

1 **When can we stop wearing masks? Agent-based modeling to identify when vaccine**
2 **coverage makes nonpharmaceutical interventions for reducing SARS-CoV-2 infections**
3 **redundant in indoor gatherings**
4

5 **Authors:** Trevor S. Farthing¹ & Cristina Lanzas^{1*}

6 ¹North Carolina State University, Raleigh, North Carolina, USA

7 *Correspondence to Cristina Lanzas (Mailing Address: 1051 William Moore Dr., RB410,

8 Raleigh, NC 27606 | Email: clanzas@ncsu.edu | Phone: 919-513-6202)

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11

12 **Abstract:** As vaccination efforts to combat the COVID-19 pandemic are ramping up worldwide,
13 there are rising concerns that individuals will begin to eschew nonpharmaceutical interventions
14 for preventing SARS-CoV-2 transmission and attempt to return to pre-pandemic normalcy
15 before vaccine coverage levels effectively mitigate transmission risk. In the U.S.A., some
16 governing bodies have already weakened or repealed guidelines for nonpharmaceutical
17 intervention use, despite a recent spike in national COVID-19 cases and majority population of
18 unvaccinated individuals. Recent modeling suggests that repealing nonpharmaceutical
19 intervention guidelines too early into vaccine rollouts will lead to localized increases in COVID-
20 19 cases, but the magnitude of nonpharmaceutical intervention effects on individual-level SARS-
21 CoV-2 infection risk in fully- and partially-vaccinated populations is unclear. We use a
22 previously-published agent-based model to simulate SARS-CoV-2 transmission in indoor
23 gatherings of varying durations, population densities, and vaccination coverage levels. By
24 simulating nonpharmaceutical interventions in some gatherings but not others, we were able to
25 quantify the difference in SARS-CoV-2 infection risk when nonpharmaceutical interventions

26 were used, relative to scenarios with no nonpharmaceutical interventions. We found that
27 nonpharmaceutical interventions will often reduce secondary attack rates, especially during brief
28 interactions, and therefore there is no definitive vaccination coverage level that makes
29 nonpharmaceutical interventions completely redundant. However, the reduction effect on
30 absolute SARS-CoV-2 infection risk conferred by nonpharmaceutical interventions is likely
31 proportional to COVID-19 prevalence. Therefore, if COVID-19 prevalence decreases in the
32 future, nonpharmaceutical interventions will likely still confer protective effects but potential
33 benefits may be small enough to remain within “effectively negligible” risk thresholds.

34

35 **Keywords:** agent-based model, COVID-19, indoor transmission, nonpharmaceutical
36 interventions, SARS-CoV-2, vaccine

37 **Introduction**

38 Global vaccine rollout to combat the Coronavirus Disease 2019 (COVID-19) pandemic is
39 well underway, with at least different seven vaccines approved for distribution by different
40 countries (WHO 2021). In the U.S.A., where three vaccines have been approved for distribution
41 (CDC 2021a), 24.8% of the population has been fully vaccinated against COVID-19 as of April
42 17th 2021 (CDC 2021b). Despite ongoing vaccine rollouts, as of April 17th 2021, there is an
43 indication that COVID-19 cases are surging in some U.S. states (NY Times 2021). In spite of
44 rising case numbers, several U.S. states have recently rescinded, or allowed to expire, policies
45 mandating use of nonpharmaceutical intervention in public spaces, with seemingly no intention
46 of reinstating them in the near future (State of Iowa 2021; State of Mississippi 2021; State of
47 Texas 2021). Population-level epidemiological models of vaccine rollout effects on COVID-19
48 transmission suggest that discontinuing nonpharmaceutical intervention use early into the
49 vaccination effort leads to a subsequent surge in COVID-19 cases and related hospitalizations
50 and deaths (Gozzi et al. 2021; Moore et al. 2021).

51 The magnitude of nonpharmaceutical intervention effects on individual-level SARS-
52 CoV-2 infection risk in fully- and partially-vaccinated populations is unclear. This information is
53 crucial for identifying vaccination levels at which it would be appropriate to scale-back
54 guidelines for nonpharmaceutical interventions, as it would allow governing bodies to base
55 policies on concrete risk estimates. The United States Centers for Disease Control and
56 Prevention (CDC) has updated guidelines on safe gathering protocols, recommending that groups
57 of fully-vaccinated people can now safely interact amongst themselves, or with small groups of
58 unvaccinated people at low risk for developing severe COVID-19, without utilizing any
59 nonpharmaceutical Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2)

60 transmission interventions (e.g., face coverings, 2-m social distancing, etc.) (CDC 2021c).

