Modeling the Effect of School Closures in a Pandemic Scenario: Exploring Two Different Contact Matrices

Isaac Chun-Hai Fung,1,2 Manoj Gambhir,2,3,4 John W. Glasser,2 Hongjiang Gao,2 Michael L. Washington,2,5 Amra Uzicanin,2 and Martin I. Meltzer2,5

1Department of Epidemiology, Jiann-Ping Hsu College of Public Health, Georgia Southern University, Statesboro, 2Centers for Disease Control and Prevention, and 3IHRC, Inc, Atlanta, Georgia; 4Epidemiological Modelling Unit, Department of Epidemiology and Preventive Medicine, Monash University, Melbourne, Australia; and 5Division of Preparedness and Emerging Infections, National Center for Emerging and Zoonotic Infectious Diseases, Atlanta, Georgia

Background. School closures may delay the epidemic peak of the next influenza pandemic, but whether school closure can delay the peak until vaccine is ready to be deployed is uncertain.

Methods. To study the effect of school closures on the timing of epidemic peaks, we built a deterministic susceptible-infected-recovered model of influenza transmission. We stratified the U.S. population into 4 age groups (0–4, 5–19, 20–64, and ≥65 years), and used contact matrices to model the average number of potentially disease transmitting, nonphysical contacts.

Results. For every week of school closure at day 5 of introduction and a 30% clinical attack rate scenario, epidemic peak would be delayed by approximately 5 days. For a 15% clinical attack rate scenario, 1 week closure would delay the peak by 9 days. Closing schools for less than 84 days (12 weeks) would not, however, reduce the estimated total number of cases.

Conclusions. Unless vaccine is available early, school closure alone may not be able to delay the peak until vaccine is ready to be deployed. Conversely, if vaccination begins quickly, school closure may be helpful in providing the time to vaccinate school-aged children before the pandemic peaks.

Keywords. influenza; mathematical model; social distancing.

In response to the 2013 emergence of human infections with the novel avian influenza A(H7N9) in China associated with reported high mortality [1], the Emergency Operations Center of the United States Centers for Disease Control and Prevention (CDC) was activated. The Joint Modeling Unit was tasked with simulating hypothetical scenarios to assist with potential pandemic influenza planning should sustained human-to-human transmission occur in the United States.

Community mitigation, such as school closure, is part of public health planning in the event of influenza pandemics. Transmission among school children is believed to be one of the drivers of influenza epidemics [2, 3]. In the event of a pandemic, delaying the epidemic peak by using community mitigation may slow the pandemic long enough for vaccines to be produced and distributed [2]. Prompted by the avian influenza A(H7N9) outbreaks in China, we estimated the effect of school closures in response to a hypothetical influenza pandemic. Specifically, we estimated, if, and by how much, school closures of various durations would delay the time to peak and reduce the total number of cases. Such information will help public health officials better understand the benefits of school closures and thus how to best integrate school closures into pandemic response plans.

METHODS

Our mathematical model simulates how 4 age groups of a population interact when schools are in session and when they are not. This model allows us to track the spread of
an influenza virus in an age-stratified population, using the number of daily contacts between person; and thus the probability of contact and onward transmission among different age groups.

We estimated the effect of school closure on the time to epidemic peak by varying the number of days schools were closed from 7 through to 140 days, with school closure beginning 5 days after 10 infected persons were introduced into the United States (Table 1). We assumed clinical attack rate (CAR) scenarios of 15% and 30% without any intervention [5]. We also conducted sensitivity analyses by varying the number of contacts per day in the contact matrices.

The Model
We used an age-structured S-I-R (susceptible-infected-recovered) compartmental model to deterministically model the effect of school closure in a hypothetical pandemic scenario. We expanded a previously published model [6] from 2 to 4 age-groups, namely 0–4, 5–19, 20–64, and ≥65 years. We programmed our model in R (versions 2.15.1 to 2.15.3).

