

1 **Estimated effectiveness of traveller screening to prevent international spread of 2019**
2 **novel coronavirus (2019-nCoV)**

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13
14 **Abstract**

15 Traveller screening is being used to limit further global spread of 2019 novel coronavirus (nCoV)
16 following its recent emergence. Here, we project the impact of different travel screening
17 programs given remaining uncertainty around the values of key nCoV life history and
18 epidemiological parameters. Even under best-case assumptions, we estimate that screening will
19 miss more than half of infected travellers. Breaking down the factors leading to screening
20 successes and failures, we find that most cases missed by screening are fundamentally
21 undetectable, because they have not yet developed symptoms and are unaware they were
22 exposed. These findings emphasize the need for measures to track travellers who become ill
23 after being missed by a travel screening program. We make our model available for interactive
24 use so stakeholders can explore scenarios of interest using the most up-to-date information. We
25 hope these findings contribute to evidence-based policy to combat the spread of nCoV, and to
26 prospective planning to mitigate future emerging pathogens.

27
28 **Introduction**

29 As of January 28, 2020, the novel 2019 coronavirus (nCoV) outbreak has been intensifying
30 rapidly in China, and has demonstrated potential for international spread. Many jurisdictions
31 have imposed traveller screening and other travel restrictions (World Health Organization,
32 2020). It is widely recognized that screening measures are imperfect barriers to spread (Bitar et
33 al., 2009; Gostic et al., 2015; Mabey et al., 2014), due to: the absence of detectable symptoms
34 during the incubation period; variation in the severity and detectability of symptoms once the
35 disease begins to progress; imperfect performance of screening equipment or personnel; or
36 active evasion of screening by travellers. Previously we estimated the effectiveness of traveller
37 screening for a range of pathogens that have emerged in the past, and found that arrival
38 screening would miss 50–75% of infected cases even under optimistic assumptions (Gostic et
39 al., 2015). Yet the quantitative performance of different policies matters for planning
40 interventions and will influence how public health authorities prioritize different measures as the
41 international and domestic context changes. Here we use a mathematical model to analyse the
42 expected performance of different screening measures for nCoV, based on what is currently
43 known about its natural history and epidemiology and on different possible combinations of
44 departure and arrival screening policies.

45 Our previous analysis considered the contributions of both departure and arrival screening
46 programs, focusing on the context of international spread of infections via air travel. In the
47 current context of the nCoV outbreak, both departure and arrival screening have been proposed
48 and implemented in some countries, though neither approach is likely to be applied uniformly to
49 all air travellers. Traveller screening is also being applied in other contexts, including at
50 roadside spot checks on major routes out of Wuhan. These are directly analogous to departure
51 screens in our earlier analysis, i.e. one-off screening efforts with no delay due to travel duration.

52
53 As of January 28, 2020, the Chinese government has been expanding the geographic area and
54 modes of transportation subject to strong travel restrictions. If there was perfect compliance and
55 the restricted area encompassed all areas with community transmission of the virus, then these
56 measures could in theory eliminate the necessity of wider traveller screening. However,
57 multiple factors point to on-going risk, including the existence of substantial numbers of cases in
58 several population centers outside Wuhan (World Health Organization, n.d.), and very early in
59 the outbreak, reports of citizens seeking to elude the restrictions or leaving before restrictions
60 were in place. As the virus continues to spread within China, and as cases continue to appear in
61 other countries, the risk of exportation of cases from beyond the current travel-restricted area is
62 likely to grow.

63
64 As a result, increasing emphasis has been placed on the effectiveness of arrival screening to
65 prevent importation of cases to areas without established spread. At the same time, there is
66 great concern about potential public health consequences if nCoV spreads to developing
67 countries that lack health infrastructure and resources to combat it effectively. Limited
68 resources also could mean that some countries cannot implement large-scale arrival screening.
69 In this scenario, departure screening would be the sole barrier -- however leaky -- to importation
70 of cases into these countries. It is also important to recognize that, owing to the lag time in
71 appearance of symptoms in imported cases, any weaknesses in screening would continue to
72 have an effect on case importations for up to two weeks (roughly, the maximum reported
73 incubation period) after changes in screening policy or epidemic context in the source region.
74 Accordingly, we consider scenarios with departure screening only, arrival screening only, or
75 both departure and arrival screening. The model can also consider the consequences when
76 only a fraction of the traveller population is screened, due either to travel from a location not
77 subject to screening, or due to deliberate evasion of screening.

78
79 The central aim of our analysis is to assess the expected effectiveness of screening for nCoV,
80 taking account of current knowledge and uncertainties about the natural history and
81 epidemiology of the virus. We therefore show results using the best estimates currently
82 available, in the hope of informing policy decisions in this fast-changing environment. We also
83 make our model available for public use as a user-friendly online app, so that stakeholders can
84 explore scenarios of particular interest, and results can be updated rapidly as our knowledge of
85 this new viral threat continues to expand.

86

87 **Results**

88

89 *Model*

90

91 The core model has been described previously (Gostic et al., 2015), but to summarize briefly, it
92 assumes infected travellers can be detained due to the presence of detectable symptoms (fever
93 or cough), or due to self-reporting of exposure risk via questionnaires or interviews. Before
94 screening, travellers can be classified into one of four categories: (1) symptomatic and aware
95 that exposure may have occurred, (2) symptomatic but not aware of exposure risk, (3) aware of
96 exposure risk but without detectable symptoms, and (4) neither symptomatic nor aware of
97 exposure risk (Fig. 1). Travellers in the final category are fundamentally undetectable, and
98 travellers in the third category are only detectable if aware that they have been exposed and
99 willing to self report.