61 However, the guidelines also recommend to continue avoiding medium to large gatherings, and
62 the use of nonpharmaceutical interventions in public and when gathering with unvaccinated
63 individuals. This caution stems from the incomplete knowledge of vaccine effectiveness across
64 different populations, their effects on transmission, and the potential change on vaccine
65 effectiveness caused by the emergence of new SARS-Cov-2 variants.

66 The problem with citing vaccination efforts as a justification for discontinuing
67 nonpharmaceutical interventions is twofold. First and foremost, the majority of the U.S.
68 population is not yet fully vaccinated (CDC 2021b), and therefore presumably has little-to-no
69 immunity from SARS-CoV-2 infections. Secondly, while there is growing evidence that these
70 vaccines reduce SARS-CoV-2 infection risk in addition to COVID-19 incidence, vaccines may
71 not confer complete immunity or block transmission (Hall et al. 2021; Lipsitch & Kahn 2021;
72 Yellen et al. 2021). Data suggest that the BNT162b2 mRNA vaccine (i.e., the vaccine developed
73 by Pfizer-BioNtech) may be $\approx 72\%$ effective at preventing laboratory-confirmed SARS-CoV-2
74 infections after a single dose, and $\approx 86\text{-}92\%$ two weeks following the second dose (Hall et al.
75 2021; Yellen et al. 2021). Furthermore, this vaccine may reduce viral loads, a potential proxy for
76 infectiousness, in infected individuals by 3-4 times (Levine-Tiefenbrun et al. 2021). Less
77 information is available on the ability of the other two vaccines approved for U.S. distribution to
78 reduce SARS-CoV-2 infections, but Lipsitch & Kahn (2021) do estimate that mRNA-1273 (i.e.,
79 the vaccine developed by Moderna and NIAID) can reduce individual-level infection risk by at
80 least 61% following the first dose. Despite potentially-high infection-reduction efficacies,
81 without vaccines that confer complete immunity from infection or prevent transmission from
82 infectious individuals, it will be difficult to halt SARS-CoV-2 circulation in the population

83 through vaccination efforts alone (Gozzi et al. 2021; Moore et al. 2021). Considering that most
84 people also have yet to be fully vaccinated, guidelines that advocate phasing out
85 nonpharmaceutical interventions during interpersonal interactions may be premature at this time.

86 In Farthing & Lanzas (2021), we described an agent-based model (ABM) for simulating
87 indoor respiratory pathogen transmission. We previously used this model to quantify effects of
88 nonpharmaceutical interventions on reducing SARS-CoV-2 transmission risk during an indoor
89 superspreading event (Farthing & Lanzas 2021). Here, we use it to simulate SARS-CoV-2
90 transmission in indoor gatherings of varying durations, population densities, and proportional
91 vaccination coverage. By simulating nonpharmaceutical interventions in some gatherings but not
92 others, we were able to quantify the difference in SARS-CoV-2 infection risk when
93 nonpharmaceutical interventions were used in conjunction with vaccination efforts, relative to
94 scenarios with no nonpharmaceutical interventions. Using these data, we demonstrate how
95 interested parties can easily estimate the potential reduction in SARS-CoV-2 infection risk
96 attributable to nonpharmaceutical interventions, and try to answer the question: “at what point
97 during vaccine rollout are gatherings without non-pharmaceutical measures safe?”

98

99 **Methods**

100 We used the ABM we first described in Farthing & Lanzas (2021) to simulate the effect
101 of increasing vaccination coverage and nonpharmaceutical interventions on SARS-CoV-2
102 transmission risk during indoor gatherings. The simulation input levels and parameter values we
103 used are given in Table 1. We made the assumptions that any infectious individuals at gatherings
104 would be asymptomatic because symptomatic people would consciously decide to stay away,
105 and that no one with partial immunity exists within the group of attendees. Vaccinated people

106 had a fixed probability of becoming completely immune to SARS-CoV-2 infection (Table 1),
107 and those that did not become immune remained susceptible to infection (i.e., ‘all-or-nothing’
108 vaccine). Finally, we only simulated use of cloth face coverings, rather than notably more-
109 effective masks like N95s, because we make the assumption that the majority of Americans have
110 ready access to, and are more-likely to use cloth masks.

111 All simulations were carried out within the open-source modeling software, NetLogo
112 (Ver. 6.1.1 – Wilensky 1999). We executed a factorial simulation run in the NetLogo
113 BehaviorSpace using our specified input levels, and ran 200 simulations replicates of each
114 parameter set combination when the nonpharmaceutical interventions were included and when
115 they were not. We ran these factorial combination sets separately in order to save computation
116 time as there were two inputs (i.e., mask efficacy, attempted social distance) that only changed
117 when nonpharmaceutical interventions were simulated. We ultimately produced 1,612,800
118 simulations without nonpharmaceutical interventions, and 9,676,800 including them (i.e.,
119 11,289,600 total simulations). We recorded the number of susceptible individuals infected in
120 each simulation, and aggregated this information into a single data set prior to analysis.

