

1 **Standardization and Age-Distribution of COVID-19: Implications for**
2 **Variability in Case Fatality and Outbreak Identification**

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16 **Key words:** COVID-19; transmission model; physical distancing; epidemic; public health
17 policy

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22 **Competing interests:** none

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24

25 **Abstract**

26

27 **Background:** Epidemiological data from the COVID-19 pandemic has
28 demonstrated variability in attack rates by age, and country-to-country
29 variability in case fatality ratio (CFR).

30 **Objective:** To use direct and indirect standardization for insights into the
31 impact of age-specific under-reporting on between-country variability in CFR,
32 and apparent size of COVID-19 epidemics.

33 **Design:** Post-hoc secondary data analysis (“case studies”), and mathematical
34 modeling.

35 **Setting:** China, global.

36 **Interventions:** None.

37 **Measurements:** Data were extracted from a sentinel epidemiological study by
38 the Chinese Center for Disease Control (CCDC) that describes attack rates and
39 CFR for COVID-19 in China prior to February 12, 2020. Standardized
40 morbidity ratios (SMR) were used to impute missing cases and adjust CFR.
41 Age-specific attack rates and CFR were applied to different countries with
42 differing age structures (Italy, Japan, Indonesia, and Egypt), in order to
43 generate estimates for CFR, apparent epidemic size, and time to outbreak
44 recognition for identical age-specific attack rates.

45 **Results:** SMR demonstrated that 50-70% of cases were likely missed during the
46 Chinese epidemic. Adjustment for under-recognition of younger cases decreased
47 CFR from 2.4% to 0.8% (assuming 50% case ascertainment in older
48 individuals). Standardizing the Chinese epidemic to countries with older
49 populations (Italy, and Japan) resulted in larger apparent epidemic sizes, higher

50 CFR and earlier outbreak recognition. The opposite effect was demonstrated for
51 countries with younger populations (Indonesia, and Egypt).

52 **Limitations:** Secondary data analysis based on a single country at an early
53 stage of the COVID-19 pandemic, with no attempt to incorporate second order
54 effects (ICU saturation) on CFR.

55 **Conclusion:** Direct and indirect standardization are simple tools that provide
56 key insights into between-country variation in the apparent size and severity of
57 COVID-19 epidemics.

58

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60 for Health Research (2019 COVID-19 rapid researching funding OV4-170360).

61

62 **Introduction**

63

64 Knowledge and understanding related to COVID-19 are evolving rapidly, thanks
65 in no small part to outstanding epidemiological work done under challenging
66 conditions in recent months (1). A report on 44,672 confirmed COVID-19 cases
67 from mainland China helped delineate early understanding of the outbreak's
68 epidemiology. More recent mathematical models help fill in some of the
69 informational gaps, by inferring the underlying processes, including the
70 occurrence of "silent", unrecognized infections, that must have driven this
71 epidemic (2). Modeling is an important tool for understanding epidemic
72 processes, but disease modeling expertise is not universally available. A much
73 more basic epidemiological tool (standardization) (3, 4) can be used to provide
74 important insights into both seen and unseen aspects of epidemics, and to
75 project the likely characteristics and impacts of the same epidemic process, if it
76 were to unfold in other populations.

77

78 We were struck by the absence of reported COVID-19 cases in younger
79 individuals in early reports from China. A pandemic disease is defined by the
80 novelty of the pathogen and absence of population-level immunity, such that all
81 age groups in a population should be equally susceptible to infection. Inasmuch
82 as more severe cases are more likely to be recognized, the under-recognition of
83 disease in younger individuals serves as a metric for differential disease severity
84 by age, and also provides important information that can be used to adjust case
85 fatality ratios for likely under-reporting. Furthermore, simple approaches to
86 quantify under-reporting can inform public health prevention strategies,

87 because if unrecognized cases are extremely common, control methods that
88 focus on identification of cases, isolation and quarantine alone are likely to fail.

89

90 We sought to use simple epidemiological tools, such as direct and indirect
91 standardization (i.e., calculation of standardized morbidity ratios) to gain
92 insights into likely disease under-reporting and case fatality in mainland China.

93 We then applied these insights to infer likely differences in disease severity
94 (based on CFR), and detection of epidemics occurring in countries *outside*
95 mainland China.