100

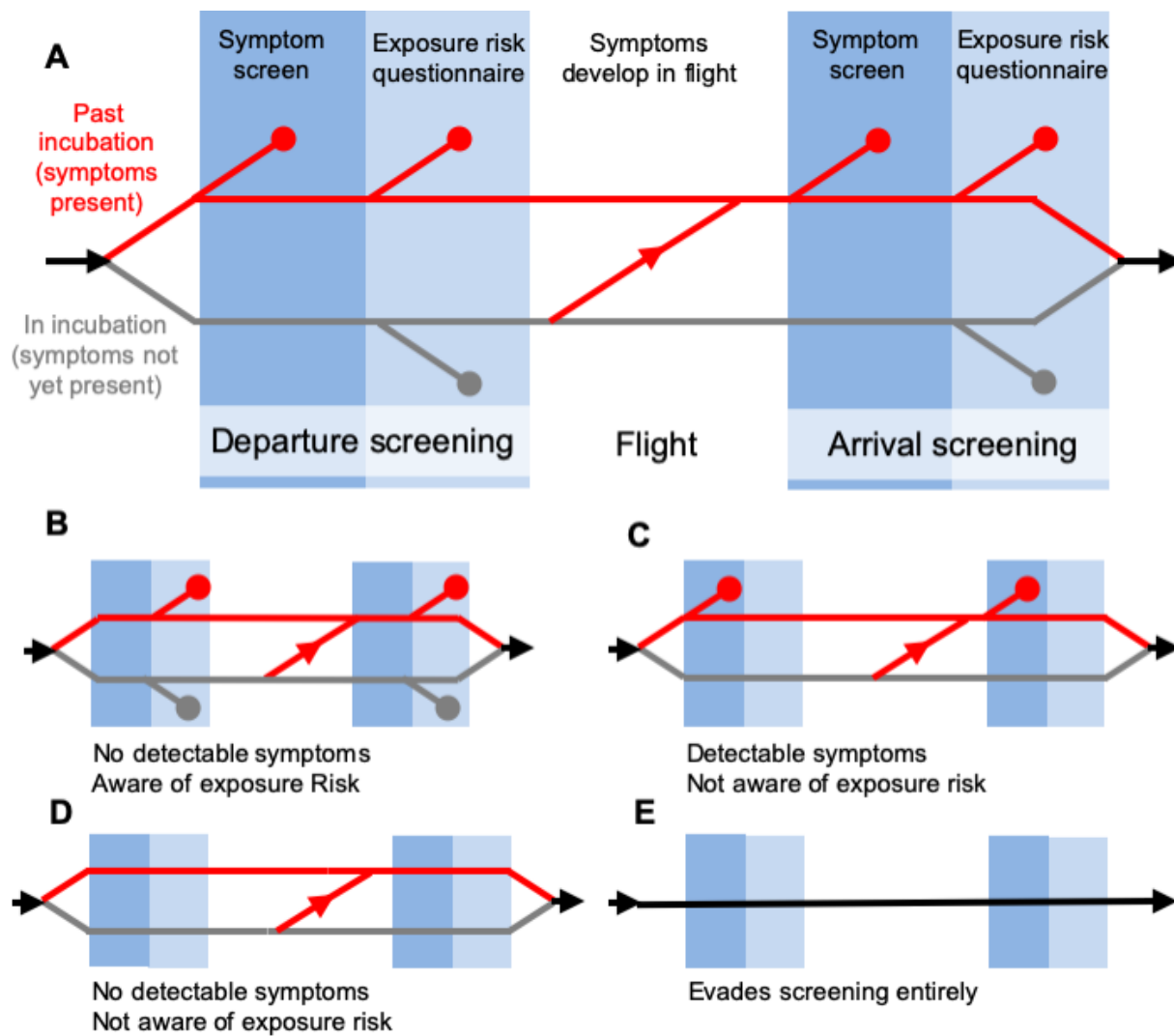
101 In the model, screening for symptoms occurs prior to questionnaire-based screening for
102 exposure risk, and detected cases do not progress to the next stage. This approach allows us to
103 track the fraction of cases detected using symptom screening or risk screening at arrival or
104 departure. Additionally, the model keeps track of four ways in which screening can miss infected
105 travellers: (1) due to imperfect sensitivity, symptom screening may fail to detect symptoms in
106 travellers that display symptoms; (2) questionnaires may fail to detect exposure risk in travellers
107 aware they have been exposed, owing to deliberate obfuscation or misunderstanding; (3)
108 screening may fail to detect both symptoms and known exposure risk in travellers who have
109 both and (4) travellers not exhibiting symptoms and with no knowledge of their exposure are
110 fundamentally undetectable. Here, we only consider infected travellers who submit to screening.
111 However, the supplementary app allows users to consider scenarios in which some fraction of
112 infected travellers intentionally evade screening (Fig. 1E).

113

114 *Parameters*

115

116 The probability that an infected traveller is detectable in a fever screen depends on: the
117 incubation period (the time from exposure to onset of detectable symptoms); the proportion of
118 subclinical cases (mild cases that never develop detectable symptoms); the sensitivity of
119 thermal scanners used to detect fever; the fraction of cases aware they have high exposure risk;
120 and the fraction of those cases who would self-report truthfully on a screening questionnaire.
121 Further, the distribution of individual times since exposure affects the probability that any single
122 infected traveller has progressed to the symptomatic stage. In a growing epidemic, the majority
123 of infected cases will have been recently exposed, and will not yet show symptoms. We used
124 methods described previously to estimate the distribution of individual times since exposure for
125 different parameter regimes (Gostic et al., 2015). Briefly, the model assumes the fraction of
126 cases who are recently exposed increases with R_0 . The distribution of times since exposure is
127 truncated at a maximum value, which corresponds epidemiologically to the maximum time from
128 exposure to patient isolation, after which point we assume cases will not attempt to travel.
129 (Isolation may occur due to hospitalization, or due to confinement at home in response to
130 escalating symptoms or nCoV diagnosis).



131
132

133 **Fig 1. Model of traveller screening process**, adapted from Gostic et al., eLife, 2015. Infected
134 travellers fall into one of five categories: (A) Symptomatic cases aware of exposure risk are
135 detectable in both symptom screening and questionnaire-based risk screening. (B) Subclinical
136 and not-yet-symptomatic cases aware of exposure risk are only detectable using risk screening.
137 (C) Symptomatic cases unaware of exposure risk are only detectable in symptom screening.
138 (D-E) Subclinical cases who are unaware of exposure risk, and individuals that evade
139 screening, are fundamentally undetectable.

140

Parameter	Best estimate (Analyses in Fig. 2)	Plausible range (Analyses in Fig. 3)	References and rationale
Mean incubation period	5.5 days Sensitivity: 4.5 days or 6.5 days	4.5-6.5 days	3-6 days (Chan et al., 2020) 4.8 days (Liu et al., 2020) 5.7 days (Backer et al., 2020) 5.2 days (Li et al., 2020)
Incubation period distribution	Gamma distribution with shape = $\frac{mean}{1.2}$, scale = 1.2.		
Percent of cases subclinical (Never detectable in symptom screen)	Best case scenario: 5% Middle case scenario: 25% Worst case scenario: 50%		n = 6: 83% fever, 67% cough (Chan et al., 2020) N = 41 98% fever, 76% cough. (Huang et al., 2020) N = 99: 83% fever, 82% cough. (Chen et al., 2020) Subclinical cases have been reported elsewhere, and may be underrepresented in the above data
R ₀	No effect in individual-level analysis.	1.5-3.5	2.2 (1.4-3.8)* (Riou and Althaus, 2020) 2.6 (1.5-3.5) (Imai et al., 2019) 3.8 (3.6-4.0) (Read et al., 2020) 2.9 (2.3-3.6) (Liu et al., 2020) 2.2 (1.4-3.9) (Li et al., 2020) 2.7 (2.5-2.9) (Wu et al., 2020) 1.6-2.9 (Kucharski et al., n.d.)
Percent of travellers aware of exposure risk	20%	5-40%	We assume a low percentage, as no specific risk factors have been identified, and known times or sources of exposure are rarely reported in existing line lists.
Sensitivity of infrared thermal scanners for fever	70%	60%-90%	Most studies estimated sensitivity between 60-88% (Bitar et al., 2009; Priest et al., 2011; Tay et al., 2015). But a handful of studies estimated very low sensitivity (4-30%). In general, sensitivity depended on the device used, body area targeted and ambient temperature.
Probability that travellers self-report exposure risk	25%	5%-25%	25% is an upper-bound estimate based on outcomes of past screening initiatives. (Gostic et al., 2015)
Time from symptom onset to patient isolation (After which we assume travel is not possible)	No effect in individual-level analysis.	3-7 days	Median 7 days from onset to hospitalization (n = 6) (Chan et al., 2020) Mean 2.9 days onset to patient isolation (n = 164) (Liu et al., 2020) Median 7 days from onset to hospitalization (n = 41) (Huang et al., 2020)

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Table 1. Parameter values estimated in currently available studies, along with accompanying uncertainties and assumptions. *Confidence interval, credible interval or range reported by each study referenced.