121 We reported the mean probability of observing ≥ 1 successful infection event(s) and
122 mean secondary attack rates in indoor gatherings when an asymptomatic person was also in
123 attendance across factorial combinations of “between-group comparison” variables (Table 1).
124 Secondary attack rates here were calculated by dividing the number of people that were infected
125 at the gathering by the number of “healthy” people at the start of the gathering, and can also be
126 considered to be the individual-level probability of a previously healthy attendee being infected
127 at the gathering. To assess the difference between protection conferred by the simultaneous
128 deployment of pharmaceutical and nonpharmaceutical interventions, versus use of only

129 nonpharmaceutical interventions, we first smoothed the observed mean secondary attack rates
130 (μ) by fitting them to a beta regression model with a fixed unknown precision parameter, ϕ using
131 a logit link function to map (0,1) values (Ferrari & Cribari-Neto 2004). The specific model is
132 given by:

$$\ln\left(\frac{\mu}{1-\mu}\right)(\phi) = (\phi)\beta_0 + \beta_1(\text{Gathering duration}) + \beta_2(\text{Intervention level}) + \beta_3(\text{Vaccine coverage}) + \beta_4(\text{Vaccine efficacy}) + \beta_5(\text{Vaccine coverage} * \text{Vaccine efficacy}),$$

135 (1)

136 where “Intervention level” is a categorical variable containing the following mutually-exclusive
137 levels: “cloth face masks & vaccination,” “cloth face masks & 2-m social distancing &
138 vaccination,” and “vaccination only.” Additionally, “Vaccine efficacy” here refers to the ability
139 of vaccines to induce complete immunity to infection. “Vaccine coverage” and “Vaccine
140 efficacy” are given in terms of decimal percent, not percentage points (e.g., 0.1, not 10%).
141 Because beta regression models assume all dependent variable values fall between 0 and 1, we
142 used the data transformation procedure described by (Cribari-Neto & Zeileis, 2010) to reconstruct
143 our proportion data without these extremities prior to model fitting. We used the pseudo- R^2
144 calculation procedure given by Ferrari & Cribari-Neto (2004) to assess the goodness of fit for
145 our regression model.

146 After fitting our data, we used the regression model to predict the mean secondary attack
147 rates during a 60-minute gathering with a single asymptomatic person in attendance across the
148 complete factorial combination of covariate inputs described in Table 2. We report the difference
149 between predicted values when all interventions (i.e., cloth face masks & 2-m social distancing
150 & vaccination) are utilized, and predicted values assuming vaccinations are the only
151 interventions. All analyses and plotting were carried out using functions from the “betareg”

152 (Ferrari & Cribari-Neto 2004) and “ggplot2” (v. 3.3.2, Wickham 2016) R packages, respectively,
153 in RStudio (v. 1.1.463, RStudio Team, Boston, MA) (RStudio Team 2018) running R (v. 3.6.2, R
154 Foundation for Statistical Computing, Vienna, Austria) (R Core Team 2020).

155

156 **Results & Discussion**

157 We found that the probability of ≥ 1 successful transmission event generally increased
158 with population density (Fig. 1). This is unsurprising, as SARS-CoV-2 transmission in this ABM
159 is highly sensitive to within-room population density (Farthing & Lanzas 2021). We observed
160 that at low population densities and/or short-duration gatherings, the use of nonpharmaceutical
161 interventions can significantly reduce the probability of successful transmission. Furthermore, it
162 is clear that at low population densities, 2-m social distancing confers additional protective
163 effects when used in conjunction with cloth face coverings, even during relatively-long duration
164 gatherings. This is consistent with what we observed when we used the same ABM to directly
165 compare the effectiveness of varied nonpharmaceutical interventions to prevent SARS-CoV-2
166 transmission during a superspreading event (Farthing & Lanzas 2021). We found that cloth face
167 masks alone conferred few protective effects in long-duration gatherings.

