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Early pandemic molecular diversity of SARS-CoV-2 in children

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26

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29

30 Summary

- 31 Using sequencing and a novel technique for quantifying SARS-CoV-2 diversity, we
- 32 investigated 169 SARS-CoV-2 genomes (83 <21 years old). This analysis revealed
- 33 unexpected diversity especially in children. No clear differences in clinical presentation
- 34 were associated with the different virus lineages.

35 Abstract

36 Background

- In the US, community circulation of the SARS-CoV-2 virus likely began in February
- 38 2020 after mostly travel-related cases. Children's Hospital of Philadelphia began testing
- 39 on 3/9/2020 for pediatric and adult patients, and for all admitted patients on 4/1/2020,
- 40 allowing an early glimpse into the local molecular epidemiology of the virus.

41 Methods

- 42 We obtained 169 SARS-CoV-2 samples (83 from patients <21 years old) from March
- through May and produced whole genome sequences. We used genotyping tools to
- 44 track variants over time and to test for possible genotype associated clinical
- 45 presentations and outcomes in children.

46 **Results**

- 47 Our analysis uncovered 13 major lineages that changed in relative abundance as cases
- 48 peaked in mid-April in Philadelphia. We detected at least 6 introductions of distinct viral
- 49 variants into the population. As a group, children had more diverse virus genotypes than
- 50 the adults tested. No strong differences in clinical variables were associated with
- 51 genotypes.

52 **Conclusions**

- 53 Whole genome analysis revealed unexpected diversity, and distinct circulating viral
- variants within the initial peak of cases in Philadelphia. Most introductions appeared to
- 55 be local from nearby states. Although limited by sample size, we found no evidence that
- 56 different genotypes had different clinical impacts in children in this study.
- 57

58 Background

59 After an initial period in January 2020 when most severe acute respiratory 60 coronavirus 2 (SARS-CoV-2) infections in the US were travel-related, the virus quickly 61 established itself during February with sustained, community spread[1]. Studies tracking the spread of the virus using whole genome phylogenetics suggested multiple 62 63 introductions during this time period from Europe and Asia [2-7], as well as multiple 64 waves of transmission of distinct variants that differ locally[8]. 65 Understanding genotypic diversity in local molecular epidemiology is critical for 66 tracking spread and new introductions, identifying hotspots, and enhancing contact 67 tracing[2, 4, 5, 7]. However, the biological significance of viral diversity is not known. For 68 instance, it is unclear if lineages differ in virulence or transmissibility[4, 9]. It is also 69 unclear if the immune response will be equally protective against all variants of the 70 virus, highlighting the need to understand SARS-CoV-2 diversity and evolution for 71 vaccine development[2, 10]. Moreover, there is little known about viral diversity across 72 the lifespan, with limited data on SARS-CoV-2 genomic diversity in pediatric 73 populations[11]. The first case of coronavirus disease 2019 (COVID-19) in Philadelphia was 74 75 reported on March 10, 2020 (https://www.media.pa.gov/pages/health-76 details.aspx?newsid=734), 14 days after the first non-travel related case was confirmed 77 in California[1] and less than a week after the first cases of community spread in New 78 York State (https://www.governor.ny.gov/news/during-coronavirus-briefing-governorcuomo-signs-40-million-emergency-management-authorization). On March 9th the 79 80 infectious disease diagnostic laboratory (IDDL) at Children's Hospital of Philadelphia

(CHOP) became one of the first locations in the region to offer PCR-based testing for
SARS-CoV-2, and worked with local authorities to provide testing for both children and
adults in the community. On April 1st, CHOP instituted universal screening for all
admitted children.

85 To track the molecular epidemiology of the virus locally in Philadelphia, and 86 especially in a pediatric population, we obtained 169 samples from the initial period of 87 testing between 3/19/2020 to 5/4/2020 and performed whole genome sequencing 88 (WGS). Eighty-three samples were from patients less than 21 years old. We used our 89 genotyping tool GNUVID[8] to classify and compare these strains to the growing global 90 database of SARS-CoV-2 sequences at GISAID[12] (Supplementary Table 1)[13]. Here 91 we show that the early pandemic and peak in Philadelphia were characterized by 92 multiple, diverse, circulating viral variants, especially amongst children. We also 93 observed multiple introductions from distinct geographical origins. We report statistics 94 for clinical presentation and outcomes associated with each viral genotype in children.