96

97

98 **Methods**

99

100 *Data Sources*

101

102 COVID-19 case counts by age were based on confirmed cases, by age, reported
103 in (5). 2020 country population projections for China by age were obtained from
104 the United Nations using the UNWPP package in R (6, 7). While the Chinese
105 COVID-19 epidemic was centered on the province of Hubei, the epidemic rapidly
106 spread to involve all Chinese provinces. Therefore, we used the total Chinese
107 population data by age to calculate age-specific cumulative incidence over the
108 initial 9 weeks of the epidemic. We used these initial observations to perform all
109 subsequent analyses.

110

111 *Standardized Morbidity Ratios*

112

113 We calculated overall cumulative incidence per 100,000 population in the 66-
114 days from December 8, 2019 (the date of onset in the first recognized human
115 COVID-19 case) to February 11, 2020 (8). Crude and age-specific cumulative
116 incidence were calculated as the ratio of case numbers to population size.
117 Standardized morbidity ratios (SMR) were then calculated as $100 \times (\text{observed}$
118 $\text{cases}/\text{expected cases})$ where expected cases are the product of crude
119 cumulative incidence and the population size of a given age group (4).

120

121

122

123 *Under-Ascertainment of Younger Cases and Implications for Case-Fatality*

124

125 Given that COVID-19 is an emerging communicable disease and there is no pre-
126 existing immunity in the population, attack rates should be similar across age
127 groups, or possibly even higher in children due to their more intense contact
128 structure (9). The elevated SMR in older age groups, combined with their higher
129 case fatality, is suggestive of increased case ascertainment in this group due to
130 greater clinical severity. Indeed, when active case finding has been performed
131 for pediatric cases, attack rates in younger groups have been similar to those in
132 the older age groups. We examined a series of “case studies” where incidence in
133 older individuals (age > 59) was assumed to be measured accurately, and
134 cumulative incidence in older individuals was then applied to younger age
135 groups to generate estimates of the fraction of cases under-ascertained in these
136 age groups. We then revised the expected case fatality proportions based on
137 case counts adjusted for likely under-reporting in younger individuals.

138

139 *Population Standardization, Case Fatality and Observed Outbreak Size*

140

141 We evaluated the anticipated size, timing, and impact of an epidemic with
142 identical age-specific cumulative incidence and case fatality as observed in
143 China but applied to four countries outside of China. We standardized to
144 countries and areas with older age than China (Japan, Italy) and younger age
145 (Indonesia, Egypt) as a means of isolating the impact of age structure on
146 outbreak characteristics. While somewhat arbitrary, these regions have all
147 either been impacted by COVID-19 to some degree (Japan, and Italy) (10-12);

148 have had large numbers of exported cases without large national epidemics
149 (Egypt)(13); or have been notable for the relatively limited number of cases
150 identified notwithstanding close links to China (Indonesia) (14).

151

152 Since China's large population size results in a far larger epidemic for a given
153 incidence, we used a ratio-of-ratio approach. The ratio of population in the
154 other, comparator country (P_O) to the Chinese population (P_C) was defined as R_P
155 $= P_O/P_C$. The ratio of the observed epidemic size in the other, comparator
156 country (E_O) to observed Chinese epidemic size (E_C) was defined as $R_E = E_O/E_C$.
157 The ratio of ratios was thus R_E/R_P , and can be interpreted as the relative
158 apparent outbreak size when an outbreak with identical age-specific attack
159 rates occurs in a population with an age-structure that differs from that of
160 China.

161

162 *Age Structure and Outbreak Detection*

163

164 We estimated the incidence of observed infection among susceptible older
165 individuals (age > 59) in the Chinese population required for the observed
166 epidemic to have taken place over 66 days using the relation $\lambda = -\ln(1-P)/t$. This
167 hazard was then applied to 1) the Chinese population, and 2) the populations of
168 the other four "case study" countries, over a 66-day period under the
169 assumption that the most severe illness would be seen in those aged > 59 years.
170 We modeled time to observation of deaths by modeling time to symptoms,
171 severe pneumonia, ICU admission, and death using parameter estimates
172 presented in **Table 1**, assuming exponential failure time.