168 The probability of transmission events occurring was unlikely to reach $\approx 0\%$ outside of
169 scenarios with low population density and multiple nonpharmaceutical interventions, or $\geq 95\%$
170 vaccine coverage and vaccines that were 100% effective at preventing infections. Given that 1)
171 current estimates place SARS-CoV-2 vaccine efficacies against infection between 60-90% (Hall
172 et al. 2021; Lipsitch & Kahn 2021; Yellen et al. 2021), 2) historical precedence suggesting adult
173 populations will fall well short of these high vaccination levels (Applewhite et al. 2020; CDC
174 2020), and 3) the difficulty government institutions have had enforcing nonpharmaceutical

175 intervention policies (Jacobs & Ohinmaa 2020; Pedersen & Favero 2020), it is unlikely that these
176 scenarios will be representative of average real-world gatherings. Moreover, in 60-min gathering
177 scenarios, the probability of ≥ 1 successful transmission event occurring is relatively high even
178 when gathering attendees utilize nonpharmaceutical interventions and most are vaccinated.

179 The probability that ≥ 1 SARS-CoV-2-positive individual is in attendance at a gathering
180 can be calculated as

$$181 \qquad \qquad \qquad 1 - (1 - p)^n, \qquad \qquad \qquad (2)$$

182 where p is the local COVID-19 prevalence, and n is the number of people at the gathering
183 (Chande et al. 2020). The prevalence of infectious cases (p) can be highly uncertain because of
184 the variable testing effort across time and space, but it can be estimated by assuming that any
185 SARS-CoV-2-positive individuals are infectious at time of testing and will remain infectious for
186 a given period of time. Additionally, ascertainment bias can be factored in. The probability that a
187 given individual will be infected at a gathering is then

$$188 \qquad \qquad \qquad (1 - (1 - p)^n)q_i, \qquad \qquad \qquad (3)$$

189 where q_i is the probability that individual i will be infected given exposure to an asymptomatic
190 individual at the gathering. Effectively, what we report in Fig. 2 are estimates of q_i under
191 different circumstances. Our findings suggest that cloth-based mask use, with or without 2-m
192 social distancing, often does not confer significant protective effects during long-duration
193 gatherings (Fig. 2), we have also shown that implementing these nonpharmaceutical
194 interventions can reduce overall transmission probability (Fig. 1) and secondary attack rates (Fig.
195 2, Table 3) during brief interactions or gatherings with relatively-few people (e.g., fewer than 10
196 people, the limit for indoor and/or outdoor social gatherings enforced by some U.S. states
197 (MultiState 2021)). This effectively means that strict guidelines for continued nonpharmaceutical

198 intervention use will likely help to mitigate SARS-CoV-2 spread, and therefore COVID-19
199 incidence, for as long as these policies are in effect.

200 As vaccine coverage increases, the question now becomes “how much elevated risk is
201 acceptable in the absence of nonpharmaceutical interventions?” If we let q'_i denote the
202 probability that individual i will be infected given exposure to an asymptomatic individual at a
203 gathering where no nonpharmaceutical interventions were in place, and q_i^* denote the probability
204 that individual i will be infected given exposure to an asymptomatic individual at a gathering
205 where some level of nonpharmaceutical interventions were in place, then the relative effect of
206 nonpharmaceutical interventions on reducing infection risk is equal to

$$207 \quad \frac{q_i^*}{q'_i} * 100\%. \quad (4)$$

208 By quantifying covariate effects in our beta-regression model, we provide interested
209 parties with a formula that can be used to quickly determine generalized q'_i or q_i^* values, without
210 the need for running a large number of simulations. Due to the logit link function we used, the
211 mean secondary attack rates in our ABM simulations (μ) can be predicted using the equation

$$213 \quad \mu = \frac{e^{\beta_0 + \beta_1(\text{Gathering duration}) + \beta_2(\text{Intervention level}) + \beta_3(\text{Vaccine coverage}) + \beta_4(\text{Vaccine efficacy}) + \beta_5(\text{Vaccine coverage} * \text{Vaccine efficacy})}}{1 + e^{\beta_0 + \beta_1(\text{Gathering duration}) + \beta_2(\text{Intervention level}) + \beta_3(\text{Vaccine coverage}) + \beta_4(\text{Vaccine efficacy}) + \beta_5(\text{Vaccine coverage} * \text{Vaccine efficacy})}} \quad (5)$$

215 (Ferrari & Cribari-Neto 2004). Our regression model had a pseudo- R^2 of 0.37. Given the number
216 of stochastic processes in our ABM and the variability purposely introduced into simulations
217 (Table 1), we believe the explanatory power of the model is acceptable for our purposes here.
218 Assuming mean population-level vaccine efficacies of 60% and 80%, which we believe are
219 conservative estimates for U.S.-approved vaccine efficacies, our regression model consistently

