1   **Estimation of Individual Probabilities of COVID-19 Infection, Hospitalization, and**

2   **Death From A County-level Contact of Unknown infection Status**

3

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Abstract

Objective: Our objective is to demonstrate a method to estimate the probability of a laboratory confirmed COVID19 infection, hospitalization, and death arising from a contact with an individual of unknown infection status.

Methods: We calculate the probability of a confirmed infection, hospitalization, and death resulting from a county-level person-contact using available data on current case incidence, secondary attack rates, infectious periods, asymptomatic infections, and ratios of confirmed infections to hospitalizations and fatalities.

Results: Among US counties with populations greater than 500,000 people, during the week ending June 13,2020, the median estimate of the county level probability of a confirmed infection is 1 infection in 40,500 person contacts (Range: 10,100 to 586,000). For a 50 to 64 year-old individual, the median estimate of the county level probability of a hospitalization is 1 in 709,000 person contacts (Range: 177,000 to 10,200,000) and the median estimate of the county level probability of a fatality is 1 in 6,670,000 person contacts (Range 1,680,000 to 97,600.000).

Conclusions and Relevance: Estimates of the individual probabilities of COVID19 infection, hospitalization and death vary widely but may not align with public risk perceptions. Systematically collected and publicly reported data on infection incidence by, for example, the setting of exposure, type of residence and occupation would allow more precise estimates of probabilities than possible with currently available public data. Calculation of secondary attack rates by setting and better measures of the prevalence of seropositivity would further improve those estimates.

Introduction

During infectious disease epidemics, human perception of risk modifies disease

transmission, and motivates, or not, protective behaviors such as hand hygiene,

wearing masks and social distancing at the individual level and quarantine, travel

restrictions, and restrictions on gatherings at the societal level. Novel infectious agents

such as the COVID-19 virus, with immature understanding of susceptibility,

transmission, and lethality, challenge accurate risk estimation.

Predictive models, government surveillance, and epidemiological studies have

characterized the risk of COVID-19, in terms of aggregate, and not individual,

outcomes, primarily including County-level counts of reported infections,

hospitalizations, and deaths. (1) Research has attempted to estimate case fatality rates

and identified risk factors for adverse outcomes from COVID-19 disease, such age and

chronic disease status. (2, 3) We are not aware of any published research that

estimates individual level probabilities of infection, hospitalization, and death from

exposure in the general community.

In the United States, publicly accessible data does not yet permit estimating the

individual risks of COVID-19 transmission in specific exposure settings, including

workplaces, prisons, nursing homes, hospitals and group residential housing settings.

However, a starting point for estimation can be the average individual-level probability of

acquiring infection across all settings at the level of a county. One can modify those

66   estimates as data on setting specific infection incidence rates, susceptibility and

67   secondary attack rates permit.

68

69   Here, we contribute to COVID-19 risk assessment by demonstrating a method to

70   estimate the individual probabilities of acquiring infection, being hospitalized, and dying

71   in U.S. Counties. We identify areas of available and future knowledge that could make

72   risk assessment more precise and context specific.

73

74   **Materials and Methods**

75

76   Our objective is to estimate the probability of acquiring COVID-19 infection from a

77   "contact" with a random individual of unknown infection status. We conceptualize this

78   probability under steady state conditions (e.g. no epidemic growth or decline) as a

79   function of individual susceptibility, the current reported case incidence, accounting for

80   undetected infection, the share of infection transmission occurring without a known

81   contact, the chance of transmission per contact (e.g., the secondary attack rate), and

82   the duration of infectiousness, accounting for pre-symptomatic transmission.

83

84   We use the formulae below to compute probabilities of infection, confirmed infection,

85   hospitalization, and death.