95

96 Methods

All nasopharyngeal swab samples that had residual volume after initial laboratory
processing, from individuals that had positive PCR testing for SARS-CoV-2, were
obtained for this study. RNA was extracted from nasopharyngeal swab samples using
either the Roche MagNA Pure LC (Roche) or EZ1 virus mini kit (Qiagen) using magnetic
bead technology. Whole genome sequencing was done by the Children's Hospital Los
Angeles (CHLA) Center for Personalized Medicine and the Virology Laboratory. Briefly,
WGS of extracted viral RNA was performed as previously described using Paragon

104 Genomics CleanPlex SARS-CoV-2 Research and Surveillance NGS Panel[11, 14]. 105 Libraries were quantified using the Agilent High Sensitivity D1000 ScreenTape assay 106 then normalized and pooled on the Biomek i7 liquid handler (Beckman Coulter Life 107 Sciences) to approximately 1nM. The resulting pool was guantified again using the 108 TapeStation High Sensitivity D1000 assay and diluted to a final concentration of 500pM; 109 libraries were denatured and diluted according to Illumina protocols and loaded on the 110 NextSeq 500 at 0.6pM. Paired-end and dual-indexed 2x150bp sequencing was done 111 using NextSeg 500 High Output Kit (300 Cycles).

112 All SARS-CoV-2 genomes (n=169)[13] were gueried against the GNUVID database (version August 17th 2020) that has 32,719 high coverage complete 113 114 genomes[8, 12]. Each genome was assigned an ST profile and CC. A minimum 115 spanning tree (MST) was then constructed using the goeBURST algorithm[15, 16] to 116 group STs into larger taxonomic units, clonal complexes (CCs), which we define as 117 clusters of >20 STs that are single or double allele variants away from a "founder"[8, 118 17]. Temporal plots were extracted using a custom script and plotted in GraphPad 119 Prism v7.0a. The genomes were also assigned to a lineage[2] using pangolin 120 (https://github.com/hCoV-2019/pangolin). A custom script was used to check the 121 specific combinations of 9 GISAID genetic markers, and genomes were assigned to the 122 GISAID clades. The genomes were grouped by different age groups and the relative 123 abundance of the STs and the 13 CCs were calculated. To compare the Shannon 124 diversity index between the different groups[18], a t-test was used to determine whether 125 the indices were significantly different[19].

126 To show the relationship amongst the genomes of the 169 isolates and the global 127 diversity of SARS-CoV-2, a maximum likelihood tree was constructed. Briefly,

128 consensus SARS-CoV-2 sequences for the 169 CHOP isolates were combined with full-

length SARS-CoV-2 sequences of 25,807 additional isolates from GISAID[12] that are

130 part of the GNUVID August database release[17] and have an assigned CC and date of

isolation (Supplementary Table 1)[13] to generate a multiple sequence alignment using

132 MAFFT's FFT-NS-2 algorithm[20] (reference MN908947.3[21], options: --add --

keeplength). The 5' and 3' untranslated regions were masked in the alignment file using

a custom script. A maximum likelihood tree using IQ-TREE 2[22] was then estimated

using the HKY model of nucleotide substitution[23], default heuristic search options, and

ultrafast bootstrapping with 1000 replicates[24]. The tree was rooted to MN908947.3.

137 The tree and the six GISAID clades data were visualized in iTOL[25]. The tree and the

tip dates were then used in TempEst[26] to estimate the evolutionary rate. Similar

procedures were used to construct two trees for both CC4 and CC258 and then

140 estimate the evolutionary rates. Commands used for producing the figures are available

141 in Supplementary Material.

Manual review of the electronic health record was performed for all patients who tested positive for SARS-CoV-2 to obtain data on test characteristics, demographic data, exposures, comorbidities, symptomatology, clinical severity, and treatment information and deidentified. Samples were obtained under CHOP IRB protocol 17-014648 as part of routine clinical care, solely for non-research purposes, carrying minimal risk, and were therefore granted a waiver of informed consent. Summary statistics were used to describe demographic and outcome data. Non-parametric

methods were used due to our small samples size, and to minimize the effect of outliers
on statistical associations. Multivariable logistic regression was used to evaluate the
association between viral sequence types and clinical outcomes. All statistics were
performed with STATA version 15.0, (Stata Corp., College Station, TX). **Results**

Over the time period of this study, CHOP IDDL performed 4486 tests for SARS-CoV-2 of which 246 (5.48%) were positive. Of the 246 positives in patients <21 years of age, we were able to obtain samples from 71 patients. Of the 71 patients, 15 were admitted, 3 to the intensive care unit (ICU), and 2 needed respiratory support. We also obtained samples from 12 other children and 86 adults tested by the CHOP IDDL for a total of 169 sequences in this study.