145 At the time of this writing, nCoV-specific estimates are available for most of these parameters,
146 but almost all have been derived from limited or preliminary data sources and remain subject to
147 considerable uncertainty. Table 1 and the Methods summarize the current state of knowledge.
148 Here, we used two distinct approaches to incorporate this uncertainty into our analysis.

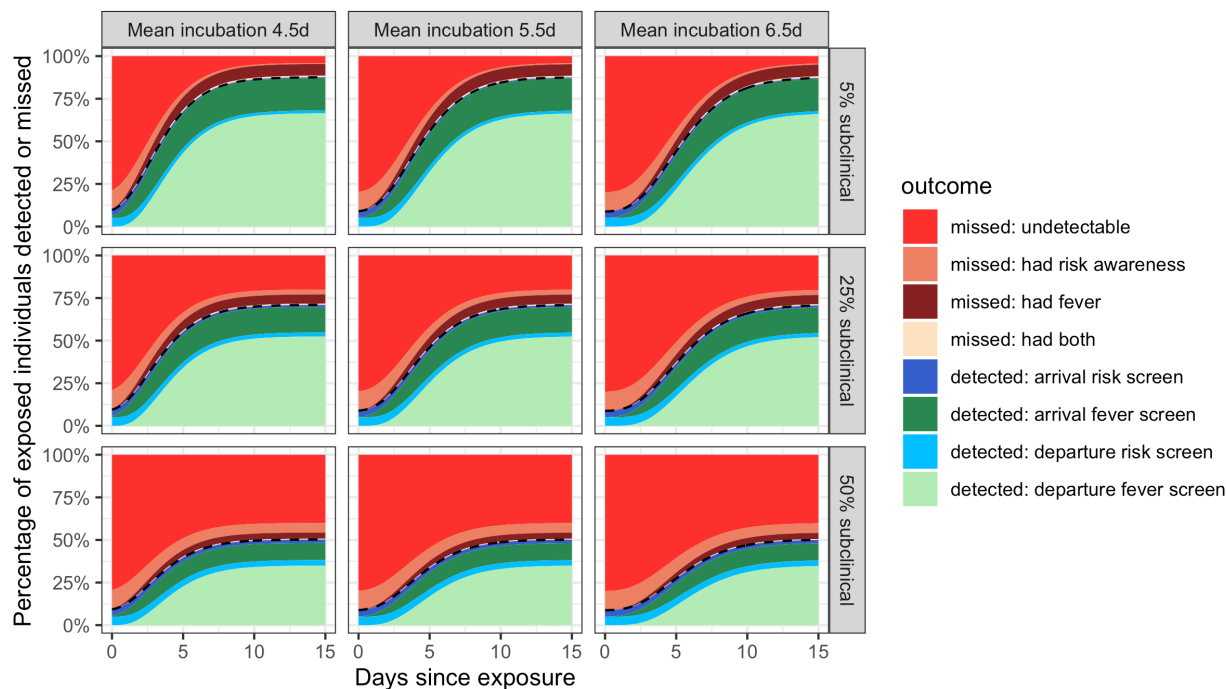
149
150 First, to estimate the probability that an infected individual would be detected or missed (Fig. 2),
151 we considered a range of plausible values for the mean incubation time, and the fraction of
152 subclinical cases. We focus on these two parameters because screening outcomes are
153 particularly sensitive to their values. All other parameters used to generate Fig. 2 were fixed to
154 the best available estimates listed in Table 1.

155
156 Second, we considered a population of infected travellers, each with a unique time of exposure,
157 and in turn a unique probability of having progressed to the symptomatic stage. Here, the model
158 used a resampling-based approach to simultaneously consider uncertainty from both (1)
159 stochasticity in any single individual's screening outcome, and (2) uncertainty as to the true,
160 underlying natural history parameters driving the epidemic. Details are provided in the methods,
161 but briefly, we constructed 1000 plausible parameter sets, drawn using Latin hypercube
162 sampling from plausible ranges for each parameter (Table 1). Using each parameter set, we
163 simulated screening outcomes for a population of 100 infected individuals. Fig. 3A shows the
164 distribution of infected travellers detected per simulation, and Fig. 3B shows the mean fraction
165 of individuals with each screening outcome from across all simulations.

166
167

168 *Individual probabilities of a given screening outcome*

169
170 Our model outputs the probability of different screening outcomes through time, including the
171 overall likelihood of detecting the infected traveller and the different contributions to success or
172 failure. First, we explored the probability that any particular infected individual would be detected
173 by a screening program, as a function of the time between exposure and the initiation of travel
174 (Fig. 2). A crucial driver of the effectiveness of traveller screening programs is the duration of
175 the incubation period, particularly since infected people are most likely to travel before the onset
176 of symptoms. Here we considered three scenarios with different mean incubation periods: 5.5
177 days is most consistent with most existing estimates, while 4.5 and 6.5 days provide a
178 sensitivity analysis roughly consistent with ranges, confidence or credible intervals reported
179 elsewhere (Backer et al., 2020; Chan et al., 2020; Li et al., 2020; Liu et al., 2020). Even within
180 the narrow range tested, screening outcomes were sensitive to the incubation period mean. For
181 longer incubation periods, we found that larger proportions of departing travellers would not yet
182 be exhibiting symptoms – either at departure or arrival – which in turn reduced the probability
183 that screening would detect these cases, especially since we assume few infected travellers will
184 realize they have been exposed to nCov.



185
186 **Fig 2. Individual outcome probabilities for travellers who screened at given time since**
187 **infection.** Columns show three possible mean incubation periods, and rows show three
188 plausible probabilities that an infected person is subclinical. Here, we assume screening occurs
189 at both arrival and departure; see Fig. 2 - supplementary figure 1 and Fig. 2 - supplementary
190 figure 2 for departure or arrival screening only. The black dashed lines separate detected cases
191 (below) from missed cases (above). Here, we assume flight duration = 24 hours, the probability
192 that an individual is aware of exposure risk is 0.2, the sensitivity of fever scanners is 0.7, and
193 the probability that an individual will truthfully self-report on risk questionnaires is 0.25. Table 1
194 lists all other input values.

