

Applications of a Modified Age-Structured SIR Model

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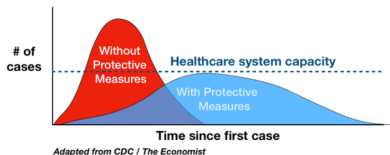
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Importance and Motivation

Models provide a useful tool for planning and decision making.

- COVID-19 Pandemic
- Predicting Spread
- Understanding effect of
 - Social-distancing measures
 - Opening schools?
 - Stress on healthcare systems
 - ICU Capacity
 - Vaccine Distribution



SIR (Susceptible, Infected, Removed)

The number of individuals in each compartment is given by certain functions of time $S(t)$, $I(t)$, $R(t)$ respectively. ($\frac{dS}{dt} + \frac{dI}{dt} + \frac{dR}{dt} = 0$)

SIR Model

$$\begin{aligned}\frac{dS}{dt} &= -\beta \cdot I \cdot \frac{S}{N} \\ \frac{dI}{dt} &= \beta \cdot I \cdot \frac{S}{N} - \gamma \cdot I \\ \frac{dR}{dt} &= \gamma \cdot I\end{aligned}$$

Population size N , transmission rate β , removal rate $\gamma = 1/D$ where D is recovery time.

SIR Dynamics



Figure: Transfer of individuals between compartments

Adding Age Specificity

Vector valued functions $S(t), I(t), R(t)$ with X_i denoting the number of individuals in compartment X in the i th age-bracket.

Age-Specific SIR Model

$$\frac{dS_i}{dt} = -\beta \cdot \frac{S_i}{N} \cdot \sum_{j=1}^n \mathcal{M}_{ij} \cdot I_j$$

$$\frac{dI_i}{dt} = \beta \cdot \frac{S_i}{N} \cdot \sum_{j=1}^n \mathcal{M}_{ij} \cdot I_j - \gamma \cdot I_i$$

$$\frac{dR_i}{dt} = \gamma \cdot I_i$$

We can also compute the number of individuals hospitalized, in critical care, and deceased: $\frac{dH_i}{dt} = \gamma \cdot h_i \cdot I_i$, $\frac{dC_i}{dt} = \gamma \cdot h_i \cdot c_i \cdot I_i$, $\frac{dM_i}{dt} = \gamma \cdot m_i \cdot I_i$.

Contact Matrix and Reproductive Number

- Basic reproduction number (R_0) is the initial expected growth rate in a fully susceptible population.
- $R_0 = 5.7$ for COVID-19.
- If λ and \mathbf{v} are the dominant eigenvalue and eigenvector of $\mathcal{M} \cdot \text{diag}(\mathbf{p})$.
 - $\beta = \frac{R_0 \cdot \gamma}{\lambda}$.
 - Initial $I = \mathbf{v} \cdot I_{\text{tot}}$.

Age	0-9	10-19	20-29	30-39	40-49	50-59	60-69	70-79	80+
0-9	19.2	4.8	3.0	7.1	3.7	3.1	2.3	1.4	1.4
10-19	4.8	42.4	6.4	5.4	7.5	5.0	1.8	1.7	1.7
20-29	3.0	6.4	20.7	9.2	7.1	6.3	2.0	0.9	0.9
30-39	7.1	5.4	9.2	16.9	10.1	6.8	3.4	1.5	1.5
40-49	3.7	7.5	7.1	10.1	13.1	7.4	2.6	2.1	2.1
50-59	3.1	5.0	6.3	6.8	7.4	10.4	3.5	1.8	1.8
60-69	2.3	1.8	2.0	3.4	2.6	3.5	7.5	3.2	3.2
70-79	1.4	1.7	0.9	1.5	2.1	1.8	3.2	7.2	7.2
80+	1.4	1.7	0.9	1.5	2.1	1.8	3.2	7.2	7.2

Figure: Contact Matrix \mathcal{M}

Social-distancing policy in Washington State

Since late May, the Safe Start policy has been implemented in Washington:

- Phased reopening plan that gradually relaxes social distancing measures based on assessments of health care system readiness.
- We model health care system stress by considering the proportion of occupied ICU beds (based on an average of 3.47 beds per 100,000 residents).

$$\mathcal{M} \rightarrow \frac{1}{\lambda \cdot |C|/C_{\max}} \mathcal{M}.$$

- We denote $\frac{1}{\lambda \cdot |C|/C_{\max}}$ as the mitigation-factor and select $\lambda = 0.2$ based on real infection points in infection count.