161 Using the GNUVID classifier[8, 12], we genotyped all 169 genomes and assigned 162 a sequence type (ST), which we define as the group of sequences that have exactly the 163 same allelic haplotype. When possible, each ST was then classified into a clonal 164 complex (CC), defined as a group of STs that differ by only one or two alleles from a 165 central "founder" sequence determined by minimum-spanning clustering[8]. Overall, we 166 identified 112 distinct STs in our data, 108 (165 genomes) of which could be assigned 167 to one of 13 CCs when compared to the most recent global GISAID genome 168 database[8, 12, 17]. While 13 STs (56 genomes) had an exact genotype match in the 169 global database, 99 STs (113 genomes) were novel, with previously unobserved alleles 170 that were not due to sequencing ambiguity based on sequence quality. The genomes 171 were widely distributed across the global SARS-CoV-2 phylogeny suggesting multiple

172 introductions (Figure 1A, Supp Fig. 1A). Temporal mapping of the viral CCs by week of 173 isolation showed the persistent predominance of CC258, but also persistence of 174 multiple, diverse haplotypes in the population (Figure 1B). 175 We estimated the number of putative introductions into our population by 176 comparing our data to high quality sequences from the global GISAID dataset[8, 12, 177 17], and requiring an identical ST to have been isolated in another geographic location 178 at least 10 days prior to the isolation date in our sample. Using this criterion, we 179 identified 6 independent STs that were likely introductions into our population (Table 1). 180 One of these putatively introduced genotypes, ST6228, had only ever been observed in 181 New York State before, and thus likely represents an introduction from this neighboring 182 state. ST338 and ST258 were also observed in New York State in the 10 days prior to 183 appearing in our population, but they were also widespread internationally during this 184 time period, and therefore could have been introduced from other sources. For ST258, 185 isolates were observed during this time window in 24 countries and 22 States including 186 Pennsylvania and other nearby states such as New Jersey. ST4 and ST1531 were 187 observed closest to Philadelphia in Washington DC and Virginia in the 10 days prior to 188 appearing in our population. The most likely international introduction was ST6134, 189 which was seen previously only in Australia. If we shortened the criterion to isolation 5

days prior, we detected 3 more putative introductions. All 3 of these STs were firstobserved in New York.

192 To detect any exportations of viral genotypes, we looked for STs that were seen 193 in our dataset 10 days prior to isolation in another geographic location. Only one 194 possible exportation event was detected of ST13162 to Wisconsin.

It should be noted that our method of detecting introductions relies on robust sampling both in our population and in other locations. The detected number of importations and exportations is likely much higher than the numbers we were able to find here, and estimates may grow as more genome sequences are added from retrospective sampling.

200 The relative abundance of the 13 CCs found in our dataset was distributed 201 differently between children and adults, with the pediatric population showing 202 considerably more diversity (Shannon Entropy=1.815 vs 1.412, P = 0.0132). CC4, an 203 early lineage originally seen in Wuhan, was more prevalent in pediatric cases (20%) 204 compared to adults (14%). CC258, a lineage that predominated in Europe and New 205 York, was more prevalent in adults (55%) compared to children (40%). A more granular 206 analysis of STs recapitulated the higher diversity of viral types in the pediatric 207 population, but did not achieve statistical significance (Shannon Entropy= 2.624 vs 208 2.456, P= 0.3557).

209 One clear difference between our dataset and data from neighboring states over 210 the same time period is the increased diversity of CCs and the presence of the early 211 genotype CC4 (e.g., for NY v. our sample Shannon Entropy=1.69 vs 1.15, P = 4.23E-7). 212 It is unclear whether this reflects specific epidemiology of Philadelphia, our focus on 213 pediatric samples, or other biases in this convenience sample. Interestingly, while there 214 were only 6 STs observed in CC4 (5 STs in children and 2 in adults), there were 57 STs 215 from CC258 (25 STs in children and 38 in adults) demonstrating the much higher 216 diversity of genotypes associated with the CC258 lineage, and potentially the large 217 amount of diversification of this lineage as it peaked to very high numbers in nearby

New York City. To address the cause of this diversity, we calculated mutation rates for CC4 and CC258 genomes using our genomes as well as genomes from the GISAID database using TempEst[26] (Supp Fig 1B). The mutation rate for CC4 was $2.2x10^{-4}$ sites/year while the mutation rate for CC258 was $5.9x10^{-4}$ sites/year. The rate across all GISAID sequences was $7.1x10^{-4}$ in line with previous estimates. It is possible that both had a higher mutation rate and a large effective population size through increased transmission contributed to the higher diversity seen in CC258.

