

1 **Calibrating COVID-19 Community Transmission Risk Levels to Reflect Infection Prevalence**

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42 **Abstract**

43 Many organizations, including the US Centers for Disease Control and Prevention, have
44 developed risk indexes to help determine community transmission levels for the ongoing
45 COVID-19 pandemic. These risk indexes are largely based on newly reported cases and
46 percentage of positive SARS-CoV-2 diagnostic nucleic acid amplification tests, which are well-
47 established as biased estimates of COVID-19 transmission. However, transmission risk indexes
48 should accurately and precisely communicate community risks to decision-makers and the
49 public. Therefore, transmission risk indexes would ideally quantify actual, and not just reported,
50 levels of disease prevalence or incidence. Here, we develop a robust data-driven framework for
51 determining and communicating community transmission risk levels using reported cases and
52 test positivity. We use this framework to evaluate the previous CDC community risk level
53 metrics that were proposed as guidelines for determining COVID-19 transmission risk at
54 community level in the US. Using two recently developed data-driven models for COVID-19
55 transmission in the US to compute community-level prevalence, we show that there is
56 substantial overlap of prevalence between the different community risk levels from the
57 previous CDC guidelines. Using our proposed framework, we redefined the risk levels and their
58 threshold values. We show that these threshold values would have substantially reduced the
59 overlaps of underlying community prevalence between counties/states in different community
60 risk levels between 3/19/2020-9/9/2021. Our study demonstrates how the previous CDC
61 community risk level indexes could have been calibrated to infection prevalence to improve
62 their power to accurately determine levels of COVID-19 transmission in local communities

63 across the US. This method can be used to inform the design of future COVID-19 transmission
64 risk indexes.

65

66 **Introduction**

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68 Many organizations have developed risk indexes to help determine community transmission
69 levels for the ongoing COVID-19 pandemic¹⁻³. The US Centers for Disease Control and
70 Prevention’s “community transmission risk level” (hereafter, “CDC risk level”) was
71 recommended for use in local public health decision-making up to March 4th, 2022⁴. Such
72 transmission risk indexes should accurately and precisely communicate community risks to
73 decision-makers and the public. Therefore, transmission risk indexes would ideally quantify
74 actual, and not just reported, levels of disease prevalence or incidence. However, these risk
75 indexes are largely based on newly reported cases and percentage of positive SARS-CoV-2
76 diagnostic nucleic acid amplification tests, both of which are well-established as highly and
77 heterogeneously biased estimates of COVID-19 transmission^{5,6}. Reported case rate and test
78 positivity rate have been shown to provide inaccurate estimate of the magnitude and trend of
79 COVID-19 prevalence in the US with the inaccuracy level varying between states and over time⁶.
80 Here, we evaluate the CDC risk level as a metric for COVID-19 community transmission risk and
81 demonstrate how this index can be calibrated to infection prevalence and redefined to improve
82 its power to accurately determine levels of COVID-19 transmission risk in communities across
83 the United States.

84

85 **Methods**

86

87 Using reported cases and test positivity time-series data from 3/19/2020-9/9/2021³, we
88 determined the state, metro/metropolitan, or county risk level based on CDC risk level criteria
89 for reported cases only, test positivity only, and combined⁴. The CDC classified transmission risk
90 level values as Low, Moderate, or High according to the following metrics:

91 Community transmission risk level was defined as “Low” if newly reported cases per 100,000
92 persons in the past 7 days were less than 10 and the percentage of positive nucleic acid
93 amplification tests in the past 7 days was less than 5%. The transmission risk level was defined
94 as “Moderate” if newly reported cases per 100,000 persons in the past 7 days were greater
95 than 10 and less than 50 and the percentage of positive nucleic acid amplification tests in the
96 past 7 days was greater than 5% and less than 8%. The transmission risk level was defined as
97 “Substantial” if newly reported cases per 100,000 persons in the past 7 days were greater than
98 50 and less than 100 and the percentage of positive nucleic acid amplification tests in the past 7
99 days was greater than 8% and less than 10%. The transmission risk level was defined as “High”
100 if newly reported cases per 100,000 persons in the past 7 days were greater than 100 and the
101 percentage of positive nucleic acid amplification tests in the past 7 days was greater than 10%.
102 Finally, If the two indicators suggested different transmission levels, the higher level was
103 selected.