Table 1. Primary Assumptions and Parameter Values in Our Model

<table>
<thead>
<tr>
<th>Assumptions/Parameters</th>
<th>Value</th>
<th>Reference/Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of infected persons initially introduced to the population</td>
<td>10</td>
<td>Assumption defined by the prescribed scenario</td>
</tr>
<tr>
<td>Day of arrival of the infected persons (number of days after the beginning of the pandemic)</td>
<td>14 d</td>
<td>Assumption defined by the prescribed scenario</td>
</tr>
<tr>
<td>Day school closure starts</td>
<td>5 d after the introduction</td>
<td>Assumption defined by the prescribed scenario</td>
</tr>
<tr>
<td>Length of school closures</td>
<td>7 to 140 d</td>
<td>Assumption defined by the prescribed scenario</td>
</tr>
<tr>
<td>Total population</td>
<td>310 000 000</td>
<td>Approximation of US population*</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Age group</th>
<th>Probability of transmission given a contact (P)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0–4 y</td>
<td>0.25 d⁻¹</td>
</tr>
<tr>
<td>5–19 y</td>
<td>0.640%</td>
</tr>
<tr>
<td>20–64 y</td>
<td>20.204%</td>
</tr>
<tr>
<td>64+ y</td>
<td>6.440%</td>
</tr>
<tr>
<td>Recovery rate (γ)</td>
<td>0.011047 Estimated, assuming a 15% attack rate with the matrices used in the main analysis</td>
</tr>
</tbody>
</table>

Assumptions
We assumed that half of the infected people were asymptomatic and therefore would not be clinically observed [7]. We further assumed that asymptomatic patients were as infectious as symptomatic ones. The duration of infectiousness was assumed to be 4 days (ie, the recovery rate was assumed to be 0.25 per day). We assumed that 10 infected persons arrived on day 14 after the detection of the pandemic strain and that school closure began 5 days after that (ie, on day 19).

Scenarios
We used the following standardized scenarios: 30% and 15% total CAR in 365 days in the absence of any interventions. To achieve the specified total CAR in the baseline scenario, we adjusted the probability of transmission given contact (P) for all age groups: 0.016487 for 30% CAR and 0.011047 for 15% CAR.

Contact Matrices
We modeled school closures by assuming that when schools closed during a pandemic, the resultant contact matrix was the same as that measured during school vacations. We adapted the contact matrices of Eames et al [8], that were based on data from the United Kingdom, as follows: the “term time” (ie, semester in American English) matrix in our model represents school in session and “school holidays” (ie, vacations in American English) matrix represents in our model pandemic-related school closure. The major difference between the “term time” matrix and the “school holidays” matrix is a reduction of intra-group contacts among members of age group 2 (representing ages: 5–18 years) by 58% and a concomitant increase of intra-group contacts among members of age group 1 (ages: 0–4 years) by 62% during vacations. To make groups consistent with US Census age groups, we changed them from 0 to 4, 5 to 18, 19 to 64, and ≥65 years, to 0–4, 5–19, 20–64, and ≥65 years. In theory, contact between two groups should be symmetric because an encounter between someone in one group and someone in another group (group i and group j in our model) should be reported by both. However, in practice, contact matrices derived from self-reported data are rarely the case. To correct for this, we converted the contact matrix into a symmetrical matrix by taking the square root of the element-wise product of the contact matrix and its transpose, ie, \( \sqrt{C \cdot C^T} \) (Figure 1 and Table 1; see Supplementary Materials for details of the equations and the matrices).

Analysis Using Alternative Matrix pair
To test the impact of choice of contact matrix, we re-ran the model using an alternative pair of matrices from Eames et al [8], namely, their “B matrices”. The B matrices were derived to correct for the differences in the number of self-reported contacts between groups. The element of the matrices was calculated by taking an
average of the total number of contacts made by people in group i with people in group j, and the total number of contacts made by people in group j with people in group i, in other words, $B_{ij} = (n_iC_{ij} + n_jC_{ji})/2n_i$. To make it relevant to our study, we replace $n_i$ with US population data. Please note that the resultant contact matrices were not symmetrical (Figure 1). We assumed that the probability of transmission given contact remains the same as in the main analysis (see Supplementary Materials for further details).