225 To assess the possibility that different genotypes were associated with distinct 226 clinical outcomes and presentations, we collected demographic and clinical information 227 for 71 pediatric viral genomes from patients in the CHOP Care Network. Although 228 limited by the sample size, we were unable to detect any significant differences in 229 specific clinical variables associated with the different genotypes (Tables 2 and 3 and 230 Figure 2). However, exploratory analysis of the data suggested that pediatric patients 231 infected with CC4 lineage virus and early pandemic genotypes (e.g., GISAID lineage L 232 and Pangolin lineage B) may have had increased rates of admission to the hospital 233 (odds ratio, OR 17.2, 95% confidence interval 2.23 to 132.13, P = 0.006) compared to 234 those infected with the CC258 lineage (Supplementary Tables 2, 3 and 4) and lineages 235 considered to be more derived (eq., GISAID lineage GH and Pangolin lineage B.1). In 236 addition, two of the single nucleotide polymorphisms (SNPs) (Table 4 and 237 Supplementary Tables 5 and 6) from more ancestral haplotypes (e.g., C241T, C3037T) 238 were also significantly associated with admission (Supplementary Tables 7, 8, 9 and 239 10). The D614G (SNP; A23403G) spike protein mutation was associated with less 240 hospital admission, albeit not statistically significant (OR 0.23, 95% CI 0.05-1.13)

241	(Supplementary Table 11), but it was the only SNP tested that was significantly
242	associated with decreased odds of being asymptomatic (OR 0.11, 95% CI 0.01-0.92)
243	(Supplementary Table 12).

244

245 Discussion

246 We have shown that the early pandemic in Philadelphia was diverse and 247 dynamic, with multiple likely introductions, most probably from local spread of the virus 248 from neighboring states. Although CC258, the clonal complex thought to have been 249 introduced from Europe that dominated in New York[4, 8], also predominated in our 250 sample across the early pandemic, other CCs were robustly present. For instance, CC4, 251 one of the earliest genotypes seen in Wuhan, persisted throughout the study period 252 demonstrating sustained spread in the community. Other CCs (e.g., CC3530, CC300, 253 CC1508) were also seen persistently in this sample implying sustained community 254 spread. This finding suggests that there was enough viral diversity early in the 255 pandemic that contact tracing may have been significantly enhanced by whole genome 256 (or targeted SNP detection) comparisons.

It is important to note that most of the putative introductions into our population could be traced to nearby states surrounding the Philadelphia area, and only one putative international introduction was detected. This may reflect international travel restrictions in place at this time, but it also suggests that most spread was local, and that there were missed opportunities to limit these events particularly in travel to and from New York. It is important to note that as the database of SARS-CoV-2 genomes grows and more genome sequences are available from the Philadelphia area, we may

find new evidence for introductions or importations, which likely far outnumber thosedetected in our analysis.

266 Although the viral genotypes in our sample differed at several putatively key 267 amino acid locations, we did not detect any stark differences in clinical presentation or 268 outcome in children (Tables 2 and 3). Previous studies have shown that different nucleotide variants or deletions may be associated with higher or lower severity [27, 28]. 269 270 However, the small sample size and higher than expected viral diversity might have led 271 to an inability to discriminate smaller effect sizes. It should also be noted that the 272 retrospective nature of this study, incomplete sampling, and inconsistent capture of 273 symptoms and severity, could have biased these data. Nonetheless, it is still possible 274 that genetic differences between viral lineages may have an impact on virulence or 275 clinical outcome, and our observed differences in admission rates raises the possibility 276 that larger studies may uncover differences in the future. Notably, another recent 277 pediatric study of 141 SARS-CoV-2 in California, which assessed clinical characteristics 278 of 88 patients, demonstrated a possible association between a specific genotype and 279 disease severity[11].

It is also possible that genetic variants may have differential transmission abilities, which could not have been detected directly using our data. However, it is worth noting that the genotypes (CC4, CC750 and CC1508) that have the ancestral alanine residue at position 614 in the spike protein persisted and spread throughout the study period, suggesting that the derived allelic form (A23403G; D614G) that has been proposed to be more transmissible[29] and is predominantly represented by CC258 in our analysis, did not completely dominate the ancestral form over this amount of time.