220 predicts that secondary attack rates decrease by 55-58% when attendees utilize cloth masks and
221 2-m social distancing, regardless of gathering duration (Fig. 3). However, it is important to
222 reiterate that here we estimate the probability of infection given contact with an infectious
223 individual at a gathering (q_i) and comment on the relative risk difference attributable to
224 intervention use. This should not be confused with the absolute risk of becoming infected at a
225 gathering (*see* Equation 3). We demonstrate the difference in Figure 4, which is a simplistic
226 example intended to show that even at relatively high COVID-19 prevalence levels, 20 people
227 gathering indoors for 60 minutes have a substantially-lower individual-level risk of SARS-CoV-
228 2 infections than is suggested by q_i alone. Though predicting intervention effects on community-
229 level COVID-19 prevalence and infection-related events (e.g., symptom-onset, mortality, or
230 hospitalization) is outside the scope of our model, our simulations do suggest that secondary
231 attack rates are negatively correlated with vaccine coverage. Given that we expect local COVID-
232 19 prevalence to eventually follow similar trends (Gozzi et al. 2021), the relative impact of
233 nonpharmaceutical interventions on infection risk reduction will likely decrease over time as
234 vaccine rollouts continue.

235 In addition to being unable to comment on community-level infection metrics, there are a
236 few other limitations associated with our results that we must acknowledge. Aside from the
237 ABM design limitations outlined in Farthing et al. (2021), we make a number of assumptions in
238 our simulations. Most of these assumptions are directly tied to our parameter space detailed in
239 Table 1, and include such things as: in simulated gatherings only one asymptomatic individual
240 was in attendance, no individuals wear masks with exposure-reduction efficacies $> 50\%$ and
241 therefore we are not simulating the use of N95 or similar masks, and there is no simulated
242 forced-air ventilation or infectious individuals that produce superspreader-level of contaminated

243 aerosols (e.g., 970 quanta (Miller et al. 2020)). Additionally, we do not simulate activity-specific
244 behaviors and individuals in our simulations were unmoving. Finally, we based the
245 infectiousness of asymptomatic individuals on the estimate given by Buonanno et al. (2020) (i.e.,
246 142 quanta/hr), and to relate this estimate to ABM parameters we used the linear model
247 described in Farthing et al. (2021). However, this parameterization procedure may have over-
248 inflated virion transmissibility in certain scenarios because quanta-estimates are room-size
249 specific, and the Farthing et al. (2021) linear model was based on simulations of gatherings
250 within a relatively large room. In short, our results must be viewed through the lens of simulated
251 world parameters and behaviors, and likely will not wholly reflect all variability that may exist in
252 real-world transmission events. This is very common for ABM-based studies however, and we
253 feel that our model is sufficiently accurate to highlight general trends in indoor SARS-CoV-2
254 transmission and infection risk.

255

256 **Conclusions**

257 We found that nonpharmaceutical interventions will often reduce secondary attack rates,
258 especially during brief interactions, and therefore there is no definitive vaccination coverage
259 level that makes nonpharmaceutical interventions completely redundant. However, the beneficial
260 effect on absolute SARS-CoV-2 infection risk reduction conferred by nonpharmaceutical
261 interventions used during indoor gatherings is likely proportional to COVID-19 prevalence.
262 Therefore, if U.S. COVID-19 prevalence decreases in the future, nonpharmaceutical
263 interventions will likely still confer protective effects, but any potential benefits may be small
264 enough to remain within “effectively negligible” risk thresholds.

265

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268

269 **Author Contributions**

270 Trevor Farthing led the model creation, data analysis, and manuscript writing, but both
271 authors conceived the ideas presented herein, contributed to model development and writing
272 efforts, and gave final approval for publication. Cristina Lanzas secured the funding.

273

274 **Data availability**

275 We first made our ABM publicly available for download in Farthing et al. (2021). The
276 current iteration can be downloaded from the Lanzas lab's github repository at
277 <https://github.com/lanzaslab/droplet-ABM>.

278

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396

397 Tables

Parameter/Model Input	Purpose [‡]	Value(s)	Reference(s)
<i>Infectiousness parameters</i>			
Droplet count (droplets/expectoration)[†]	Fixed value	1.42e ⁵	Buonanno et al. 2020, Farthing & Lanzas 2021
Droplet spread angle – not coughing (°)	Fixed value	63.5	Kwon et al. 2012
Droplet travel distance – not coughing (m)	Fixed value	0.55 (0.068) ^{§§}	Das et al. 2020
Vaccine-induced infectiousness reduction (%)	Within-group variation	0, 25, 50, 75	Vaccination may reduce infectiousness of asymptomatic individuals by as much as 75%, but effects are unclear (Levine-Tiefenbrun et al. 2021).
<i>Scenario environment and individual behavior inputs</i>			
Area (m²)[*]	Within-group variation	36, 81, 225	–
Expectoration height (m)	Fixed value	1.7	Fryar et al. 2018
Inhalation rate (m³ air/min)	Fixed value	0.023	Adams 1993
Maximum people in a single 1-m² patch (people)	Fixed value	2	–
Number of asymptomatic infectious individuals (people)	Fixed value	1	–
<i>Scenario virion behavior inputs</i>			
Virion count (virions/mL fluid)	Fixed value	2.35e ⁹	Wölfel et al. 2020
Virion decay rate (%/min)	Fixed value	1.05	van Doremalen et al. 2020