86

87   *(1)* $P_{infection \,|\, contact} = S \; I_{confirmed} \; C \; \beta \; [1 + \alpha/(1 - \alpha)\,] \, [\, \sigma \, D_{Infectious} + \eta \, (1 - \sigma) \, D_{Infectious}\,]$

88   *(2)* $P_{confirmed\text{-}infection \,|\, contact} = P_{infection \,|\, contact} / (1 - \alpha)$

89   *(3)* $P_{hospitalization \,|\, contact} = CHR \times P_{confirmed\text{-}infection \,|\, contact}$

4

90      $(4)\ P_{death\,|\,contact} = CFR \times P_{confirmed\text{-}infection|\,contact}$

91

92   We describe the parameters used in Table 1 and explain their sources below.

93   **Table 1. Parameters Used in Formulae**

Symbol	Parameter Description	Value
S	Proportion of the population susceptible	95%
$I_{confirmed}$	Incidence of confirmed (reported) infections per day	County Data
C	Proportion of infections resulting from unknown contacts	100%
α	Proportion of total infections unconfirmed (undetected and unreported)	75%
B	Probability of infection per exposure	10%
$D_{infectious}$	Average days infectious per infection	8
σ	Proportion of infectious period pre-symptomatic [a]	40%
η	Proportion non-compliant with isolation	25%
CHR	Case Hospitalization Ratio, 0 to 49 years [a]	0.026
CHR	Case Hospitalization Ratio, 50 to 64 years [a]	0.057
CHR	Case Hospitalization Ratio, Over 65 years [a]	0.1
CFR	Case Fatality Ratio, 0 to 49 years [a]	0.001
CFR	Case Fatality Ratio, 50 to 64 years [a]	0.006
CFR	Case Fatality Ratio, Over 65 years [a]	0.032

94

95   [a] US CDC COVID-19 Pandemic Planning Scenarios. Scenario 4 Estimates

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97

98   The prevalence of susceptibility to COVID-19 is unknown. Pre-existing immunity due to

99   previous COVID-19-related coronaviral infections is plausible but speculative. Reliable

100   estimates for the proportion of the population who have acquired immunity is unknown

101   but non-zero. We have conservatively estimated the prevalence of susceptibility to be

102   95%.

103

104   We acquired COVID-19 confirmed infection incidence data from publicly reported

105   statistics compiled by The New York Times. (4) Confirmed infection rates underestimate

106   the true incidence of infection in the community because of undetected infections that

107   can be both symptomatic and asymptomatic. Several studies have estimated the

108   asymptomatic fraction. (5-7) In one meta-analytic review, the proportion of

109   asymptomatic infections ranged from 6% to 41%. (8) A weighted mean estimate from

110   those studies suggests that about 1 out of 6 persons, or 16%, may be asymptomatic.

111   On the other hand, seroprevalence studies aim to capture both the confirmed and

112   unconfirmed fractions together without regard to symptoms. Some seroprevalence

113   studies suggest that up to 90% of infections may be unconfirmed. (9) The US CDC

114   gives 50% as their most conservative estimate of the proportion of asymptomatic

115   infections. (10) We estimate 75% of all infections are unconfirmed which includes both

116   symptomatic and asymptomatic unconfirmed infections.

117

118   Limited data is available on the share of reported infections arising without a known

119   contact. As of this date, the US CDC has not included any statistics on this attribute of

6

120   confirmed infections. The State of Oregon currently publicly reports infections without a

121   known contact a varying between 30 and 50%%. Because of limited national data, we

122   use 100% for this parameter; we leave the parameter in the equation for the purpose of

123   future applications.

124

125   The attack rate for an exposure varies by exposure intensity, context, proximity, and

126   duration. For this analysis, contact means any substantive exposures that happen in a

127   community, household, workplaces, or group living situations. Examples of substantive

128   contacts outside households might include dining with a friend or business contact,

129   working in a shared office space or having close or physical contact without the types of

130   precautions now recommended for prevention of infection transmission (e.g. avoiding

131   handshaking, embraces, wearing a mask or indoor ventilation). We do not consider

132   contacts to be short-term events, such as passing by a person on the street. Contact

133   within households involves habitual and typically unprotected close physical. We

134   understand that attack rates will vary across such diverse exposure settings.