- Here we also showed much higher diversity in the CC258 lineage and a higher
- estimated mutation for this CC in general. It is possible that this diversity is driven by
- higher transmissibility and a large effective population size.
- 290 Overall, our findings suggest that whole genome sequencing and genotyping of
- 291 circulating clones could be used to track viral spread and identify opportunities for
- intervention to stop spread from specific hotspots. The relationship between viral
- 293 genotype, rate of transmission, and clinical presentation and outcomes deserves further
- 294 exploration with increased sample size.
- 295

296 List of abbreviations

- 297 GNUVID Gene Novelty Unit-based Virus Identification
- 298 ST Sequence Type
- 299 CC Clonal Complex
- 300 SARS-CoV-2 Severe Acute Respiratory Syndrome Corona Virus 2
- 301 COVID-19 Corona Virus Disease 2019
- 302 wgMLST whole genome Multilocus Sequence Typing
- 303

304 Data Sharing Statement

The 169 genomes from our dataset will be available from the corresponding author and available online for download through a permanent Zenodo DOI[13]. Other de-identified clinical data used in the manuscript are available upon request from the corresponding author. The GNUVID compressed database and GNUVID source code can be found in its most up-to-date version here, https://github.com/ahmedmagds/GNUVID, under the

310 GNU General Public License.

311 Authors' contributions

312 AMM & PJP designed and conceptualized the study. AMM contributed to the data 313 collection, data analysis, coding, data interpretation, figures, literature review and 314 tables. WO contributed to the data collection, data analysis, data interpretation, tables, 315 and writing. XG, UP, AR, MB, DTM, LS, DR and DO contributed to the data collection, 316 data analysis, and data interpretation. JDB, JSG, RMH and PJP supervised the study 317 and contributed to the data collection, data analysis, data interpretation, and literature 318 review. AMM and PJP wrote the first draft of the manuscript. All authors reviewed and 319 approved the final manuscript. 320

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334

335 Conflict of Interest Statement

- 336 The authors declare that they have no competing interests and they do not have a
- 337 commercial or other association that might pose a conflict of interest.
- 338

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405	Table 1: Introductions to Philadelphia.
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Specimen Date	ST	CC	Days	Countries in last 10 days before	First time Seen Date
				appearance	
3/19/20	4	4	10	China Iceland Malaysia Singapore United	China/Wuhan 2019-12-30
				Kingdom USA (CA, MI, WI)	
3/24/20	258	258	10	Australia Austria Canada Chile Colombia	Singapore 2020-02-16
				Costa Rica Czech Republic Denmark	
				France Germany Greece Iceland Israel	
				Luxembourg Netherlands Portugal Russia	
				Singapore South Korea Sweden Taiwan	
				United Kingdom USA (AZ, CA, CO, CT,	
				FL, GA, IL, IN, ME, MI, MN, NJ, NM,	
				NY, PA, TX, UN, VA, VI, VT, WA, WI)	
3/30/20	1531	258	10	Denmark USA (DC, VA, CA)	USA/NY 2020-03-14
3/31/20	6134	258	10	Australia	Australia 2020-03-19
3/31/20	6228	258	10	USA (NY)	USA/NY 2020-03-21
4/6/20	338	338	10	Australia, Colombia, USA (NY, WI, MA,	USA/CA 2020-02-29
				CA, CT, MD, FL)	
3/20/20	1623	258	5	USA (NY)	USA/NY 2020-03-12
3/24/20	2261	258	5	USA (NY)	USA/NY 2020-03-19
3/27/20	1841	3530	5	New Zealand, USA (FL)	USA/NY 2020-03-18

406

408 Table 2: Overall characteristics, grouped by clonal complex (excluding those with single isolate or no clonal

409 complex identified).