Virion infection risk (%/inhaled virion)	Fixed value	6.24	Farthing & Lanzas 2021
Scenario airflow inputs			
Diffusion rate (m³/min)	Fixed value	1.5e ⁻³	Castillo & Weibel 2018
Forced airflow	Fixed value	off	–
Scenario intervention inputs			

Nonpharmaceutical intervention scenarios	Between-group comparison: intervention combinations	Within-group variation: mask efficacy	<ul style="list-style-type: none"> Mask use (10% exposure-reduction efficacy), 2m attempted social distancing 	
			<ul style="list-style-type: none"> Mask use (25% exposure-reduction efficacy), 2m attempted social distancing 	
			<ul style="list-style-type: none"> Mask use (50% exposure-reduction efficacy), 2m attempted social distancing 	Mask use is intended to represent use of <i>cloth</i>
			<ul style="list-style-type: none"> Mask use (10% exposure-reduction efficacy), no attempted social distancing 	masks to prevent exposure to infectious media.
			<ul style="list-style-type: none"> Mask use (25% exposure-reduction efficacy), no attempted social distancing 	Cloth mask efficacy is highly variable (O’kelly et al. 2020).
			<ul style="list-style-type: none"> Mask use (50% exposure-reduction efficacy), no attempted social distancing 	
			<ul style="list-style-type: none"> No nonpharmaceutical interventions 	

Gathering duration (min)	Between-group comparison	10, 60	–
Vaccine efficacy for preventing infection (%)	Between-group comparison	50, 65, 80, 100	–
Vaccine coverage (%)	Between-group comparison	0:100 by 5	–
Population density (people/m ²)**	Between-group comparison	0.17, 0.33, 0.67, 1	–

398 **Table 1.** Model parameter and scenario-specific input descriptions for transmission simulations.

399 *All simulated worlds were square-shaped. ¶The Purpose column describes why the parameter or
400 input was included as it relates to analyses. Specifically, “Fixed value” indicates that values are
401 unchanged across all simulations, and are thus irrelevant for analyses. “Between-group
402 comparison” indicates that levels were used in factorial combinations for data aggregation and
403 reporting. “Within-group variation” indicates that different levels were included to increase the
404 variation in simulation results, and by doing so increase model realism. †Based on linear
405 modeling described in Appendix S2 of Farthing & Lanzas (2021), this value equates to 142
406 quanta/hr, the average quanta emission rate for asymptomatic people calculated by Buonanno et
407 al. (2020). ‡Standard deviation is given in parentheses. §Das et al. (2020) estimated the average
408 travel distance of a 100-micrometer droplet expelled from a height of 1.7 m at a velocity of 0.5
409 m/s to be 0.55 m. They also found that the majority of 100-µm droplets will fall 0.55-2.35 m
410 away from the expelling individual, depending on initial velocity, but droplets may settle up to
411 3.2 m away very rarely. A random draw of 10,000,000 samples from a log-normal distribution
412 parameterized using 1.7-m and 0.2095-m droplet spread distance mean and standard deviation
413 values, respectively, generated a distribution in line with this finding. The standard deviation we
414 use in simulations for non-coughing exhalation is proportionate to the one used in this random
415 draw. **Instead of specifying a fixed number of individuals in simulations, we scaled the
416 simulated population with world size.

417

Covariate	Value(s)
Gathering duration	60 min
Intervention level	<ul style="list-style-type: none"> • cloth face masks & 2-m social distancing & vaccination • vaccination only
Vaccine coverage	0:1 by 0.1
Vaccine efficacy	0.6, 0.8

418 **Table 2.** Covariate values used for prediction in our example.

419

Coefficient	Estimate	<i>p</i>
Intercept	-3.786 (-3.857, -3.716)	–
ϕ	28.899 (28.336, 29.462)	–
Gathering duration (min)	0.012 (0.011, 0.012)	< 0.001
Intervention level		
<i>Cloth face masks & 2-m social distancing & vaccination*</i>	0 (0, 0)	–
<i>Cloth face masks & vaccination</i>	0.761 (0.737, 0.785)	< 0.001
<i>Vaccination only</i>	0.889 (0.866, 0.913)	< 0.001
Vaccine coverage	0.783 (0.660, 0.905)	< 0.001
Vaccine efficacy	0.385 (0.297, 0.472)	< 0.001
Vaccine coverage X Vaccine efficacy	-2.652 (-2.816, -2.487)	< 0.001

420 **Table 3.** Logit scale estimates associated with 1-unit increases in covariate values given by our
 421 beta-regression model. Wald 95% confidence intervals are given in parentheses. *This is the
 422 reference level used to establish a baseline for binary dummy variables.