135

136   Overall, secondary attack rates from contact tracing studies on COVID-19 range from

137   0.7% to 16.3%. One study in Taiwan estimated a mean attack rate of 0.7% with an

138   attack rate of ~5% among household and non-household family contacts. (11) A Hong

139   Kong study of the quarantined contacts of visitors from China estimated a secondary

140   attack rate of 11.7%. (12) Two published study within China found a household attack

141   rate of 16.3% and 11.2% respectively. (13-14)

142

143   We assume an average plausible attack rate across all settings of exposure based on

144   these range of estimates to be 10% in the absence of more setting and activity specific

145   data. We acknowledge that this estimate may overestimate the attack rate for a non-

146   household contact and underestimate it for a household contact.

147

148   We estimate the total duration of infectiousness as 8 days. Research suggests that

149   individuals who develop symptoms may be infectious two to three days before the onset

150   of symptoms. (15) We apply the US CDC's estimates that the proportion of

151   infectiousness before symptom onset is 40% of the total duration. (10) Conservatively,

152   we treat infections in the unreported fraction as being infectious for the same duration

153   as those with reported infections.

154

155   Compliance with self-isolation affects the number of infectious people circulating with

156   infection after symptoms develop. Current research within the context of the COVID-19

157   pandemic finds that compliance with isolation ranges from 57% without financial

158   compensation to 94% with compensation. (16) Given the current US context and the

159   availability of sick leave compensation, we assume that 75% of individuals with

160   confirmed infection will voluntarily self-isolate after symptoms develop. We do not alter

161   the duration of infectiousness for the unconfirmed fraction of infections.

162

163   We estimate the probabilities per contact of reported infections, hospitalizations and

164   deaths as fixed ratios of the estimated but unobserved probability of infection. The

8

165   relationship between total infections and confirmed infections is fixed and defined by the

166   parameter alpha above.

167

168   We estimate the probability of hospitalizations and deaths per contact using US CDC

169   estimates of case hospitalization ratios and case fatality ratios from their pandemic

170   planning scenario four, which is their most conservative current estimate of disease

171   severity and transmissibility. (10) (Table 1) Based on these fixed ratios, we expect 18

172   reported infections and 70 total infections for every hospitalization in an individual in the

173   50-64 year old age group. And we expect 167 reported infections, and 667 total

174   infections for every death in the 50-64 year old age group.

175

176   These estimated case fatality ratios are within the range of published values in the

177   United States. One study of deaths through the early part of the epidemic estimated the

178   case fatality ratio for symptomatic cases to be 1.3% (95% CI: 0.6% to 2.1%). (2)

179

180   We compared estimated weekly hospitalization incidence rates produced using the

181   estimated probabilities per contact against observed incidence rates of laboratory

182   confirmed COVID-19 hospitalization in several US multi-county regions where the US

183   CDC conducts active hospital case surveillance. (17) To estimate weekly

184   hospitalizations, we multiplied our estimates of age specific probabilities of

185   hospitalization per contact and a modest number of daily contacts equal to the number

186   of other household members plus one.

187

Results

Among US Counties with populations greater than 500,000 people (N= 1224), for the week ending June 13, 2020, the median observed county-level daily case incidence is 6.78 per 100,000 (Range, 0.41- 24). In those counties, the median estimate of the county-level probability of a confirmed COVID-19 infection is 1 infection in 40,500 person-contacts (Range: 10,100 - 586,000). These estimates reflect the probability per contact at a single point in time averaged across all types of contacts and settings, within and outside households.

In the same counties, for a 50 to 64 year old individual, , the median estimate of the county-level probability of a hospitalization is 1 in 709,000 person-contacts (Range: 177,000 – 10,200,000) and the median estimate of the county-level probability of a fatality is 1 in 6,670,000 person-contacts (Range 1,680,000 – 97,600.000). Table 2 lists probabilities for other age groups.