		Clonal Con	nplex						
	Total	CC258	CC4	CC3530	CC300	CC255	CC844	CC1	CC750
								508	
	71	32	10	7	6	4	3	2	2
Age (years), median	10.91	11.18	7.32 (2.55,	9.96 (4.73,	5.37 (.45,	10.8 (6.6,	8.84	16.5	8.5 (7.6,
(IQR)	(5.6, 17.0)	(7.1, 17.2)	14.75)	18.11)	13.19)	12.8)	(8.84,	(15.8	9.3)
							8.84)	, 19)	
Age Group									
0-12 months	6 (8%)	1 (3%)	1 (10%)	1 (14%)	3 (50%)	0 (0%)	0 (0%)	0	0 (0%)
								(0%)	
1-5 years	12 (17%)	6 (19%)	4 (40%)	1 (14%)	0 (0%)	1 (25%)	0 (0%)	0	0 (0%)
								(0%)	
6-11 years	20 (28%)	10 (31%)	1 (10%)	2 (29%)	1 (17%)	2 (50%)	1 (100%)	0	2
								(0%)	(100%)
12-18 years	24 (34%)	12 (38%)	4 (40%)	1 (14%)	2 (33%)	1 (25%)	0 (0%)	2	0 (0%)
								(67	
								%)	
18-21 years	9 (13%)	3 (9%)	0 (0%)	2 (29%)	0 (0%)	0 (0%)	0 (0%)	1	0 (0%)
								(33	
								%)	
Male sex	32 (45%)	13 (41%)	4 (40%)	5 (71%)	3 (50%)	3 (75%)	2 (67%)	0	1 (50%)
								(0%)	
Race/Ethnicity									
Non-Hispanic White	19 (27%)	8 (25%)	5 (50%)	0 (0%)	2 (33%)	0 (0%)	1 (100%)	0	1 (50%)
								(0%)	
Non-Hispanic Black	38 (54%)	18 (56%)	3 (30%)	7 (100%)	2 (33%)	3 (75%)	0 (0%)	2	1 (50%)
								(67	
								%)	
Hispanic or Latino	7 (10%)	3 (9%)	1 (10%)	0 (0%)	1 (17%)	1 (25%)	0 (0%)	0	0 (0%)
								(0%)	
Multi-racial	2 (3%)	1 (3%)	1 (10%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0	0 (0%)
								(0%)	

Hawaiian or Pacific	1 (1%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	1	0 (0%)
Islander								(33	
								%)	
Other Race or	4 (6%)	2 (6%)	0 (0%)	0 (0%)	1 (17%)	0 (0%)	0 (0%)	0	0 (0%)
Unknown								(0%)	
Insurance status									
Commercial	26 (37%)	13 (41%)	4 (40%)	3 (43%)	2 (33%)	0 (0%)	0 (0%)	0	0 (0%)
Insurance								(0%)	
Government or	40 (56%)	18 (56%)	4 (40%)	4 (57%)	4 (67%)	4 (100%)	1 (100%)	2	1 (50%)
Public Insurance								(67	
								%)	
Self-pay	1 (1%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0	1 (50%)
								(0%)	
Other or Unknown	4 (6%)	1 (3%)	2 (20%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	1	0 (0%)
								(33	
								%)	
Previously Healthy	23 (32%)	12 (38%)	3 (30%)	2 (29%)	2 (33%)	1 (25%)	0 (0%)	1	1 (50%)
								(33	
								%)	
Admitted	15 (21%)	3 (9%)	5 (50%)	3 (43%)	1 (17%)	1 (25%)	1 (33%)	0	1 (50%)
								(0%)	
ICU admission	3 (4%)	0 (0%)	0 (0%)	0 (0%)	1 (17%)	1 (25%)	0 (0%)	0	1 (50%)
								(0%)	
Need for respiratory	2 (3%)	0 (0%)	1 (10%)	0 (0%)	1 (17%)	0 (0%)	0 (0%)	0	0 (0%)
support								(0%)	
Clinical Severity									
Asymptomatic	7 (10%)	2 (6%)	3 (30%)	1 (14%)	1 (17%)	0 (0%)	0 (0%)	0	0 (0%)
								(0%)	
Mild	60 (86%)	29 (94%)	6 (60%)	6 (86%)	4 (67%)	4 (100%)	3 (100%)	2	1 (50%)
								(100	
								%)	
Severe	3 (4%)	0 (0%)	1 (10%)	0 (0%)	1 (17%)	0 (0%)	0 (0%)	0	1 (50%)
								(0%)	

411 Table 3: Symptoms, grouped by clonal complex (excluding those with single isolate or no clonal complex

412 identified).

