	0; progressive symptoms leading to hospitalization within 24-hours.
46	Male	1	2; progressive symptoms leading to hospitalization.

Table S3. Description of progressors from Cohort 2

Age	Sex	Days of symptoms prior to enrollment	Days to Hospitalization/ED visit post assessment of mild COVID-19
44	Female	8	8; worsening respiratory symptoms
54	Male	2	1; sent by study team to ED for worsening respiratory symptoms and leg swelling, resulted in hospitalization
57	Male	4	2; sent by study team to ED for worsening respiratory symptoms; hospitalized
46	Male	5	3; worsening symptoms and new rash
63	Female	10	5; sent by study team to ED for worsening symptoms
52	Male	4	10; sent by study team to ED for worsening respiratory symptoms; hospitalized
50	Female	8	3; sent by study team to ED for worsening respiratory symptoms; hospitalized

Table S4: Demographics of the Stanford Adult Vaccination Cohort

Characteristics	
Age, years (median, 95%CI)	36(28.3-43.7)
Sex Female	11(64.7%)
Race/Ethnicity	
Latinx	0(0.0%)
White	7(41.2%)
Asian	8(47.1%)
Others	2(11.8%)