We also programmed the differential equation model (that models time continuously) as a difference equation model (that models time discretely), both in R and in Excel, as a teaching tool. The R codes and Excel file are provided as Supplementary files.

### RESULTS

#### Main Results

For the 30% attack rate scenario, we found that for every week the school closed (up to 12 weeks), the peak would be delayed by approximately 5 days. School closure for 84 days could delay the peak for approximately 60 days. Closing schools for 1 to 12 weeks would not significantly change the magnitude of the peak of the epidemic (approximately 16.5 million cases). However, if schools were closed for an extensive period of time, the magnitude of the peak and the attack rate would be reduced slightly. For example, closing schools for 20 weeks would reduce the peak incidence to 16.1 million and the attack rate to 29.96% (Figure 2 and Table 2).
In the 15% attack rate scenario, we found that, for every week the school closed, the peak would be delayed for approximately 9 days. If schools were closed for 140 days, the peak would be delayed for more than 1 year. Similarly, closing schools would not significantly change the magnitude of the peak of the epidemic (approximately 3.6 million cases) (Figure 3 and Table 2).

**Analysis Using Alternative Matrix Pair**

We found that the baseline attack rate was slightly lower than that for the main analysis: 28% instead of 30% and 13% instead of 15%. The delay of the peak was slightly less than that with the main analysis. For example, if schools were closed for 84 days, the peak would be delayed by either 58 days (high attack rate scenario) or 108 days (low attack rate scenario) (Figures 4 and 5, Table 3).

**DISCUSSION**

The avian influenza A(H7N9) emergency response in spring 2013 gave us an opportunity to revisit the issue of the effect of school closure as a measure to control influenza pandemics by using an age-stratified dynamic compartmental S-I-R model.

Our results show that although extended school closure may not reduce the magnitude of the peak of the epidemic, we can delay the peak for as many as 100 days (after a 140 day closure); for every week of school closure, the epidemic peak was delayed by 5 or 9 days depending on the attack rate assumed in the model (30% or 15%). We used alternative contact matrices and found that these results were robust. Unless vaccine is available early, school closure (of realistic length) alone may not be able to delay the peak until the vaccine is ready to be deployed.

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**Table 2. School Closure and Delay in the Peak of Epidemic in the Main Analysis**

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Baseline</th>
<th>7 d</th>
<th>14 d</th>
<th>21 d</th>
<th>28 d</th>
<th>56 d</th>
<th>84 d</th>
<th>140 d</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>30% attack rate</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Peak time (day)</td>
<td>84</td>
<td>90</td>
<td>95</td>
<td>100</td>
<td>105</td>
<td>124</td>
<td>144</td>
<td>184</td>
</tr>
<tr>
<td>Delay in peak time (day)</td>
<td>n/a</td>
<td>6</td>
<td>11</td>
<td>16</td>
<td>21</td>
<td>40</td>
<td>60</td>
<td>100</td>
</tr>
<tr>
<td>Peak incidence (millions of cases)</td>
<td>16.5</td>
<td>16.5</td>
<td>16.5</td>
<td>16.5</td>
<td>16.5</td>
<td>16.5</td>
<td>16.5</td>
<td>16.1</td>
</tr>
<tr>
<td>Attack rate (%)</td>
<td>30.0</td>
<td>30.0</td>
<td>30.0</td>
<td>30.0</td>
<td>30.0</td>
<td>30.0</td>
<td>30.0</td>
<td>29.96</td>
</tr>
<tr>
<td><strong>15% attack rate</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Peak time (day)</td>
<td>196</td>
<td>205</td>
<td>214</td>
<td>224</td>
<td>233</td>
<td>269</td>
<td>306</td>
<td>≥365</td>
</tr>
<tr>
<td>Delay in peak time (day)</td>
<td>n/a</td>
<td>9</td>
<td>18</td>
<td>28</td>
<td>37</td>
<td>73</td>
<td>110</td>
<td>≥169</td>
</tr>
<tr>
<td>Peak incidence (millions of cases)</td>
<td>3.6</td>
<td>3.6</td>
<td>3.6</td>
<td>3.6</td>
<td>3.6</td>
<td>3.6</td>
<td>3.6</td>
<td>3.6</td>
</tr>
<tr>
<td>Attack rate (%)</td>
<td>15.0</td>
<td>15.0</td>
<td>15.0</td>
<td>15.0</td>
<td>15.0</td>
<td>14.99</td>
<td>14.82</td>
<td></td>
</tr>
</tbody>
</table>

Abbreviation: n/a, not applied.