173

174 **Results**

175

176 Based on data in (8), the crude cumulative incidence of observed COVID-19 in
177 mainland China up until February 11, 2020 was 3.1 per 100,000. By contrast,
178 cumulative incidence in those aged > 59 years was 5.6 per 100,000. Age-
179 specific cumulative incidence and SMR by age are presented in **Table 2** and
180 **Supplementary Figure 1**. It can be seen that SMR for age groups < 50 was
181 substantially lower than that in older age groups and most deaths were also
182 observed in older age groups (**Table 2**). When we assumed complete or near
183 complete ascertainment of cases in individuals aged >59, and adjusted
184 incidence in younger age groups accordingly, the adjusted CFR fell, and was
185 0.8% if we assume that only 50% of older cases were ascertained (**Figure 1**).
186 Even if all cases were ascertained in older individuals, it was estimated that
187 46% of total cases were missed; if only 50% of older cases were ascertained it
188 was estimated that 75% of cases were missed (**Figure 1**).

189

190 When the Chinese epidemic was age-standardized using population pyramids
191 from other countries, standardization to younger populations (Indonesia, Egypt
192 and Iran) markedly reduced CFR, while adjustment to older countries or regions
193 (Japan, Italy) elevated CFR (**Table 3**). The ratio-of-ratios, R_E/R_P , was less than 1
194 for countries with younger populations, but greater than 1 for countries with
195 older populations. In other words, apparent epidemics, adjusted for population
196 size, would be expected to be smaller in countries with younger populations

197 (shorter life expectancy) than in those with older populations (increased life
198 expectancy), even with identical age-specific attack rates.

199

200 When we simulated the mainland China epidemic in other countries, we found
201 that at any threshold of deaths required for outbreak detection, outbreaks
202 would be detected more quickly in countries with high life expectancy, and
203 more slowly in those with low life expectancy (**Figure 2** and **Online Appendix**
204 [\(https://art-bd.shinyapps.io/time_to_outbreak_detection/\)](https://art-bd.shinyapps.io/time_to_outbreak_detection/)).

205

206

207 **Discussion**

208

209 As the COVID-19 pandemic has expanded its reach, the role of unrecognized
210 infection has received increased scrutiny (2, 15). While individuals with
211 unrecognized infection may be important in the epidemic's spread, those with
212 more severe illness are more likely to be recognized clinically, and more likely to
213 be referred for virological testing, a practice which the age distribution of
214 identified cases in China early in the pandemic, foretold (8).

215

216 Age-related increases in severity, which may be confounded by increasing
217 prevalence of chronic medical conditions with age, are now well described in
218 countries outside China (16, 17). Greater recognition of individuals with more
219 severe illness, and undercounting of those with mild infection, is likely to inflate
220 apparent case fatality. While serological testing will ultimately help determine
221 the true infection fatality ratio for COVID-19, estimates of undercounting may
222 be derived if it is assumed that all in the population, regardless of age, are
223 equally vulnerable to infection. We demonstrate such an approach in this
224 paper.

225

226 The key driver of pandemic disease is a fully susceptible population; novel
227 pathogens have higher reproduction numbers when they first emerge but the
228 number drops once some proportion of the population has become immune
229 (18). This leads to very high attack rates early in a pandemic. Furthermore,
230 vulnerability to infection should be equally distributed across the population,
231 with incidence expected to be highest in children, who have the highest rates

232 and intensity of person-to-person contact. As such, an absence of pediatric
233 cases in national reporting data represents an index of under-reporting rather
234 than immunity to infection and can be used as a means of quickly adjusting
235 models for under-reported fractions through simple, easily applied methods
236 such as direct and indirect standardization, which we employ here. Bayesian
237 methods provide a more computationally intensive and more technically
238 challenging approach to the same problem (2).

239

240 The extraordinary case-fatality in the COVID-19 pandemic (as high as 10-12%
241 in Spain and Italy as of April 3, 2020) (19), also underscores the unusual
242 epidemiology of pandemics, since with endemic diseases (and some pandemics,
243 such as the 2009 (H1N1) influenza A pandemic) early life immune experience
244 protects those who would be vulnerable to severe disease conditional on
245 infection (i.e., older individuals), while permitting infection of younger
246 individuals less likely to experience severe disease (20). While case-fatality is
247 driven at least in part by the extent of testing, standardizing these epidemics to
248 different populations (in effect, letting an identical epidemic run out in a
249 different population) allows us to see that demographic structure alone can
250 explain many between country differences in apparent epidemic size and case
251 fatality. Adjusting for population size, identical epidemics will appear larger and
252 more severe in “older” countries (like those in Western Europe) and smaller and
253 milder in “younger” countries (like Egypt, and Indonesia).