10

203   Table 2. Estimated County-level Probabilities for the Week Ending June 13, 2020 of

204   COVID-19 Events in Counties with Populations Greater Than 500,000 (N = 1224)

Event	Age Group	Average	Median	Minimum	Maximum
Confirmed Case	All	0.002833%	0.002470%	0.000171%	0.009892%
Hospitalization	Under 49 yr	0.000074%	0.000064%	0.000004%	0.000257%
	50- 64 yr	0.000162%	0.000141%	0.000010%	0.000564%
	Over 65 yr	0.000283%	0.000247%	0.000017%	0.000989%
Fatality	Under 49 yr	0.000003%	0.000002%	0.000000%	0.000010%
	50- 64 yr	0.000017%	0.000015%	0.000001%	0.000059%
	Over 65 yr	0.000091%	0.000079%	0.000005%	0.000317%

205

206   Figure 1 illustrates the average estimated probabilities of confirmed infection,

207   hospitalization and fatality per contact as a function of daily case incidence. Figure 2

208   Illustrates the estimated number of hospitalizations and fatalities per 1 million contacts

209   in a subset of analyzed US counties with populations greater than 1.5 million.

210

211   We found good concordance between the estimated weekly hospitalization rates and

212   rates from US CDC hospitalization surveillance data in most of our comparison regions

213   under the assumption that average daily contacts equaled the average number of other

214   household members plus one. (Table 3) CDC acknowledges that more recent data

215   values are subject to revision.

216   Table 3. Estimated weekly hospitalization rates per 100,000 people for the week ending

217   June 13, 2020 compared to weekly laboratory confirmed hospitalization rates observed

218   by US CDC regional surveillance.

County	Alameda, CA	Denver CO	Fulton GA	Montgomery, MD	Wayne, MI
Assumption of Contacts Per Day	2.8	2.3	2.47	2.79	2.52
Estimated Weekly New Cases per 100,000	32.94	37.55	28.2	127.4	53.8
Estimated Weekly Hospitalization Rate (per 100,0000 people)					
18-49 years	0.86	0.98	0.7	3.3	1.4
50-64 years	1.88	2.14	1.6	7.3	3.1
Over 65 years	3.29	3.76	2.8	12.7	5.4
COVID-NET Observed Regional Weekly Hospitalization Rates					
18-49 years	1	1.1	1	5.3	0.4
50-64 years	1	3.2	2	6.6	0.8
Over 65 years	3.3	2.2	1.7	13.5	0.5

219

220

221   **Discussion**

222

223   We demonstrate a method to estimate the average county-level probabilities of COVID-

224   19 confirmed infections, hospitalizations, and deaths in the U.S resulting from a contact

225   with a random person in the population. Those estimates reflect current reported

226   COVID-19 confirmed infection incidence in US counties with more than 500,000 people

227   for the week ending June 6, 2020. Probabilities vary across a wide range reflecting the

228   varying case incidences in different counties.

229

230   Our method is limited by the availability of publicly available data on infection

231   transmission on COVID-19, including setting and occupational specific case incidence

232   rates, data on antibody seroprevalence, the share of infection with known contacts, and

233   activity-specific attack rates. The estimates therefore reflect the average probability

234   across a wide range of exposure contexts. Nevertheless, observed rates of

235   hospitalization for laboratory confirmed COVID-19 disease in several US CDC active

236   surveillance areas generally corroborate our estimates under the assumption of a

237   modest level of social contact.

238

239   Our estimates of the average probabilities per contact do not accurately estimate risks

240   for specific subsets of people. Infections occur within geographically and socially

241   constrained chains of transmission, for example, within clusters of related or socially

242   connected individuals or among those living in congregate living facilities such as

243   nursing homes. Clusters of COVID-19 infections have been reported associated with

244   prisons, workers dormitories, religious services, nightclubs, schools, cruise ships,

245   sporting events, and professional conferences. (18) Disaggregating confirmed infection

246   incidence rates into fractions representing those with and without known contacts and

247   those within and without congregate living settings would allow for more setting and

248   population specific risk estimates. This requires the systematic public reporting of

249   confirmed infection exposure factors.

250

13

251   As mentioned above, systematic data on the share of confirmed infections arising

252   without a known contact is not currently available. Appling this fraction to the model

253   would reduce our estimates based on the assumption of a 100% share.

254

255   Available estimates of the secondary attack rate come from observations outside the

256   US and at an earlier time period in the pandemic, prior to normalization of behaviors

257   that reduce the risk of infection transmission, such as increased hand washing,

258   observing physical distance, forgoing physical greetings, and wearing masks.