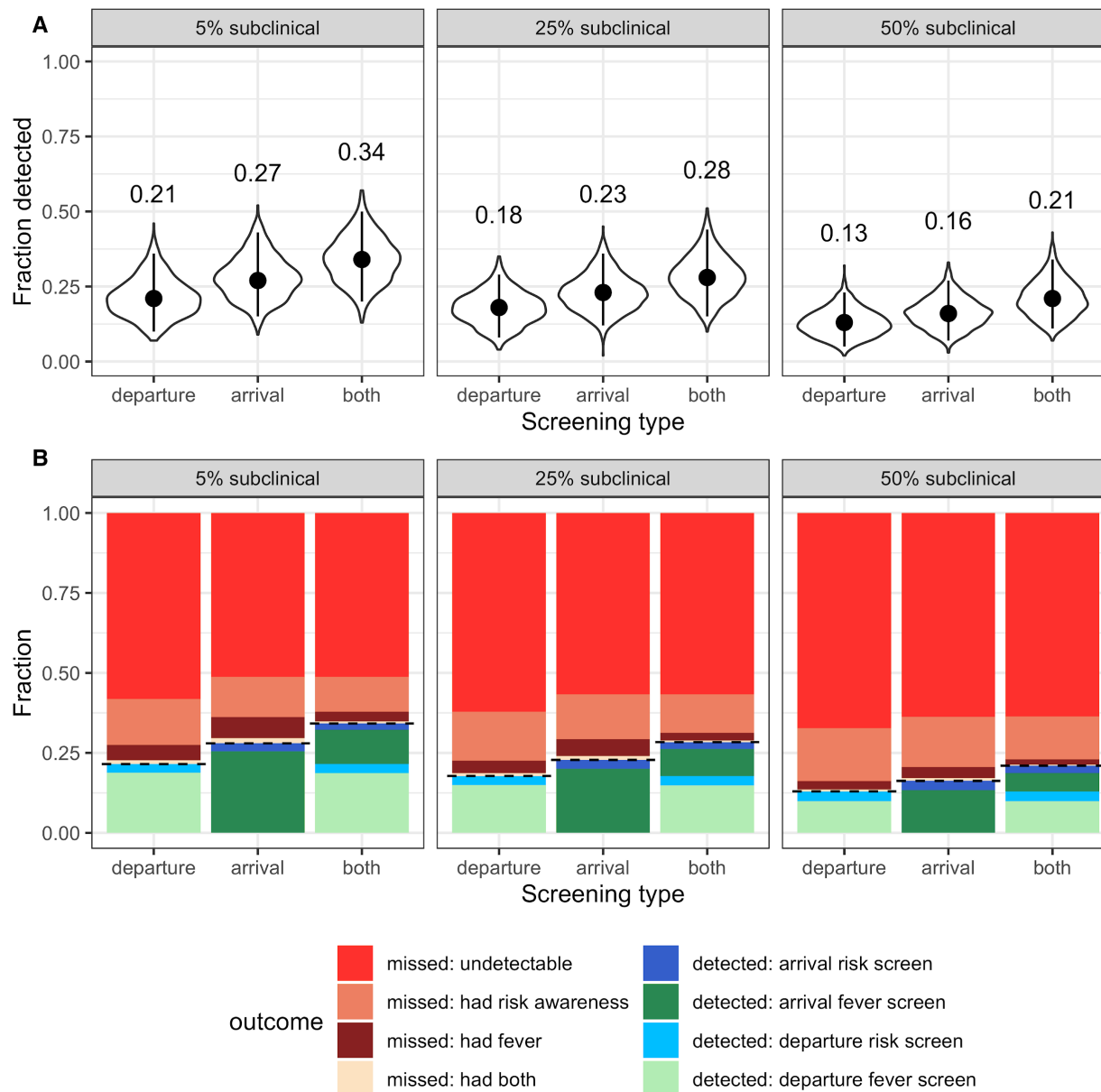
195 A second crucial uncertainty is the proportion of cases that will develop detectable symptoms.
196 We considered scenarios in which 5%, 25% and 50% of cases are subclinical, representing a
197 best, middle and worst-case scenario, respectively. The middle and worst-case scenarios have
198 predictable and discouraging consequences for the effectiveness of traveller screening, since
199 they render large fractions of the population undetectable by fever screening (Fig. 2).
200 Furthermore, mild cases who are unaware of their exposure risk are never detectable, by any
201 means. This is manifested as the bright red 'undetectable' region which persists well beyond the
202 mean incubation period. For a screening program combining departure and arrival screening, as
203 shown in Fig. 2, the greatest contributor to case detection is the departure fever screen. The
204 arrival fever screen is the next greatest contributor, with its value arising from two factors: the
205 potential to detect cases whose symptom onset occurred during travel, and the potential to
206 catch cases missed due to imperfect instrument sensitivity in non-contact infrared thermal
207 scanners used in traveller screening (Table 1). Considering the effectiveness of departure or
208 arrival screening only (Fig 2 - Supplementary figure 1-2), we see that fever screening is the
209 dominant contributor in each case, but that the risk of missing infected travellers due to
210 undetected fever is substantially higher when there is no redundancy from two successive
211 screenings.

212
213

214 *Overall screening effectiveness in a population of infected travellers during a growing epidemic*

215
216 Next we computed population-level estimates of the effectiveness of different screening
217 programs, as well as the uncertainties arising from the current partial state of knowledge about
218 this recently-emerged virus. To do so, we modeled plausible population-level outcomes by
219 tracking the fraction of infected travellers detained, given a growing epidemic and current
220 uncertainty around parameter values. We separately consider the best, middle and worst-case
221 scenarios for the proportion of infections that are subclinical, and for each scenario we compare
222 the impact of departure screening only, arrival screening only, or programs that include both.

223
224 The striking finding is that even under the best-case assumptions, with just one infection in
225 twenty being subclinical and all travellers passing through departure and arrival screening, the
226 median fraction of infected travellers detected is only 0.34, with 95% interval extending from
227 0.20 up to 0.50 (Fig. 3A). The total fraction detected is lower for programs with only one layer of
228 screening, with arrival screening preferable to departure screening owing to the possibility of
229 symptom onset during travel. Considering higher proportions of subclinical cases, the overall
230 effectiveness of screening programs is further degraded, with a median of just one in ten
231 infected travellers detected by departure screening in the worst-case scenario. The key driver of
232 these poor outcomes is that, even in the best-case scenario, nearly two thirds of infected
233 travellers will not be detectable (as shown by the red regions in Fig. 3B). This is because in a
234 growing epidemic, the majority of travellers will have been recently infected and hence will not
235 yet have progressed to the symptomatic stage, and because we assume that few are aware of
236 their exposure risk. As above, the dominant contributor to successful detections is fever
237 screening.