* The peak has been delayed beyond the scope of the simulation. Our calculation of the incidence is based on one single year, as the simulation lasts for 365 days only.

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**Figure 3.** The effect of school closure of various lengths upon the epidemic curve of a hypothetical influenza pandemic in the United States (Alternative analysis). Assumption = high attack rate in the baseline. Probability of transmission given a contact (P) = .016487. All other parameters and assumptions are the same as Figure 2.

**Figure 4.** The effect of school closure of various lengths upon the epidemic curve of a hypothetical influenza pandemic in the United States (Main analysis). Assumption = 15% attack rate in the baseline. Probability of transmission given a contact (P) = .011047. All other parameters and assumptions are the same as Figure 2.
Conversely, if vaccination begins quickly, school closure may be helpful in providing the time to vaccinate school-aged children before the pandemic peak.

Jackson et al reviewed 45 models of impact of school closure and found that: "Most papers predicted that closing schools would delay the epidemic peak, usually by no more than 1–3 weeks" [9]. The biggest difference between our results and others is that many models estimated that school closures will reduce cumulative incidence and incidence at peak. The estimated impact of incidence depended upon many factors in their models, such as increasing household/community contacts following school closure (as we did – Figure 1), and level of attack ($R_0$ values), with some models showing school closure could increase the attack rate. Two components could contribute to these differences between these models and ours. First, researchers have used different population age structures, resulting in different sizes of groups. Further, the models often used very different contact matrices and, as shown by Jackson et al [9], made very different assumptions regarding how those matrices changes due to school closures. It is therefore likely that we used more conservative assumptions, including those relating to contact matrices, thereby limiting the predicted effect of school closures in our model.

Our study has a number of limitations. First, we assumed that the contact data reported in the United Kingdom were applicable to the United States (with some adjustments to the age groups). US data, when they become available, could be used in future studies. Second, we assumed that the contact matrices for school closure for pandemic influenza were the same as the contact matrices reported for scheduled school vacations. This assumption may not hold for prolonged school closure (when children and adults readjust their daily routine and social gatherings) or for a very severe pandemic (when both fear of illness and the actuality of severe illness reduce social contacts). Third, we assumed that the contact matrices were not time-dependent (except for opening and closure of schools). However, social contact patterns may change from the beginning of school closure (when everyone is more alert to the threat of influenza) to the end of school closure (when people become complacent). Fourth, we assumed that half of those infected were asymptomatic (and therefore were not counted as "cases" in the epidemic curves) and as infectious as symptomatic patients. If we assumed all those infected were symptomatic, the number of cases would double given the same parameter sets. Likewise, if we assume that asymptomatic persons are less infectious than the symptomatic persons, the attack rate would be reduced, given the same parameter sets.

Although the model illustrates the potential benefits of school closure, it cannot realistically model the likelihood of successful compliance in the necessary changes in human behavior. Further, because American schools have decentralized systems of
governance, it will likely be challenging to achieve a uniform response to school closure recommendations. Thus, it becomes a priority for public health officials, school officials, and parents to work together to draw up realistic plans for such events. The results presented in this article should help all those drawing up such plans to understand both the potential benefits and limitations of school closure to aid the response to an influenza pandemic.

**Supplementary Data**

Supplementary materials are available at Clinical Infectious Diseases online (http://cid.oxfordjournals.org). Supplementary materials consist of data provided by the author that are published to benefit the reader. The posted materials are not copyedited. The contents of all supplementary data are the sole responsibility of the authors. Questions or messages regarding errors should be addressed to the author.

**Notes**

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**References**