254

255 A key limitation of this work is that much of the work focusses on an epidemic
256 in a single country, at an early point in the COVID-19 pandemic. Indeed, the

257 observable case-fatality in China now approximates 4%, rather than 2.4% as
258 reported earlier, which is likely to reflect lags between clinical onset and death
259 from COVID-19, especially in individuals who receive intensive care with
260 mechanical ventilation. We have, furthermore, not attempted to incorporate
261 second order effects, such as the resulting rapid saturation of ICU resources,
262 with resultant upwards inflection in case fatality, in countries with older
263 populations (e.g. Italy). Such effects may be operative in the devastating COVID-
264 19 epidemics in Western Europe, which have CFR well beyond what our
265 standardization of the Chinese epidemic data would predict.

266

267 In conclusion, we find that standardization, both direct and indirect, provides a
268 simple, widely understood toolbox for explaining and understanding several of
269 the unusual features of COVID-19, including under-representation of pediatric
270 cases and geographic variability in apparent epidemic size and severity
271 (measured as CFR). While we are living in frightening and emotionally charged
272 times, we suggest that demographic variation, rather than misrepresentation
273 (21, 22), is likely to explain much of the between-country variability seen in the
274 current pandemic.

275

276 **Figure Legends**

277

278 **Figure 1. Case Fatality and Fraction of Cases Missed Under Varying**

279 **Assumptions of Reporting Completeness in Older Individuals.**

280 Estimates of the fraction of cases missed in the population as a whole (black
281 solid curve), and true case-fatality ratio (CFR) (black dashed curve), as a
282 function of the fraction of cases missed in older adults who are assumed to be
283 ascertained with the greatest accuracy. Decreasing case ascertainment in older
284 adults implies an even higher fraction of cases are missed in the population as
285 a whole, and CFR is lower than observed.

286

287 **Figure 2. Model Describing Differential Time To Recognition of COVID-19**

288 **Outbreaks in Countries with Different Age Structures.**

289

290 Outbreaks with identical age-specific attack rates, and otherwise identical
291 characteristics, were simulated in countries with intermediate (China), old
292 (Italy) and young (Indonesia) populations. It can be seen that for any threshold
293 of deaths that must be exceeded for an outbreak to be recognized, older
294 countries will be identified before younger countries. Model details are as
295 described in the text.

296

297 **Supplementary Figure 1. Observed Cumulative Incidence, Deaths and**

298 **Standardized Morbidity Ratios for Mainland China COVID-19 Epidemic.**

299 Figure is a graphical representation of data presented in **Table 2**. SMR are
300 estimated as $100 \times$ observed incidence divided by expected incidence, which in

301 the context of a pandemic is approximately equal in all age groups, or
302 somewhat higher in younger individuals.
303

304

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Table 1. Parameters Used for Time-To-Death Estimates

Parameter	Estimate	Reference
Proportions		
Severe pneumonia	0.15	(23)
ICU requirement with severe pneumonia	0.20	(23)
Death in ICU	0.62	(24)
Average duration (days)		
Incubation period	6	(25)
Time from onset to hospitalization	7	(26)
Time from hospitalization to ICU	3	(26)
Time from ICU admission to death	25	(25)
Force of infection (λ)	8.44×10^{-7}	Calculated based on (5).

NOTE: ICU, intensive care unit.

Table 2: Epidemiological Characteristics of China's COVID-19 Epidemic to February 11, 2020.

Age Group	Cases	Deaths	Case Fatality	Population (millions)	Cumulative Incidence*	SMR
0-9	416	0	0	170.7	0.24	7.9
10-19	549	1	0.002	166.6	0.33	10.6
20-29	3619	7	0.002	185.1	1.95	63.0
30-39	7600	18	0.002	228.8	3.32	107.0
40-49	8571	38	0.004	216.1	3.97	127.8
50-59	10008	130	0.013	222.2	4.50	145.1
60-69	8583	309	0.036	151.7	5.66	182.3
70-79	3918	312	0.080	71.5	5.48	176.6
80+	1408	208	0.148	26.6	5.29	170.4

NOTE: SMR, standardized morbidity ratio.