259

260   The limitations of published secondary attack rates and the lack of disaggregated data

261   on confirmed infection incidence also do not allow our estimates to differentiate between

262   community and household transmission. Most studies indicate that household attack

263   rates are higher than for contacts in the community. Systematic public reporting of

264   anonymized contact tracing data would provide information to assess context specific

265   attack rates.

266

267   We also cannot account for intra-individual variation in the secondary attack rate within

268   a setting. With respiratory viruses, the number of secondary cases generated by each

269   index case can vary significantly. (19-20) One recent estimate suggests that 80% of

270   COVID-19 infections are due to a small fraction (10%) of particularly infectious

271   individuals. (21)

272

273   We have assumed a high fraction of the population remains susceptible as the

274   prevalence and significance of antibodies to COVID-19 is not known. However, there

275   may well be factors conferring protection to infection or responsible for differences in

276   susceptibility. For example, cross immunity due to infection with other coronaviruses

277   may be occurring. (22) Researchers have also observed cellular immune system

278   responses to COVID-19 among unexposed individuals likely due to prior exposure to

279   related coronaviruses. (23) More data will be required before adjusting risk assessment

280   for population susceptibility or immunity.

281

282   We estimated probabilities of hospitalization and death based on CDC estimates of

283   disease severity. We chose conservative scenarios but acknowledge that estimates of

284   confirmed infection fatality ratios may further evolve over the course of the pandemic.

285   Furthermore, individual states may have different criteria for recording a death from

286   COVID-19. The risk of hospitalization and death varies with other risk factors including

287   race/ethnicity, level of deprivation, and chronic diseases such as lung disease and

288   diabetes, that are not reflected in our analysis.

289

290   Better data to address the above limitations would likely reduce estimated probabilities

291   of adverse events for a large fraction of the population; still, the estimated probabilities

292   reported here may appear considerably lower than those reflected in public opinion

293   surveys. Scientific uncertainties, media attention, dramatic governmental action and a

294   subjective perceived lack of control over exposure all may be influencing risk

295   perception. Exploring methods to communicate risk and the concordance of perceived

296   risk and risk probabilities would be an appropriate subject for further work.

297

298 Avoiding human contact in the setting of an uncertain and lethal epidemic threat is an

299 expected and self-protective human behavior. Prevalent beliefs today about the sources

300 of COVID-19 infection include 'contact with infected persons', 'people coming from

301 abroad' or 'foreign nationals.' (24) Notably, many people assume that contact with a

302 family member has a lower risk of infection transmission than contact with a stranger.

303 This may not be true for all subgroups in the population.

304

305 In the US, policy makers have taken dramatic and unprecedented steps to control

306 COVID-19, applying universal contact reductions through home confinement, limits on

307 travel, closures of schools and businesses and limits on gatherings. While heightened

308 perception of risk (e.g., fear) motivated these restrictions at the outset of the epidemic,

309 ongoing restrictions on community activity may be mediating risk perceptions. (25)

310

311 Notably, in Wuhan, the government limited exponential growth of the COVID-19

312 epidemic using isolation and quarantine, mandatory mask wearing, canceled New

313 Year's celebrations, the curtailment of intra-city and intercity transportation and

314 extension of the New Year's holiday period. (26) South Korea achieved epidemic control

315 with scaled up testing, strong contact notification practices, case isolation and strict

316 quarantine of those exposed and public awareness. (27) The lack of understanding of

317 how various countries have brought their epidemics under control maybe another

318 important factor influencing the perception of risk to COVID-19 infection in community

319 settings in the US.

320

321   Return to community workplace and social life will require individuals to be comfortable

322   with their personal risk of acquiring COVID-19 infection. Estimates on the individual

323   probabilities of infection, hospitalization and death may contribute to a more accurate

324   risk perception. Systematically collected and publicly reported data on infection

325   incidence by, for example, the geographic setting of exposure, residence type, whether

326   a case had a known exposure, and would allow more precise estimation than those

327   possible with currently available public data. Calculation of secondary attack rates by

328   setting and prevalence of seropositivity would further improve these estimates.

329

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331   the study and writing of the manuscript. Rajiv Bhatia conducted the analysis.