238
 239 **Fig 3. Population-level outcomes of screening programs in a growing epidemic.** (A) Violin
 240 plots of the fraction of infected travellers detected, accounting for current uncertainties by
 241 running 1000 simulations using parameter sets randomly drawn from the ranges shown in Table
 242 1. Dots and vertical line segments show the median and central 95%, respectively. Text above
 243 each violin shows the median fraction detected. (B) Mean fraction of travellers with each
 244 screening outcome. The black dashed lines separate detected cases (below) from missed
 245 cases (above).

246 *Interactive online app for public use*

247
248 We have developed an interactive web application using Shiny in which users can replicate our
249 analyses using parameter inputs that reflect the most up-to-date information. The
250 supplementary user interface can be accessed at
251 <https://faculty.eeb.ucla.edu/lloydsmith/screeningmodel>. Please note that while the results in Fig.
252 3 consider a range of plausible values for each parameter, the outputs of the Shiny app are
253 calculated using fixed, user-specified values only.

254
255
256

257 **Discussion**

258
259 The international expansion of nCoV cases has led to travel screening measures being
260 proposed and implemented in numerous countries. Given the rapid growth of the epidemic in
261 China, emphasis on these measures is likely to rise in an attempt to prevent community spread
262 of the virus in new geographic areas. Using a mathematical model of screening with preliminary
263 estimates of nCoV epidemiology and natural history, we found that screening will in the best
264 case only detect less than half of infected travellers. We found that two main factors influenced
265 the effectiveness of screening. First, symptom screening depends on the natural history of an
266 infection: individuals are increasingly likely to show detectable symptoms with increasing time
267 since exposure. A fundamental challenge of screening is that many infected individuals will
268 travel during their incubation period, a point at which they still feel healthy enough to travel but
269 are simultaneously most difficult to detect. This effect is amplified when the incubation period is
270 longer; infected individuals have a longer window in which they may travel with low probability of
271 detection. Second, screening depends on whether exposure risk factors exist that would
272 facilitate specific and reasonably sensitive case detection by questionnaire. For nCoV, there is
273 so far limited evidence for specific risk factors; we therefore assumed that at most 40% of
274 travellers would be aware of a potential exposure, and that a minority would self-report their
275 exposure honestly, which led to limited effectiveness in questionnaire-based screening. The
276 confluence of these two factors led to many infected travellers being fundamentally
277 undetectable. Even under our most generous assumptions about the natural history of nCoV,
278 the presence of undetectable travellers made the greatest contribution to screening failure.
279 Correctable failures, such as missing a traveller with fever or awareness of their exposure risk,
280 played a more minor role.

281
282 There are some limitations to our analysis. Parameter values for nCoV, such as the incubation
283 period, are based on the limited data currently available. For such parameters, the tail of the
284 distribution is important for understanding the potential for long delays until symptoms, but the
285 tails of skewed distributions are notoriously difficult to characterize using limited data. In
286 general, current parameter estimates may also be affected by bias or censoring, particularly in
287 the early stages of an outbreak when most cases have been recently infected, and when data
288 are primarily available for relatively severe, hospitalized cases. Another crucial uncertainty
289 highlighted by our analysis is the frequency of cases too mild or non-specific to be detected as

290 nCoV infections. At least one asymptomatic case is known to have occurred in a child (Chan et
291 al., 2020). Further, children and young adults have been conspicuously underrepresented
292 among hospitalized cases (Chen et al., 2020; Huang et al., 2020; Li et al., 2020). The possibility
293 cannot be ruled out that large numbers of subclinical cases are occurring, especially in young
294 people. If an age-by-severity interaction does indeed exist, then the mean age of travellers
295 should be taken into account when estimating screening effectiveness. Further, transmission
296 occurred before the onset of symptoms in one recent case report (Rothe et al., 2020). While it is
297 too early to draw conclusions from a single case report, determining whether pre-symptomatic
298 transmission is the norm also has major implications for the risk of establishing on-going spread
299 in new locales .

300
301 As country-specific screening policies can change rapidly in real-time, we focused on a general
302 screening framework rather than specific case studies. We also assumed traveller adherence
303 and no active evasion of screening. However, there are informal reports of people taking
304 antipyretics to beat fever screening (Mahbubani, 2020), which would further reduce the
305 effectiveness of these methods. With travel restrictions in place, individuals may also take
306 alternative routes (e.g. road rather than air), which would in effect circumvent departure and/or
307 arrival screening as a control measure. Our quantitative findings may overestimate screening
308 effectiveness if many travellers evade screening.

309
310 Our results have several implications for the design and implementation of control measures.
311 Arrival screening could delay the introduction of cases if the infection is not yet present (Cowling
312 et al., 2010), or reduce the initial rate of spread by limiting the number of parallel chains of
313 transmission initially present in a country. But because screening is inherently leaky, it is crucial
314 to also have measures in place to identify cases missed at arrival screening. For example,
315 travellers could be provided with an information card to self-screen and self-report (Public
316 Health England, n.d.), alongside increased general surveillance/alertness in healthcare settings.
317 We should not take false confidence from reports that infected travellers are being detected by
318 existing screening programs. Our findings indicate that for every case detected by travel
319 screening, one or more infected travellers were not caught, and must be found and isolated by
320 other means.

321
322 The expected high miss rate of screening programs also has implications for assessing when
323 different programs are worthwhile investments. For areas yet to experience community-based
324 transmission of the virus, and subject to substantial traveller inflows from affected areas, arrival
325 screening can delay importation of cases and build awareness among incoming travellers.
326 Even once there is some early-stage community transmission in a specific location, arrival
327 screening may still reduce the chance of multiple independent transmission chains and ease the
328 work of contact tracing teams, although the relative benefit of such screening for overall case
329 prevention with decline as local transmission increases. Once there is generalized spread which
330 has outpaced contact tracing, departure screening to prevent export of cases to new areas will
331 be more valuable than arrival screening to identify additional incoming cases. However the
332 cost-benefit tradeoff for any screening policy should be assessed in light of past experiences,
333 where few or no infected travellers have been detected by such programs (Gostic et al., 2015).

334
335 Several factors could potentially strengthen the screening measures described here. With
336 improved efficiency of thermal scanners or other symptom detection technology, we would
337 expect a smaller difference between the effectiveness of arrival-only screening and combined
338 departure and arrival screening in our analysis. Alternatively, the benefits of redundant
339 screening (noted above for programs with departure and arrival screens) could be gained in a
340 single-site screening program by simply having two successive fever-screening stations that
341 travellers pass through (or taking multiple measurements of each traveller at a single station).
342 As risk factors become better known, questionnaires could be refined to identify more potential
343 cases. Alternatively, less stringent definition of high exposure risk (e.g. contact with anyone with
344 respiratory symptoms) would be more sensitive. These approaches would boost sensitivity of
345 screening, but could also incur a large cost in terms of false positives detained, especially
346 during influenza season.