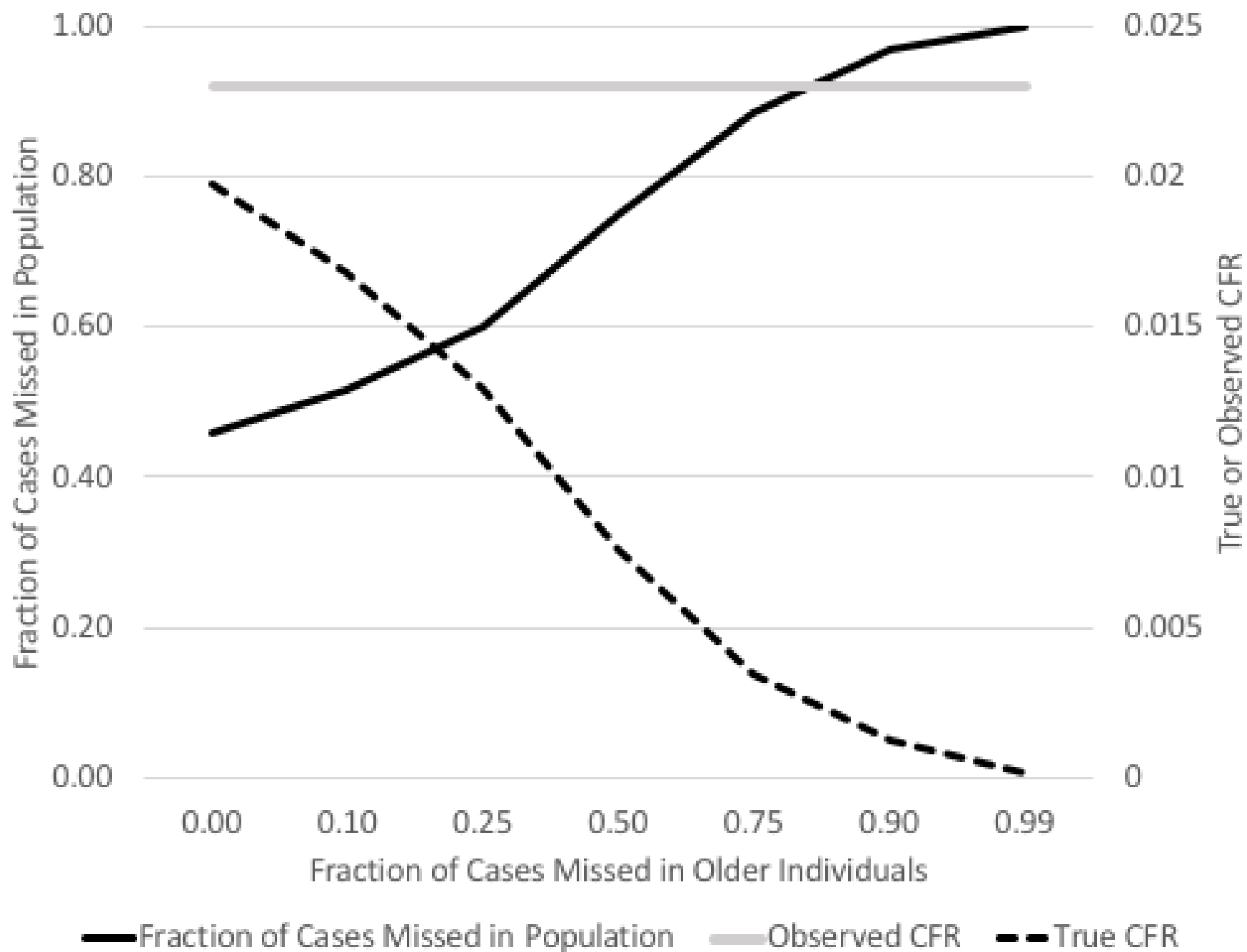
*per 100,000 population.