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105 To quantify the actual daily “COVID-19 risk” in each location, we used two recently develop
106 data-driven mathematical models of COVID-19 transmission (a semi- empirical model⁶ and the

107 IHME COVID-19 model which is SEIR-type model⁷). Though the proposed transmission risk
108 framework can readily calibrate risk indexes using total (reported and undetected) COVID-19
109 prevalence estimates, here, we illustrated it using undiagnosed COVID-19 infections prevalence
110 to better reflect the importance of undetected cases in designing community-level COVID-19
111 transmission risk indexes. The two transmission models^{6,7} were used to calculate the prevalence
112 of undiagnosed COVID-19 infections (I_U) over time. Details on the two transmission models are
113 presented in the Supplemental Materials. We chose these models because they were fitted and
114 validated against empirical data on reported COVID-19 cases, hospitalizations, and deaths⁶ and
115 seroprevalence⁷ in the US and they provide daily estimates of COVID-19 prevalence at different
116 scale.

117

118 We develop a robust data-driven framework for determining COVID-19 community
119 transmission risk levels. We use this framework to evaluate the CDC COVID-19 community risk
120 level and demonstrate how it can be calibrated to infection prevalence and redefined to
121 accurately reflect levels of COVID-19 transmission in local communities across the US.

122

123 To achieve this objective, we determined the ranges of I_U that best correspond to each CDC risk
124 level using ordered probit ordinal regression with maximum likelihood (see **Supporting**
125 **Materials** for details). We then assessed the performance of the CDC risk levels in predicting
126 the correct I_U category, summarized in a confusion matrix showing rates of predicted (CDC) and
127 actual (I_U) categories⁸. Next, we recalibrated the risk levels by first combining the “Moderate”
128 and “Substantial” categories, because of their extensive I_U overlap, and then determining the

129 optimum ranges for reported cases and test positivity for predicting I_U risk levels. We have
130 developed a Web App of our data-driven transmission risk framework which is available at
131 <https://wchiu.shinyapps.io/CDC-Risk-Level-Recalibration-alpha>

132

133 **Results**

134

135 Our analysis shows similar results using undiagnosed COVID-19 infections (I_U) from the semi-
136 empirical model and the IHME model provided similar results. Figure 1A and S1A show the I_U
137 distribution for each CDC risk level, the optimized I_U breakpoints between levels, and predictive
138 performance. The breakpoints under the recalibrated method were much greater than the CDC
139 risk levels because both transmission models account for undetected transmission and showed
140 that COVID-19 cases were substantially underreported in the US^{6,7}. For both overall and based
141 on cases alone, I_U distributions overlap substantially across CDC risk levels, with the poorest
142 performance for “Low” and “Substantial” (e.g., >40% of CDC “Low” risk levels are actually
143 “Moderate” for I_U). Test positivity alone provides very poor discriminatory power (for all levels
144 except “High,” <20% correctly categorized). To address these overlaps, we combined
145 “Moderate” and “Substantial” risk levels and recalibrated all the ranges for reported cases and
146 test positivity. By reducing the cases and positivity thresholds (Tables 1 & S1), this recalibration
147 substantially improved the ability to discriminate between risk levels while also reducing the
148 rate at which community transmission risk is underestimated (Figure 1B and Figure S1B).
149 However, it marginally increases risk overestimation by 2% for “Low” risk level communities
150 (with 4.3% of predicted “Moderate” risk level communities being actually “Low” risk level under

151 the Recalibrated risk level model and 2.4% under the Modified CDC risk level) and by 0.8% for
152 “Moderate” risk level communities (with 11.1% of predicted “High” risk level communities
153 being actually “Moderate” risk level under the Recalibrated risk level model and 10.3% under
154 the Modified CDC risk level).