Factor	Total	CC258	CC4	CC353	CC300	CC255	CC844	CC750	CC1508
				0					
	71	32	10	7	6	4	3	2	2
No Symptoms	8 (11%)	2 (6%)	4	1 (14%)	1	0 (0%)	0 (0%)	0 (0%)	0 (0%)
			(40%)		(17%)				
Fever or cough or shortness of	57	28	5	5 (71%)	5	2	3	2	2
breath	(80%)	(88%)	(50%)		(83%)	(50%)	(100%)	(100%)	(100%)
Fever	38	18	2	5 (71%)	2	2	2 (67%)	2	1 (50%)
	(54%)	(56%)	(20%)		(33%)	(50%)		(100%)	
Cough	41	20	4	4 (57%)	4	1	2 (67%)	1 (50%)	2
	(58%)	(62%)	(40%)		(67%)	(25%)			(100%)
Shortness of Breath	13	8 (25%)	1	1 (14%)	1	0 (0%)	0 (0%)	0 (0%)	1 (50%)
	(18%)		(10%)		(17%)				
Anosmia	5 (7%)	3 (9%)	0 (0%)	1 (14%)	0 (0%)	0 (0%)	1 (33%)	0 (0%)	0 (0%)
Aguesia	4 (6%)	3 (9%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	1 (50%)
Sore Throat	13	8 (25%)	0 (0%)	1 (14%)	1	0 (0%)	2 (67%)	0 (0%)	0 (0%)
	(18%)				(17%)				
Chest Pain	4 (6%)	2 (6%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	1 (50%)
Myalgias	12	5 (16%)	0 (0%)	1 (14%)	0 (0%)	0 (0%)	2 (67%)	1 (50%)	0 (0%)
	(17%)								
Chills	5 (7%)	2 (6%)	0 (0%)	1 (14%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	1 (50%)
Headache	23	11	1	3 (43%)	0 (0%)	2	2 (67%)	1 (50%)	1 (50%)
	(32%)	(34%)	(10%)			(50%)			
Fatigue	7 (10%)	5 (16%)	0 (0%)	1 (14%)	0 (0%)	1	0 (0%)	0 (0%)	0 (0%)
						(25%)			
Gastrointestinal Symptoms	12	8 (25%)	0 (0%)	1 (14%)	1	0 (0%)	0 (0%)	1 (50%)	1 (50%)
	(17%)				(17%)				

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414

415 Table 4: Outcomes, grouped by SNP (excluding those with single type)

C2411		411	1 C3037			3403	C8782	
Value	С	Т	С	Т	А	G	С	Т
71	22	49	15	56	12	59	69	2
15 (21%)	10 (45%)	5 (10%)	7 (47%)	8 (14%)	5 (42%)	10 (17%)	15 (22%)	0 (0%)
3 (4%)	3 (14%)	0 (0%)	1 (7%)	2 (4%)	0 (0%)	3 (5%)	3 (4%)	0 (0%)
2 (3%)	2 (9%)	0 (0%)	1 (7%)	1 (2%)	1 (8%)	1 (2%)	2 (3%)	0 (0%)
7 (10%)	4 (18%)	3 (6%)	3 (20%)	4 (7%)	3 (25%)	4 (7%)	7 (10%)	0 (0%)
60 (86%)	15 (68%)	45 (94%)	10 (67%)	50 (91%)	8 (67%)	52 (90%)	58 (85%)	2 (100%)
3 (4%)	3 (14%)	0 (0%)	2 (13%)	1 (2%)	1 (8%)	2 (3%)	3 (4%)	0 (0%)
	71 15 (21%) 3 (4%) 2 (3%) 7 (10%) 60 (86%)	Value C 71 22 15 (21%) 10 (45%) 3 (4%) 3 (14%) 2 (3%) 2 (9%) 7 (10%) 4 (18%) 60 (86%) 15 (68%)	71 22 49 15 (21%) 10 (45%) 5 (10%) 3 (4%) 3 (14%) 0 (0%) 2 (3%) 2 (9%) 0 (0%) 7 (10%) 4 (18%) 3 (6%) 60 (86%) 15 (68%) 45 (94%)	Value C T C 71 22 49 15 15 (21%) 10 (45%) 5 (10%) 7 (47%) 3 (4%) 3 (14%) 0 (0%) 1 (7%) 2 (3%) 2 (9%) 0 (0%) 1 (7%) 7 (10%) 4 (18%) 3 (6%) 3 (20%) 60 (86%) 15 (68%) 45 (94%) 10 (67%)	Value C T C T 71 22 49 15 56 15 (21%) 10 (45%) 5 (10%) 7 (47%) 8 (14%) 3 (4%) 3 (14%) 0 (0%) 1 (7%) 2 (4%) 2 (3%) 2 (9%) 0 (0%) 1 (7%) 1 (2%) 7 (10%) 4 (18%) 3 (6%) 3 (20%) 4 (7%) 60 (86%) 15 (68%) 45 (94%) 10 (67%) 50 (91%)	Value C T C T A 71 22 49 15 56 12 15 (21%) 10 (45%) 5 (10%) 7 (47%) 8 (14%) 5 (42%) 3 (4%) 3 (14%) 0 (0%) 1 (7%) 2 (4%) 0 (0%) 2 (3%) 2 (9%) 0 (0%) 1 (7%) 1 (2%) 1 (8%) 7 (10%) 4 (18%) 3 (6%) 3 (20%) 4 (7%) 3 (25%) 60 (86%) 15 (68%) 45 (94%) 10 (67%) 50 (91%) 8 (67%)	Value C T C T A G 71 22 49 15 56 12 59 15 (21%) 10 (45%) 5 (10%) 7 (47%) 8 (14%) 5 (42%) 10 (17%) 3 (4%) 3 (14%) 0 (0%) 1 (7%) 2 (4%) 0 (0%) 3 (5%) 2 (3%) 2 (9%) 0 (0%) 1 (7%) 1 (2%) 1 (8%) 1 (2%) 7 (10%) 4 (18%) 3 (6%) 3 (20%) 4 (7%) 3 (25%) 4 (7%) 60 (86%) 15 (68%) 45 (94%) 10 (67%) 50 (91%) 8 (67%) 52 (90%)	Value C T C T A G C 71 22 49 15 56 12 59 69 15 (21%) 10 (45%) 5 (10%) 7 (47%) 8 (14%) 5 (42%) 10 (17%) 15 (22%) 3 (4%) 3 (14%) 0 (0%) 1 (7%) 2 (4%) 0 (0%) 3 (5%) 3 (4%) 2 (3%) 2 (9%) 0 (0%) 1 (7%) 1 (2%) 1 (8%) 1 (2%) 2 (3%) 7 (10%) 4 (18%) 3 (6%) 3 (20%) 4 (7%) 3 (25%) 4 (7%) 7 (10%) 60 (86%) 15 (68%) 45 (94%) 10 (67%) 50 (91%) 8 (67%) 52 (90%) 58 (85%)