423

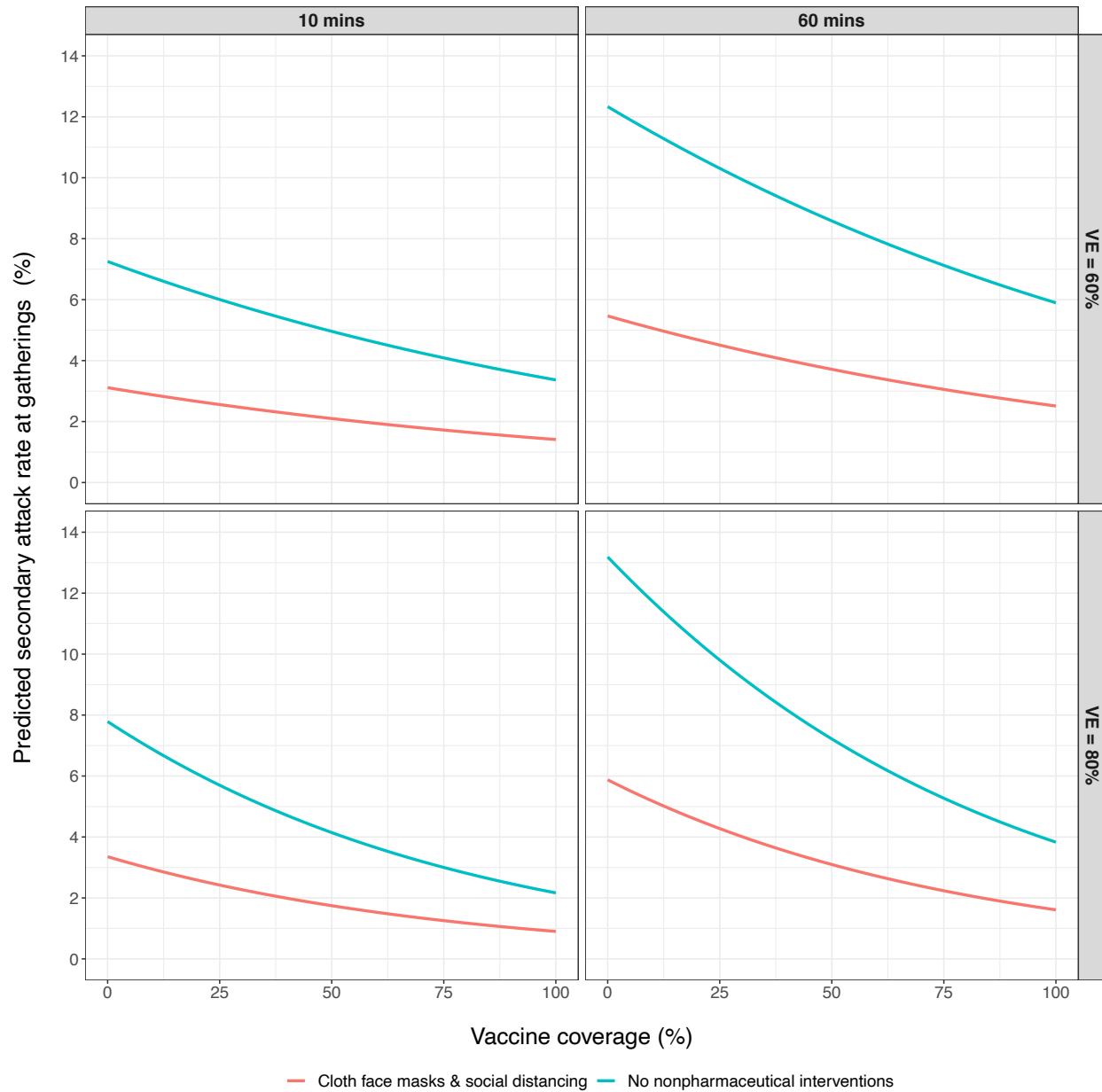
424

427 **Figure 1.** At low population densities and gathering duration limits, nonpharmaceutical
428 interventions to prevent infection and elevated vaccination rates consistently decrease the
429 probability of observing ≥ 1 successful SARS-CoV-2 transmission events in simulations.