347
348 The availability of rapid PCR tests would also be beneficial for case identification at arrival, and
349 would address concerns with false-positive detections. If such tests were fast, there may be
350 potential to test suspected cases in real time based on questionnaire responses, travel origin, or
351 borderline symptoms. However, such measures could prove highly expensive if implemented at
352 scale. There is also scope for new tools to improve the ongoing tracking of travellers who pass
353 through screening, such as smartphone-based self-reporting of temperature or symptoms in
354 incoming cases. Recent travellers could even be asked to maintain a diary of close contacts for
355 14 days following arrival, to expedite contact tracing in the event they become ill with nCoV.
356 This would be cheaper and more scalable than intense follow-up, but is likely to be limited by
357 user adherence.

358
359 Our analysis underscores the reality that respiratory viruses are difficult to detect by travel
360 screening programs, particularly if a substantial fraction of infected people show mild or
361 indistinct symptoms, and if incubation periods are long. Quantitative estimates of screening
362 effectiveness will improve as more is learned about this recently-emerged virus, and will vary
363 with the precise design of screening programs. However, we present a robust qualitative finding:
364 in any situation where there is widespread epidemic transmission in source populations from
365 which travellers are drawn, travel screening programs can slow but not stop the importation of
366 infected cases. By decomposing the factors leading to success or failure of screening efforts,
367 our work supports decision-making about program design, and highlights key questions for
368 further research. We hope that these insights may help to mitigate the global impacts of nCoV
369 by guiding effective decision-making in both high- and low-resource countries, and may
370 contribute to prospective improvements in travel screening policy for future emerging infections.

371

372 **Materials and Methods**

373

374 *Modeling strategy*

375

376 The model's structure is summarized above (Fig. 1), and detailed methods have been described
377 previously (Gostic et al., 2015). Here, we summarize relevant extensions, assumptions and
378 parameter inputs.

379

380 *Extensions*

381

382 Our previous model tracked all the ways in which infected travellers can be detected by
383 screening (fever screen, or risk factor screen at arrival or departure). Here, we additionally keep
384 track of the many ways in which infected travellers can be missed (i.e. missed given fever
385 present, missed given exposure risk present, missed given both present, or missed given
386 undetectable). Cases who have not yet passed the incubation period are considered
387 undetectable by fever screening, even if they will eventually develop symptoms in the future. In
388 other words, no traveller is considered "missed given fever present" until they have passed the
389 incubation period and show detectable symptoms. Infected travellers who progress to
390 symptoms during their journey are considered undetectable by departure screening, but
391 detectable by arrival screening. Additionally, in the supplementary user interface, we
392 implemented the possibility that some fraction of infected travellers deliberately evade
393 screening.

394

395 *Fraction of subclinical cases*

396

397 Our best-case scenario, in which only 5% of cases are subclinical, is consistent with the fact
398 that the vast majority of nCoV cases detected to date have shown fever or other detectable
399 symptoms (Chan et al., 2020; Chen et al., 2020; Huang et al., 2020). But so far the data have
400 primarily captured severe, hospitalized cases, so the true fraction of subclinical nCoV cases
401 remains a crucial unknown. Particularly given the conspicuous under-representation of children
402 and young adults among hospitalized patients (Huang et al., 2020; Li et al., 2020), our medium
403 and worst-case scenarios (75% and 50% subclinical) remain plausible.

404

405 *Incubation period distribution*

406

407 Numerous recent studies have estimated that the incubation period lasts about 5.5 days on
408 average (Backer et al., 2020; Chan et al., 2020; Li et al., 2020; Liu et al., 2020), with the tail of
409 the distribution stretching to at least 12 days (Backer et al., 2020; Li et al., 2020). Consistent
410 with these observations, a recent study by Backer, Klinkberg and Wallinga (2020) characterized
411 the incubation period distribution for nCoV, concluding that a Weibull distribution provided the
412 best fit to data, but that a gamma distribution performed almost as well. We proceed by adopting
413 their best-fit gamma distribution (mean 5.7 days, s.d. 2.6, or alternatively, shape = 4.8, scale =
414 1.2), as the gamma form is more computationally convenient within our model. In order to vary
415 the mean incubation period in our uncertainty analyses while maintaining the shape of this two-

416 parameter distribution, we fix the scale parameter to 1.2, and set the shape parameter equal to
417 $\frac{mean}{1.2}$ (Fig. 3 - supplementary figure 1).

418

419 *Effectiveness of exposure risk questionnaires*

420

421 The probability that an infected traveller is detectable using questionnaire-based screening for
422 exposure risk will be highest if specific risk factors are known. Other than close contact with a
423 known nCoV case, or contact with the Hunan seafood wholesale market in the earlier phase of
424 the outbreak in Wuhan, we are not aware that any specific risk factors have been identified.
425 Given the relative anonymity of respiratory transmission, we assume that a minority of infected
426 travellers would realize that they have been exposed before symptoms develop (20% in Fig. 2,
427 range 5-40% in Fig. 3). Further, relying on a previous upper-bound estimate (Gostic et al., 2015)
428 we assume that only 25% of travellers would self-report truthfully if aware of elevated exposure
429 risk.

430

431 Table 1 summarizes the state of knowledge about additional key natural history parameters, as
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435

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446 **Competing interests**

447 The authors declare no competing interests.

448

449 **Code and data availability**

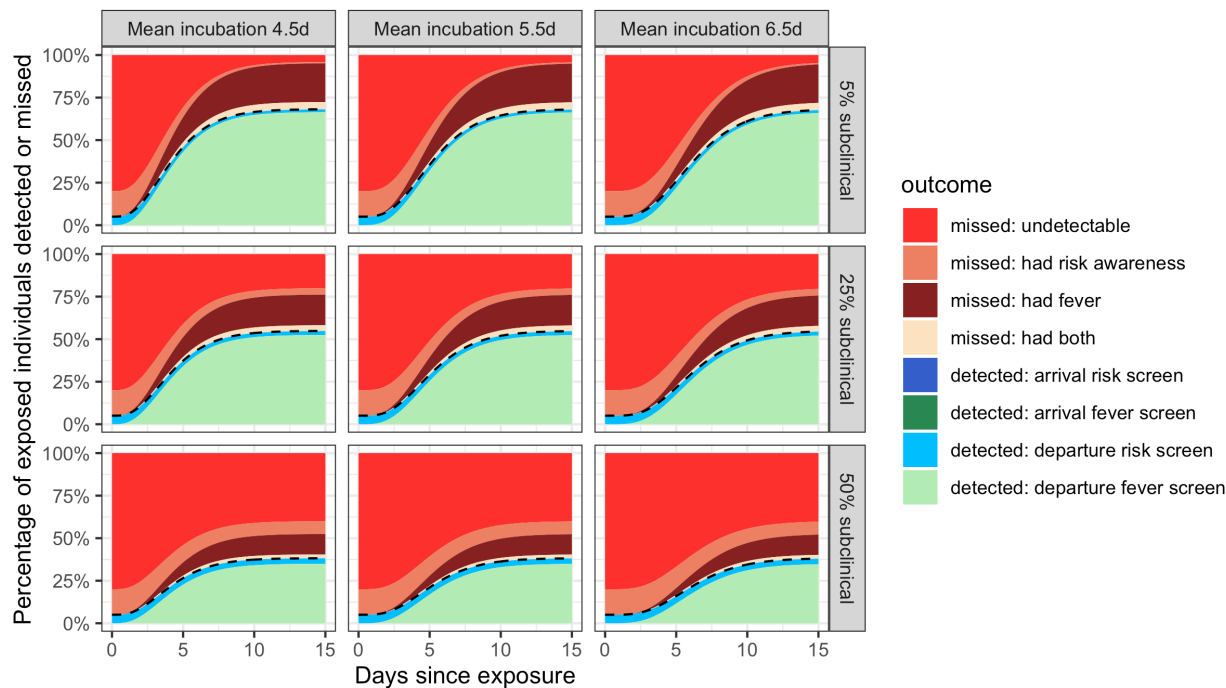
450 All code used in these analyses can be found at https://github.com/kgostic/traveller_screening.