332

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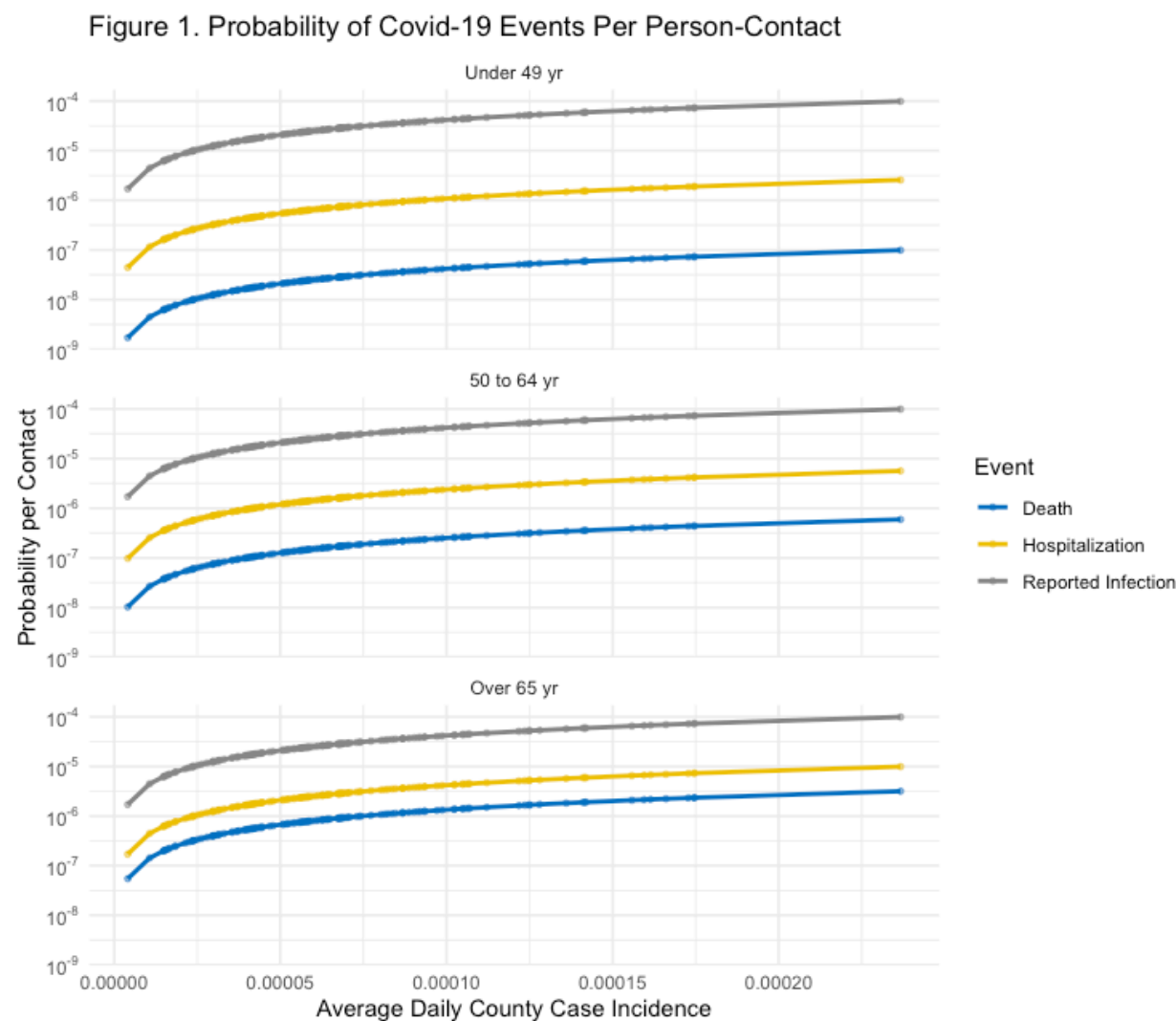429   South Korea, 2020. *Emerg Infect Dis*. 2020 Oct. doi.org/10.3201/eid2610.201886