430

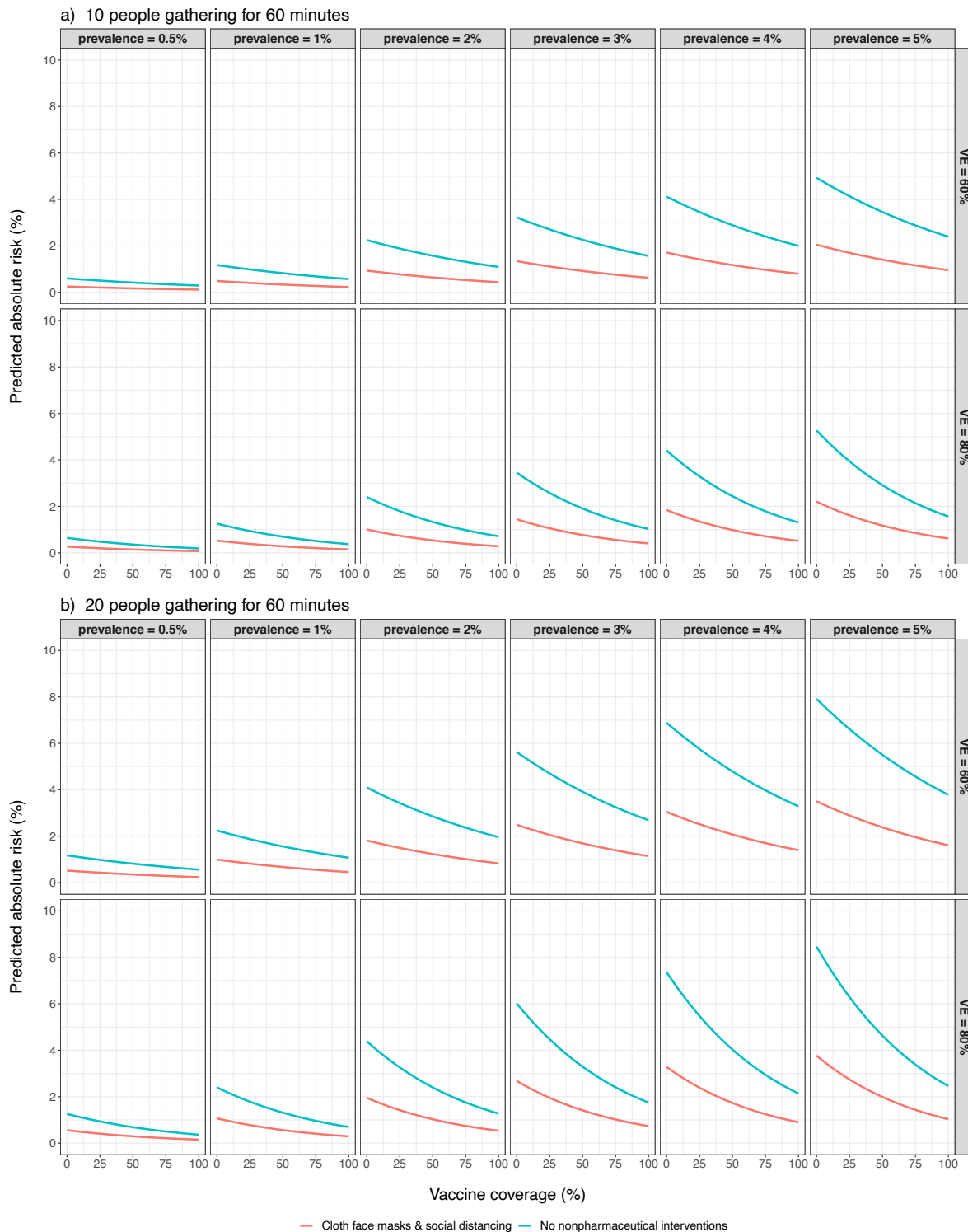
431 **Figure 2.** Mean secondary attack rates in simulations indicate substantial variability in risk.



432

433 **Figure 3.** Predicted secondary attack rates suggest that the combination of cloth face masks and
434 2-m social distancing during indoor gatherings of varying durations consistently reduces
435 secondary attack rates by 55-58%. This effect was only modeled for vaccine efficacies of 60%
436 and 80%.

437



438

439 **Figure 4.** Estimated absolute risk of being infected with SARS-CoV-2 during 60-minute

440 gatherings of varied sizes. Estimates were obtained by plugging Figure 3 predictions into
441 Equation 3 with fixed COVID-19 prevalence and n values. a) Absolute risk of SARS-CoV-2
442 transmission given that 10 people attend the gathering. b) Absolute risk of SARS-CoV-2
443 transmission given that 20 people attend the gathering.