451 References

- 452
- 453 Backer JA, Klinkenberg D, Wallinga J. 2020. The incubation period of 2019-nCoV infections
454 among travellers from Wuhan, China. *medRxiv* 2020.01.27.20018986.
455 doi:10.1101/2020.01.27.20018986
- 456 Bitar D, Goubar A, Desenclos JC. 2009. International travels and fever screening during
457 epidemics: A literature review on the effectiveness and potential use of non-contact
458 infrared thermometers. *Eurosurveillance* **14**:1–5.
- 459 Chan JF, Yuan S, Kok K, To KK, Chu H, Yang J, Xing F, Liu J, Yip CC, Poon RW, Tsoi H, Lo
460 SK, Chan K, Poon VK, Chan W, Ip JD, Cai J-P, Cheng VC-C, Chen H, Hui CK-M, Yuen
461 K-Y. 2020. Articles A familial cluster of pneumonia associated with the 2019 novel
462 coronavirus indicating person-to-person transmission : a study of a family cluster. *The*
463 *Lancet* 1–10. doi:10.1016/S0140-6736(20)30154-9
- 464 Chen N, Zhou M, Dong X, Qu J, Gong F, Han Y, Qiu Y, Wang J, Liu Y, Wei Y, Xia J, Yu T,
465 Zhang X, Zhang L. 2020. Epidemiological and clinical characteristics of 99 cases of 2019
466 novel coronavirus pneumonia in Wuhan, China: a descriptive study. *The Lancet* **0**.
467 doi:10.1016/S0140-6736(20)30211-7
- 468 Cowling BJ, Lau LL, Wu P, Wong HW, Fang VJ, Riley S, Nishiura H. 2010. Entry screening to
469 delay local transmission of 2009 pandemic influenza A (H1N1). *BMC Infect Dis* **10**:82.
470 doi:10.1186/1471-2334-10-82
- 471 Gostic KM, Kucharski AJ, Lloyd-Smith JO. 2015. Effectiveness of traveller screening for
472 emerging pathogens is shaped by epidemiology and natural history of infection. *eLife*
473 **2015**:1–16. doi:10.7554/eLife.05564
- 474 Huang C, Wang Y, Li X, Ren L, Zhao J, Hu Y, Zhang L, Fan G, Xu J, Gu X, Cheng Z, Yu T, Xia
475 J, Wei Y, Wu W, Xie X, Yin W, Li H, Liu M, Xiao Y, Gao H, Guo L, Xie J, Wang G, Jiang
476 R, Gao Z, Jin Q, Wang J, Cao B. 2020. Articles Clinical features of patients infected with
477 2019 novel coronavirus in Wuhan, China. *The Lancet* 1–10. doi:10.1016/S0140-
478 6736(20)30183-5
- 479 Imai N, Cori A, Dorigatti I, Baguelin M, Donnelly CA, Riley S, Neil M. 2019. Report 3:
480 Transmissibility of 2019-nCoV. London.
- 481 Kucharski AJ, Russell T, Diamond C, Funk S, Eggo R. n.d. Analysis of early transmission of
482 2019-nCoV and implications for outbreaks in new locations.
- 483 Li Q, Guan X, Wu P, Wang X, Zhou L, Tong Y, Ren R, Leung KSM, Lau EHY, Wong JY, Xing X,
484 Xiang N, Wu Y, Li C, Chen Q, Li D, Liu T, Zhao J, Liu M, Tu W, Chen C, Jin L, Yang R,
485 Wang Q, Zhou S, Wang R, Liu H, Luo Y, Liu Y, Shao G, Li H, Tao Z, Yang Y, Deng Z,
486 Liu B, Ma Z, Zhang Y, Shi G, Lam TTY, Wu JT, Gao GF, Cowling BJ, Yang B, Leung
487 GM, Feng Z. 2020. Early Transmission Dynamics in Wuhan, China, of Novel
488 Coronavirus–Infected Pneumonia. *N Engl J Med* **0**:null. doi:10.1056/NEJMoa2001316
- 489 Liu T, Hu J, Kang M, Lin L, Zhong H, Xiao J, He G, Song T, Huang Q, Rong Z, Deng A, Zeng
490 W, Tan X, Zeng S, Zhu Z, Li J, Wan D, Lu J, Deng H, He J, Ma W. 2020. Transmission
491 dynamics of 2019 novel coronavirus (2019-nCoV). *bioRxiv* 1–13.
- 492 Priest PC, Duncan AR, Jennings LC, Baker MG. 2011. Thermal Image Scanning for Influenza
493 Border Screening: Results of an Airport Screening Study. *PLOS ONE* **6**:e14490.
494 doi:10.1371/journal.pone.0014490
- 495 Read JM, Bridgen JRE, Cummings DAT, Ho A, Jewell CP. 2020. Novel coronavirus 2019-nCoV:
496 early estimation of epidemiological parameters and epidemic predictions. *medRxiv*.
497 doi:10.1101/2020.01.23.20018549
- 498 Riou J, Althaus CL. 2020. Pattern of early human-to-human transmission of Wuhan 2019-nCoV.
499 *bioRxiv* 1–6.
- 500 Tay MR, Low YL, Zhao X, Cook AR, Lee VJ. 2015. Comparison of Infrared Thermal Detection