155

156 **Discussion and Conclusions**

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158 Community transmission risk indexes for the ongoing COVID-19 pandemic are an essential input
159 to both personal and public health decision-making with respect to individual’s mitigation
160 actions and public health intervention measures, but substantial inconsistencies in these
161 indexes have resulted from the lack of a reliable framework for determining and
162 communicating transmission risk levels. Here, we develop such a framework, providing a more
163 consistent measure of transmission risk. We show that COVID-19 transmission risk indexes such
164 as the previous CDC community risk levels can be quantified in terms of undiagnosed infection
165 prevalence, that risk categories should be designed to minimize their overlaps, and that case
166 and positivity criteria can be calibrated to improve accuracy in reflecting underlying disease
167 transmission in the regions of interest. Though our proposed model improves accuracy of
168 community transmission risk level classification relative to the CDC transmission risk indexes, it
169 marginally increases risk overestimation for Low and Moderate risk communities. This marginal
170 increase of risk prediction will likely result in the misclassification of a handful of Low
171 (Moderate) transmission risk communities as Moderate (High) transmission risk level.
172 Community transmission risk levels are provided to public health officials and healthcare

173 facilities to help inform COVID-19 control policies and allocation of health care resources for
174 COVID-19 patients care ^{1,4}. With declining COVID-19 hospitalizations and deaths in the US, this
175 marginal increase in risk overestimation is anticipated to have minimal impact on the
176 healthcare system.

177

178 We developed a systematic approach to determine community transmission risk indexes for
179 infectious diseases that are calibrated to infection prevalence and provide a more accurate and
180 precise classification of community transmission risk levels. Because disease transmission risk is
181 a function of both reported and undetected disease cases, our approach relies on disease
182 transmission models' estimates of undiagnosed disease prevalence. Therefore, the
183 performance of these transmission models would likely affect the underlying accuracy of the
184 approach. Using transmission models whose projections that have been appropriately
185 calibrated and validated against empirical data should help improve the accuracy of the
186 community risk level predictions of the proposed method. Though the approach was developed
187 for COVID-19 in the US, it is applicable to other countries and infectious diseases. But for each
188 new setting/disease, a relevant transmission model should be used to estimate disease
189 prevalence to evaluate corresponding breakpoint values of transmission risk indexes.

190

191 Though the CDC community transmission risk levels was recently replaced by the CDC
192 community levels, this new metric is only a measure of the impact of COVID-19 illness on
193 healthcare systems rather than a measure of disease transmission risk. Our proposed approach
194 remains relevant for the design of future community transmission risk level indexes in the US or

195 other countries. The same methodology can either be applied to other existing risk indexes, or
196 be based on independently defined ranges of infection prevalence, to inform the design of
197 future COVID-19 transmission risk indexes.

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199 **Data availability:** Our code is available at: <https://github.com/wachiuphd/COVID-19-CDC-Risk->
200 [Level-Recalibration](#)

201
202 **Authors contributions:** WC and MLNM designed the project, developed the model, performed
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204