416

417 Table 4: Outcomes, grouped by SNP (excluding those with single type)

		G25	5563	T28	3144	G2	8882
	Value	G	Т	С	Т	А	G
N	71	23	48	2	69	6	65
Admitted	15 (21%)	8 (35%)	7 (15%)	0 (0%)	15 (22%)	1 (17%)	14 (22%)
ICU admission	3 (4%)	3 (13%)	0 (0%)	0 (0%)	3 (4%)	1 (17%)	2 (3%)
Need for respiratory support	2 (3%)	2 (9%)	0 (0%)	0 (0%)	2 (3%)	1 (17%)	1 (2%)
Clinical Severity							
Asymptomatic	7 (10%)	4 (17%)	3 (6%)	0 (0%)	7 (10%)	1 (17%)	6 (9%)
Mild	60 (86%)	16 (70%)	44 (94%)	2 (100%)	58 (85%)	4 (67%)	56 (88%)
Severe	3 (4%)	3 (13%)	0 (0%)	0 (0%)	3 (4%)	1 (17%)	2 (3%)

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424 Figure Legends

Figure 1. SARS-CoV-2 diversity from testing at our center. **A.** Minimum spanning tree

426 (MST) of 32,719 SARS-CoV-2 genomes showing 17,615 Sequence Types (STs) and 70

427 clonal complexes (CCs). The MST represents the most recent dataset used in GNUVID

- 428 as of August 17th. The reported 13 CCs at CHOP are in black. The pie charts show the
- 429 percentage distribution of genomes from the different geographic regions in each CC.
- 430 **B.** Temporal Plot of 13 circulating CCs representing the 169 genomes in this study and
- their relative abundance in Pennsylvania (PA) and the neighboring states; New York
- 432 (NY), New Jersey (NJ), Virginia (VA), Maryland (MD) and District of Columbia (DC).
- 433 Weeks 1, 2, 3, 4and 5 are from 03/19-03/25, 03/26-04/1, 04/02-04/08, 04/23-04/29 and
- 434 04/30-05/04, respectively. The GISAID clades corresponding to the CCs are reported in
- 435 parentheses.
- 436
- 437

Figure 2. SARS-CoV-2 diversity across different age groups in our sample. **A.** Relative abundance of circulating CCs between pediatrics (\leq 21 years old) and adults. **B.** Relative abundance of circulating STs between children (\leq 21 years old) and adults. **C.** Relative abundance of circulating CCs in 5-year age groups. **D.** Relative abundance of circulating CCs in childhood age ranges (\leq 21 years old). Relative abundance is the ratio of the number of genomes belonging a certain CC (lineage) divided by the total number of genomes in a certain time window. The numbers on the bars represent the

total number of genomes in each group.