Table 3: Direct Standardization of Mainland China’s COVID-19 Epidemic to Other Countries and Regions

Country/Region	Country-Standardized CFR (%)	Epidemic Size Ratio (R_E)*	Population Size Ratio (R_P)*	R_E/R_P
Mainland China	2.3	---	---	---
Egypt	1.6	0.05	0.07	0.69
Indonesia	1.7	0.15	0.19	0.81
Italy	3.9	0.05	0.04	1.15
Japan	4.4	0.10	0.09	1.18

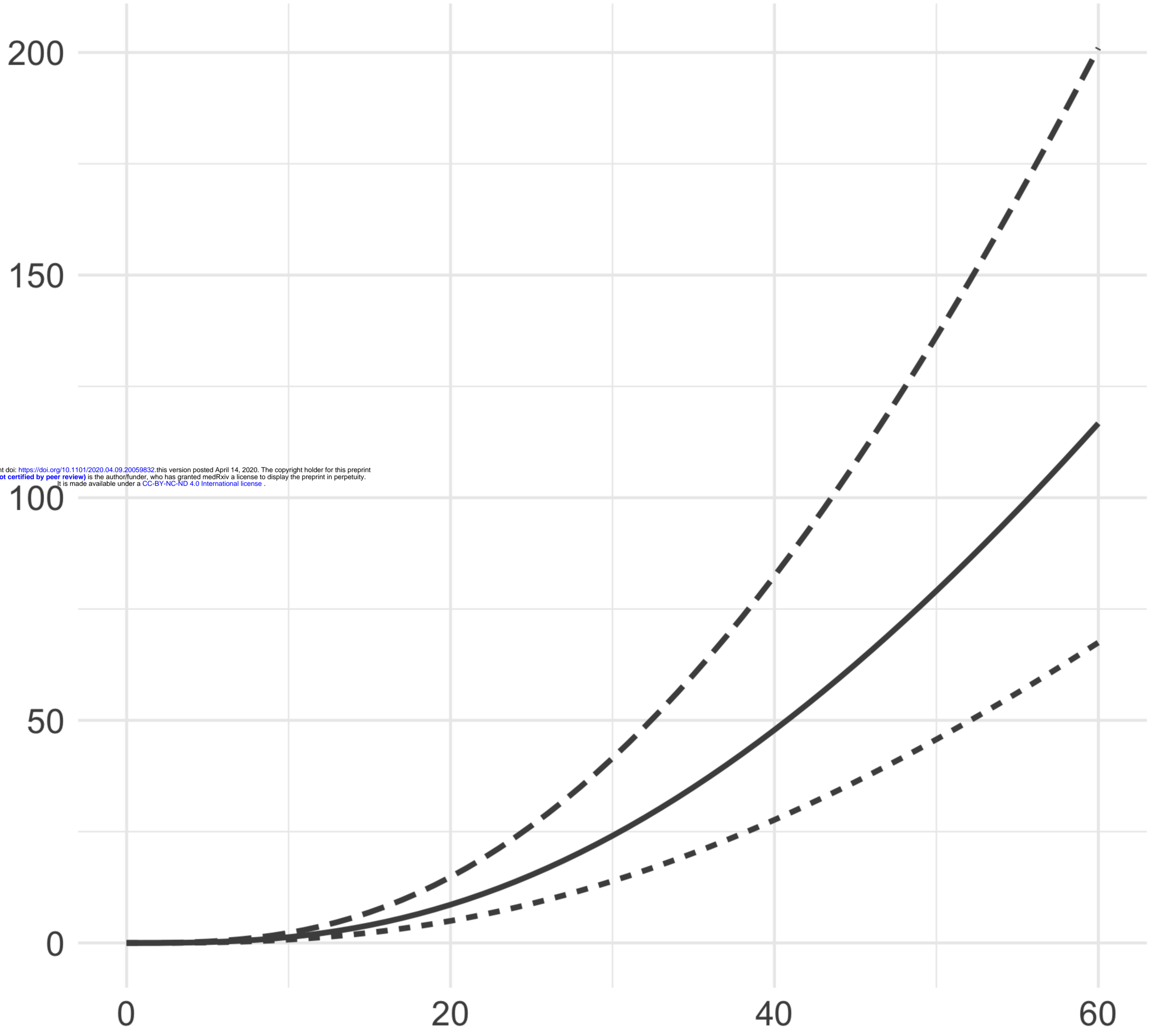
NOTE: CFR, case fatality ratio.

*Compared to Mainland China.



Number of deaths (cumulative)

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- China
- - Indonesia
- · Italy

Time (days)