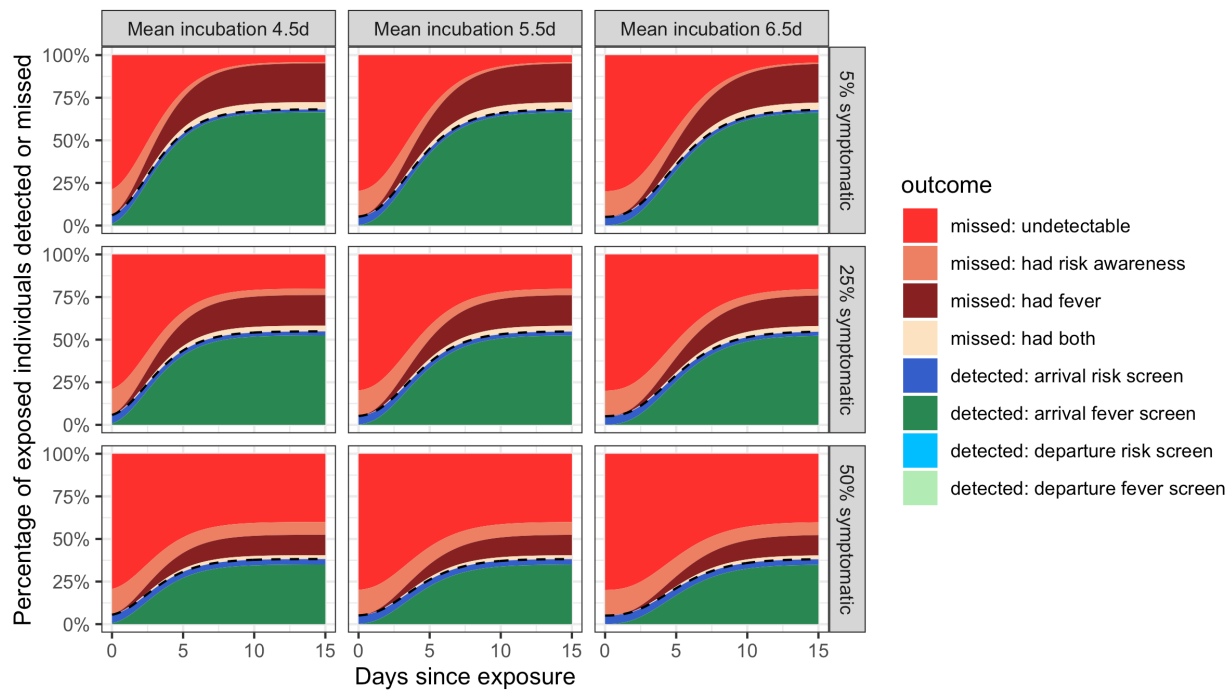
- 501 Systems for mass fever screening in a tropical healthcare setting. *Public Health*
502 **129**:1471–1478. doi:10.1016/j.puhe.2015.07.023
- 503 World Health Organization. n.d. Novel coronavirus (2019-nCov) Situation Report 12.
504 [https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200201-sitrep-](https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200201-sitrep-12-ncov.pdf?sfvrsn=273c5d35_2)
505 [12-ncov.pdf?sfvrsn=273c5d35_2](https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200201-sitrep-12-ncov.pdf?sfvrsn=273c5d35_2)
- 506 Wu JT, Leung K, Leung GM. 2020. Nowcasting and forecasting the potential domestic and
507 international spread of the 2019-nCoV outbreak originating in Wuhan, China: a
508 modelling study. *The Lancet* **0**. doi:10.1016/S0140-6736(20)30260-9

509 **Supplementary Figures**
510

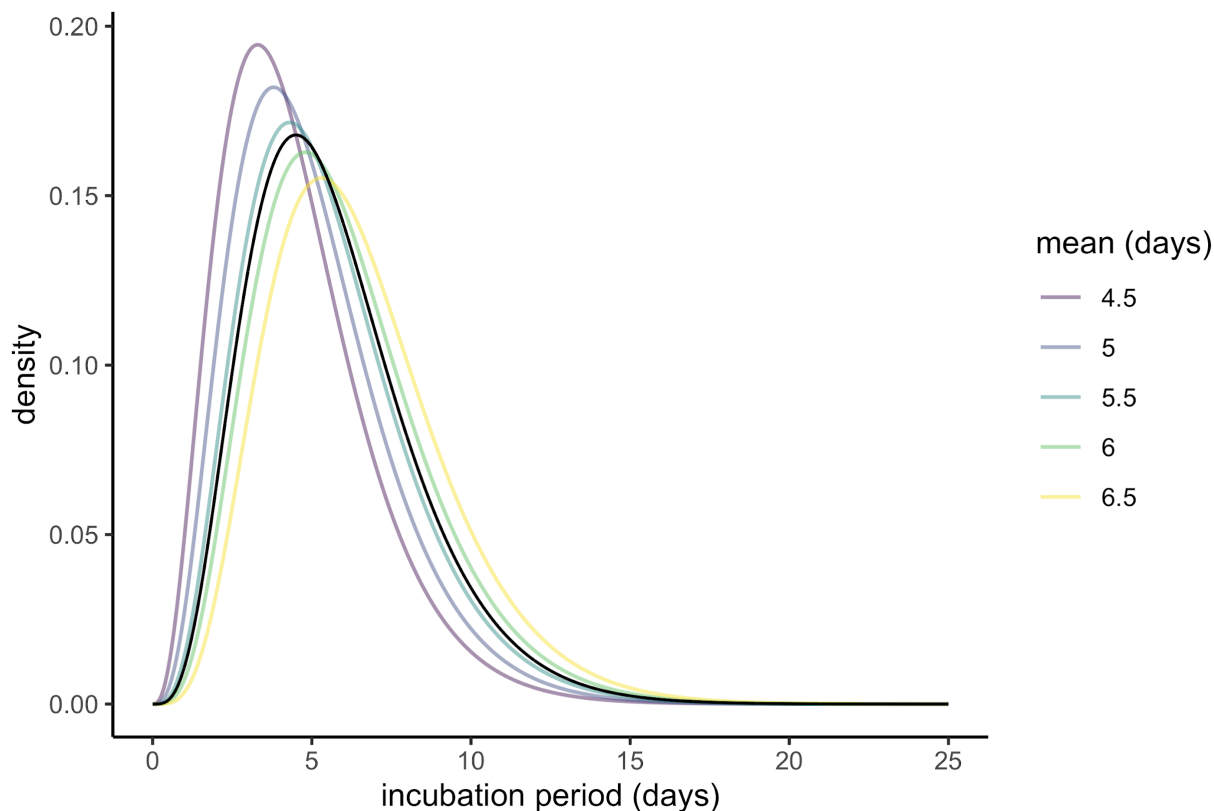


511
512 Fig 2-Supplementary figure 1. Departure screening only.

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516



517
518 Fig 2-Supplementary figure 2. Arrival screening only.



519
520 **Fig 3 - Supplementary figure 1. Plausible incubation period distributions underlying the**
521 **analyses in Fig. 3.** The black line shows the probability density function of the best-fit gamma
522 distribution reported by (Backer et al., 2020). Other lines show the probability density functions
523 for different assumptions regarding the mean incubation period. Each is a gamma distribution
524 with scale = 1.2, and shape = $\frac{mean}{1.2}$.