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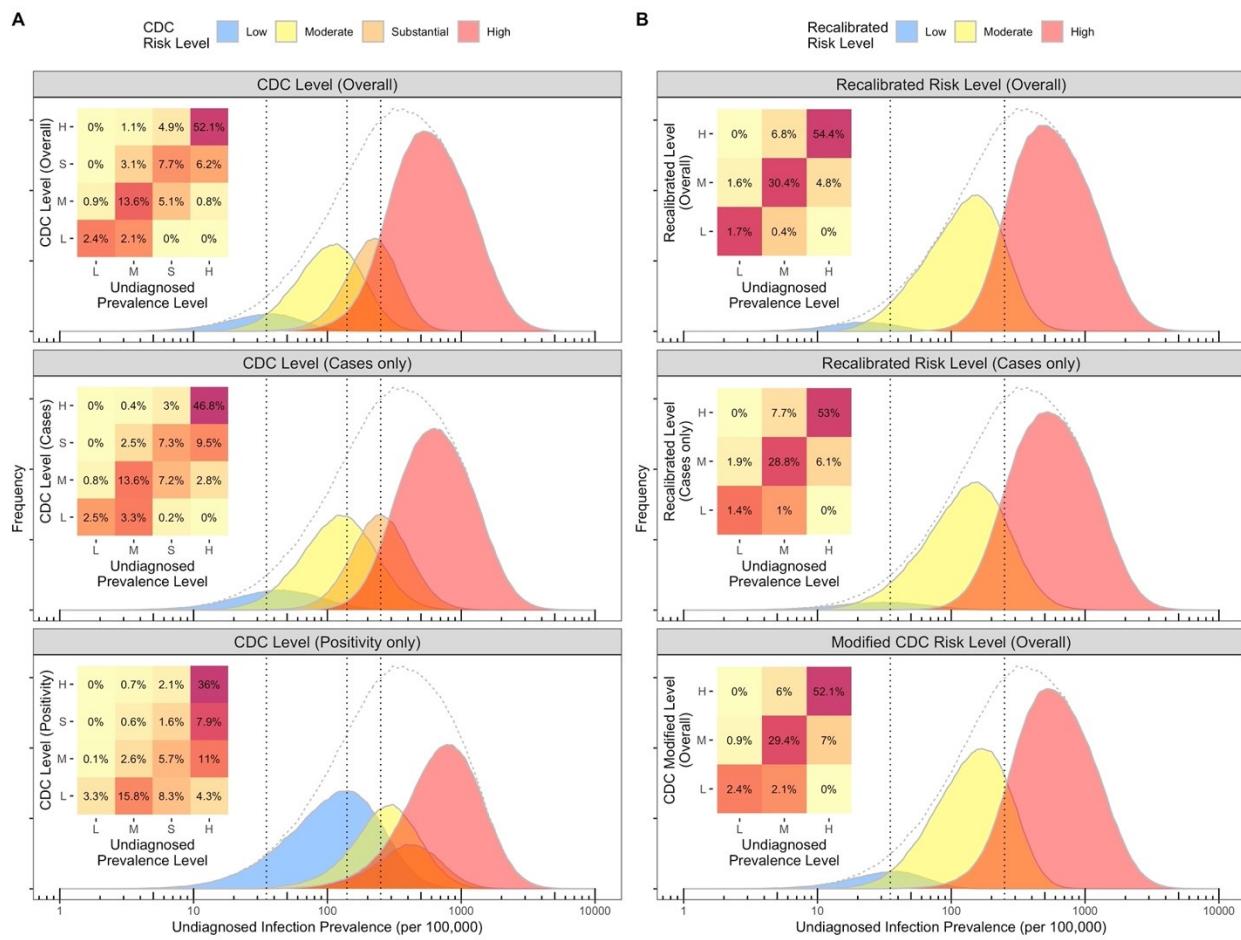
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240 **Figure 1.** Comparison of performance of CDC risk levels (A: Using both cases and positivity,
 241 using cases only, using positivity only) and recalibrated risk levels (B: Using recalibrated cases
 242 and positivity criteria [Table 1], using recalibrated cases only [Table 1], using “modified” CDC
 243 criteria combining “Moderate” and “Substantial” categories with no other changes) in
 244 predicting undiagnosed infection prevalence I_U using the semi-empirical model. The frequency
 245 distribution of I_U is shown stratified by the different risk levels; dashed curve is the overall
 246 frequency distribution of I_U ; dotted vertical lines are the cut-points in I_U defining the “true”
 247 categorization. The performance is summarized in terms of the “confusion matrix” which shows
 248 the “correct” categorization in each column and the “predicted” categorization in each row.
 249 Values along the diagonal are correctly predicted, values below the diagonal represent under-

250 predicted risk (actual risk is higher than predicted), and values above the diagonal represent

251 over-predicted risk (actual risks are lower than predicted).

252

253 **Table 1.** Summary of risk level criteria based on newly reported cases per 100,000 persons and
254 test positivity % (both during last 7 days). Recalibrated risk levels were computed using
255 prevalence estimates from the semi-empirical model.

256

CDC Risk Level Criteria				
Risk level:	Low	Moderate	Substantial	High
Cases only	<10 per 100,000 persons	10 – <50 per 100,000 persons	50 – <100 per 100,000 persons	≥100 per 100,000 persons
Positivity only	<5%	5% – <8%	8% – <10%	≥10%
Recalibrated Risk Level Criteria				
Risk Level:	Low	Moderate	High	
Undiagnosed Prevalence	<35 per 100,000 persons	35 – <250 per 100,000 persons	≥250 per 100,000 persons	
Odds of Undiagnosed Infection	<1 in 2,850 people	1 in 400 to 2,850 people	≥1 in 400 people	
Cases only	<5 per 100,000 persons	5 – <70 per 100,000 persons	≥70 per 100,000 persons	
Low Risk Positivity	<3%	<0.5%	NA	
Moderate Risk Positivity	>3%	0.5% – <10%	<4%	
High Risk Positivity	NA	≥10%	≥4%	

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