Figure 1. Estimated county-level probabilities of confirmed infection, hospitalization and death per contact as a function of daily case incidence.
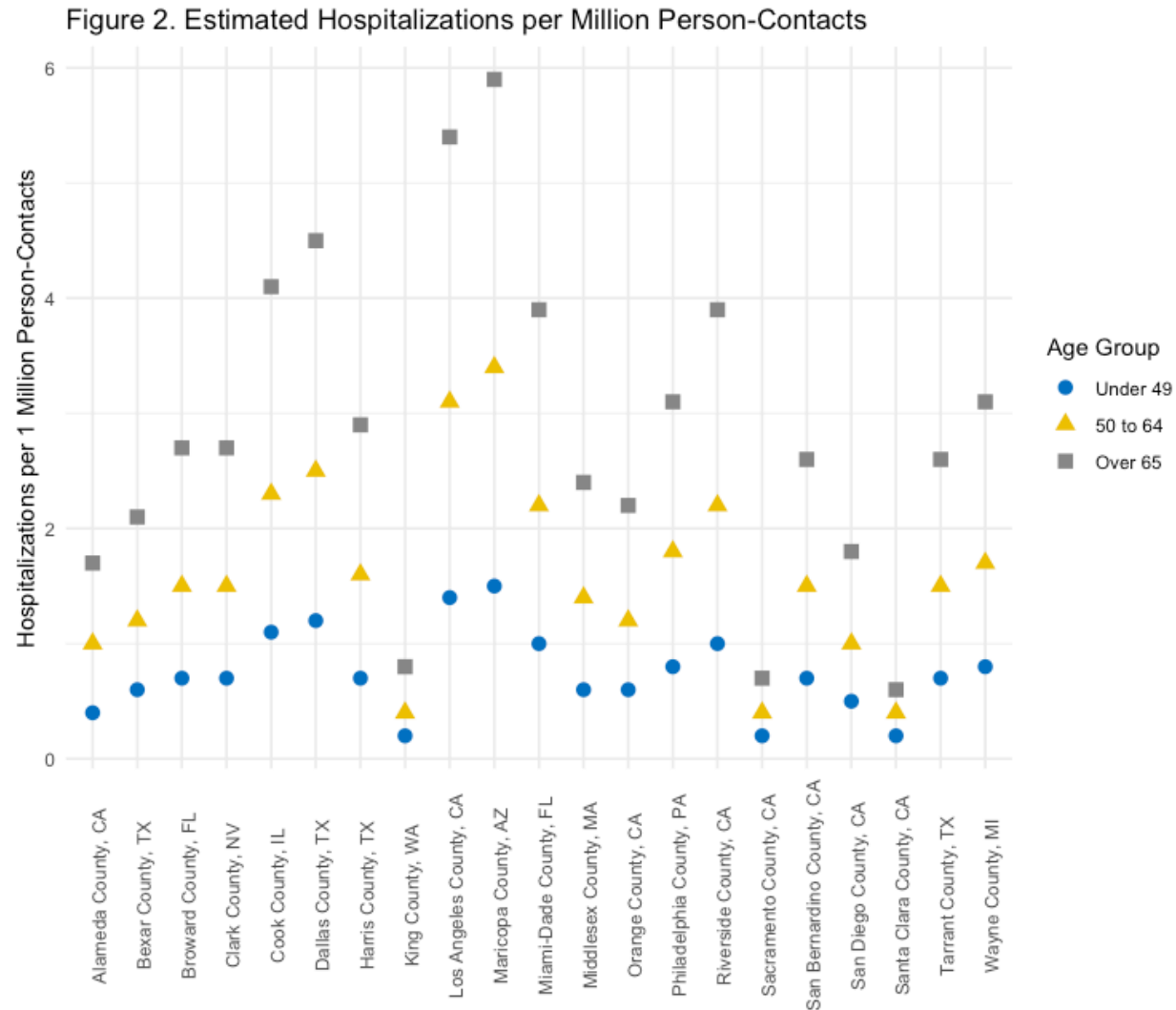
Figure 2. Estimated current number of predicted COVID-19 hospitalizations per 1 million

contacts in counties with populations greater than 1.5 million.