Population Parameters

We select four counties (Jefferson, King, Ferry, Adams with median ages 28, 36, 49, 58 respectively) and apply our model to their demographic parameters.

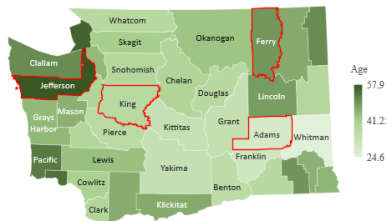


Figure: County Median Age

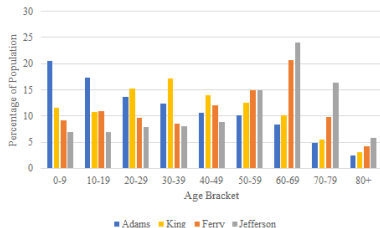


Figure: Age Distribution

SIR Application

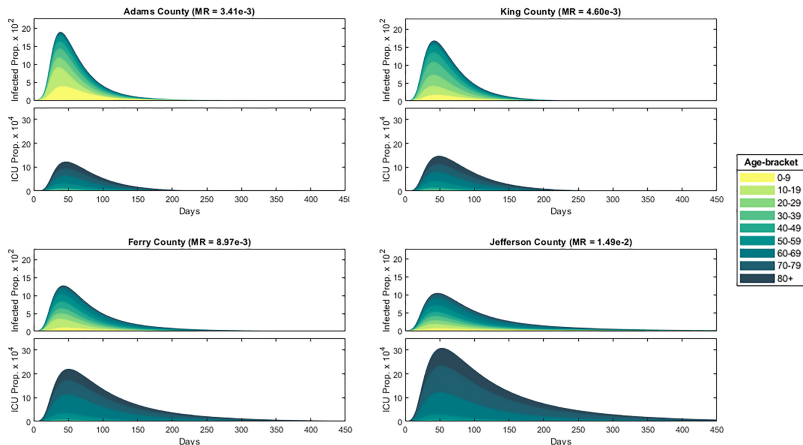


Figure: County Infected and ICU Proportion (Homogeneous Mitigation)



SIR Results

- As median age increased, peak infections decreased while peak ICU occupancy and mortality rate increased.
- For all counties, approximately the same proportion (80%) of the population were infected.
- Herd immunity threshold $1 - 1/R_0 \approx 82\%$.

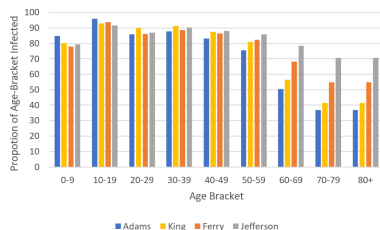


Figure: Proportion of Age-Bracket Infected

Age-Targeted Relaxation

We examine the effects of relaxing restrictions for two age groups:

- The school bracket: 0-29 years
- The work bracket: 0-69 years

We also consider relaxing at the start of the epidemic (at 0 days) and after the initial peak in infections (at 90 days).

Age	0-9	10-19	20-29	30-39	40-49	50-59	60-69	70-79	80+
0-9	19.2	4.8	3.0	7.1	3.7	3.1	2.3	1.4	1.4
10-19	4.8	42.4	6.4	5.4	7.5	5.0	1.8	1.7	1.7
20-29	3.0	6.4	20.7	9.2	7.1	6.3	2.0	0.9	0.9
30-39	7.1	5.4	9.2	16.9	10.1	6.8	3.4	1.5	1.5
40-49	3.7	7.5	7.1	10.1	13.1	7.4	2.6	2.1	2.1
50-59	3.1	5.0	6.3	6.8	7.4	10.4	3.5	1.8	1.8
60-69	2.3	1.8	2.0	3.4	2.6	3.5	7.5	3.2	3.2
70-79	1.4	1.7	0.9	1.5	2.1	1.8	3.2	7.2	7.2
80+	1.4	1.7	0.9	1.5	2.1	1.8	3.2	7.2	7.2

Figure: Blue group is not subject to the mitigation-factor when relaxing 0-39 bracket

Age-Targeted Relaxation - Application

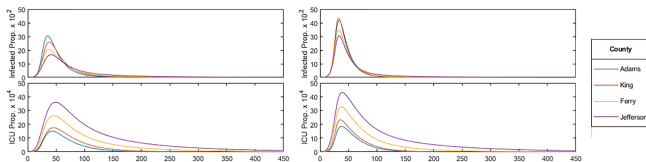


Figure: School and Work Bracket Relaxation at 0 days

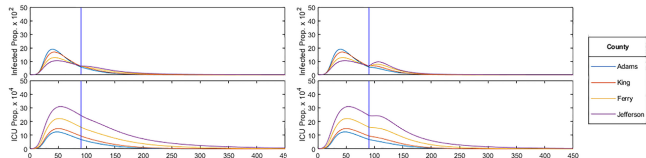


Figure: School and Work Bracket Relaxation at 90 days

Age-Targeted Relaxation - Results

At 0 days:

- Peak infections increased (on average) by 58% when relaxing school bracket and increased by 160% when relaxing work bracket.
- Although the calculated mortality rate decreased slightly (by 6% and 12% respectively), excessive stress was placed on hospitals with a 51% increase in peak ICU occupancy when relaxing work bracket.
- Placing restrictions on the school and work brackets has the effect of “flattening the curve”.

At 90 days:

- Relaxing school bracket had little effect on subsequent trajectory of epidemic with mortality rate decreasing by an average 3.5%.
- Relaxing work restrictions had a significant effect on high median age populations with Jefferson experiencing a new peak in infections and increasing ICU occupancy for over a month after 90 days.

Age-Targeted Vaccination

We examine the efficacy of age-targeted vaccine distributions.

- Individual transferred directly from susceptible to removed compartments.
- A constant ($N/720$) vaccines are administered to the population at each time step.
- Vaccines are distributed to each age-bracket according to a weight vector ω .
 - ω_C constant (homogeneous) distribution
 - ω_M moderate priority
 - ω_S strict priority

Age	ω_C	ω_M	ω_S
0-9	1	1	1
10-19	1	1	1
20-29	1	1	1
30-39	1	1	1
40-49	1	1	2
50-59	1	2	4
60-69	1	2	8
70-79	1	4	16
80+	1	4	16

Figure: Distribution Weights

Age-Targeted Vaccination - Application

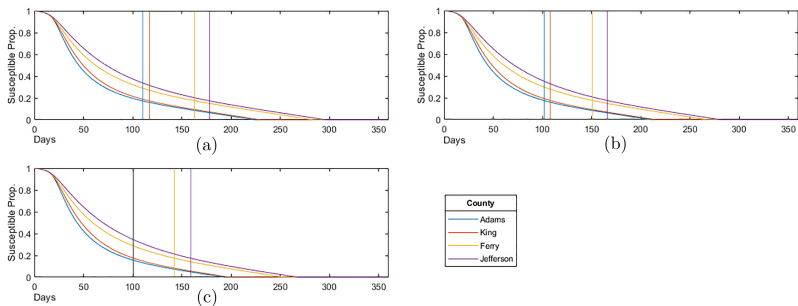


Figure: (a) Homogeneous (b) Moderate Priority (c) Strict Priority

Age-Targeted Vaccination - Results

- Homogeneous vaccine distribution reduced mortality rate by an average 28.2% compared to without vaccines. Only 59.2% of Jefferson county became infected.
- Age-targeted distributions further reduced mortality rate, especially among low median age counties: by 9.4% and 19.5% in Adams county for ω_M and ω_S respectively.
 - Time required to achieve HIT decreased by 7.3% and 11.6% on average for ω_M and ω_S respectively.

County	ω_C	ω_M	ω_S
Adams	110	102	100
King	117	108	101
Ferry	163	151	142
Jefferson	178	166	159

Figure: Days required to achieve Herd Immunity Threshold

Further Work

Some directions for potential further research:

- Model different population's social distancing patterns including restrictions based on hospitalization count or infection positive rate.
- Implement interactions between school and work populations as separate compartments.
- Consider movement of individuals between counties.
- Vaccine distribution that varies over time.

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