Epidemic models for analysis of policy measures to protect COVID-19 at-risk populations in Los Angeles County

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uscbiostats.github.io/COVID19
We develop epidemic models for analysis of policy measures to protect COVID-19 at-risk populations in Los Angeles County

Motivating research questions:

• How did the epidemic affect different at-risk populations?
• How effective were policies at preventing severe illness in at-risk populations?
Different types of COVID-19 at-risk populations

At higher risk of exposure and infection

- Social and socio-economic factors:
  - Household crowdedness
  - Employment and ability to work from home
  - Income and ability to protect oneself
  - Access to healthcare

At higher risk of severe illness given infection, i.e. of hospitalization and death

- Biological / health-related factors:
  - Age
  - Comorbidities
  - Obesity
  - History of smoking
Different types of COVID-19 at-risk populations

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Epidemic model + risk model for policy analysis

To analyze policies related to protecting populations at-risk of severe infection, we need two modeling pieces:

1. **Epidemic model** that estimates dynamics of infections, hospitalizations, and deaths

2. **Risk model** for estimating the probabilities of severe illness in different at-risk populations
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COMPARTMENT VARIABLES

S = Susceptible
E = Exposed
A = Infected/Undetected
I = Infected/Detected
H = Hospitalized
Q = ICU
D = Death
R = Recovered

Transition times
Fixed
parameters

\[ \mu(t) \beta \]
\[ r(t) \]
\[ 1-r(t) \]
\[ \alpha(t) \]
\[ 1-\alpha(t) \]
\[ \delta(t) \]
\[ 1-\delta(t) \]
\[ 1-\kappa(t) \]
\[ \kappa(t) \]
\[ 1-\kappa(t) \]
Model compartment variable projections
Reproductive Number - $R(t)$

Graph showing changes in reproductive number $R(t)$ over time, with specific events and stages marked on the x-axis.

- Stage I
- Stage II
- Stage III: Modifications
- School Year
- Halloween
- Thanksgiving
- Christmas: New Years
- New Years
Time-varying infection fatality rate (IFR)

\[ IFR = \frac{\text{deaths}}{\text{observed + unobserved infections}} \]
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Biological Risk Factors

- **Age** was categorized into five groups:
  - 0-19, 20-44, 45-64, and 65-79, and 80+.

- **Comorbidities**: diabetes, hypertension, chronic obstructive pulmonary disease (COPD), hepatitis B, coronary heart disease, stroke, cancer and chronic kidney disease.

- **Smoking**: Current smoking vs. none.

- **Obesity** was categorized as three groups:
  - $\text{BMI} < 30 \frac{kg}{m^2}$; $30 \leq \text{BMI} \leq 40 \frac{kg}{m^2}$; $\text{BMI} > 40 \frac{kg}{m^2}$
Categorizing the LA population into risk profiles

<table>
<thead>
<tr>
<th>Group</th>
<th>age</th>
<th>BMI</th>
<th>smoking</th>
<th>comorbidity</th>
<th>Pop.Prev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk 2</td>
<td>65+</td>
<td>30&lt;BMI&lt;40</td>
<td>Non Smoker</td>
<td>Comorbidity</td>
<td>0.0110</td>
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<tr>
<td>Risk 3</td>
<td>65+</td>
<td>BMI&lt;30</td>
<td>Non Smoker</td>
<td>Comorbidity</td>
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<td>BMI&lt;30</td>
<td>Smoker</td>
<td>Comorbidity</td>
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<td>BMI&lt;30</td>
<td>Non Smoker</td>
<td>No Comorbidity</td>
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<td>Comorbidity</td>
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<tr>
<td>Risk 3</td>
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<td>BMI&lt;30</td>
<td>Smoker</td>
<td>No Comorbidity</td>
<td>0.0130</td>
</tr>
<tr>
<td>Risk 4</td>
<td>45-64</td>
<td>30&lt;BMI&lt;40</td>
<td>Non Smoker</td>
<td>No Comorbidity</td>
<td>0.0219</td>
</tr>
<tr>
<td>Risk 4</td>
<td>45-64</td>
<td>BMI&lt;30</td>
<td>Non Smoker</td>
<td>Comorbidity</td>
<td>0.1510</td>
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<tr>
<td>Risk 4</td>
<td>20-44</td>
<td>BMI&lt;30</td>
<td>Smoker</td>
<td>Comorbidity</td>
<td>0.0206</td>
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<tr>
<td>Risk 4</td>
<td>45-64</td>
<td>BMI&lt;30</td>
<td>Non Smoker</td>
<td>No Comorbidity</td>
<td>0.1045</td>
</tr>
<tr>
<td>Risk 4</td>
<td>20-44</td>
<td>BMI&lt;30</td>
<td>Smoker</td>
<td>No Comorbidity</td>
<td>0.0307</td>
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<tr>
<td>Risk 4</td>
<td>20-44</td>
<td>30&lt;BMI&lt;40</td>
<td>Non Smoker</td>
<td>Comorbidity</td>
<td>0.0238</td>
</tr>
<tr>
<td>Risk 5</td>
<td>20-44</td>
<td>30&lt;BMI&lt;40</td>
<td>Non Smoker</td>
<td>No Comorbidity</td>
<td>0.0240</td>
</tr>
<tr>
<td>Risk 5</td>
<td>20-44</td>
<td>BMI&lt;30</td>
<td>Non Smoker</td>
<td>Comorbidity</td>
<td>0.1055</td>
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<tr>
<td>Risk 5</td>
<td>20-44</td>
<td>BMI&lt;30</td>
<td>Non Smoker</td>
<td>No Comorbidity</td>
<td>0.1401</td>
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<tr>
<td>Risk 5</td>
<td>0-19</td>
<td>BMI&lt;30</td>
<td>Non Smoker</td>
<td>No Comorbidity</td>
<td>0.1463</td>
</tr>
</tbody>
</table>
## Categorizing the LA population into risk profiles

| Group | age   | BMI       | smoking     | comorbidity | Pop.Prev | P(H|I).May.15 |
|-------|-------|-----------|-------------|-------------|----------|-------------|
| Risk 2| 65+   | 30<BM<40  | Non Smoker  | Comorbidity | 0.0110   | 0.2626      |
| Risk 3| 65+   | BM<30     | Non Smoker  | Comorbidity | 0.0699   | 0.1635      |
| Risk 3| 45-64 | BM<30     | Smoker      | Comorbidity | 0.0167   | 0.1690      |
| Risk 3| 65+   | BM<30     | Non Smoker  | No Comorbidity | 0.0254 | 0.1148      |
| Risk 3| 45-64 | 30<BM<40  | Non Smoker  | Comorbidity | 0.0382   | 0.1733      |
| Risk 3| 45-64 | BM<30     | Smoker      | No Comorbidity | 0.0130 | 0.1189      |
| Risk 4| 45-64 | 30<BM<40  | Non Smoker  | No Comorbidity | 0.0219 | 0.1221      |
| Risk 4| 45-64 | BM<30     | Non Smoker  | Comorbidity | 0.1510   | 0.1031      |
| Risk 4| 20-44 | BM<30     | Smoker      | Comorbidity | 0.0206   | 0.1069      |
| Risk 4| 45-64 | BM<30     | Non Smoker  | No Comorbidity | 0.1045 | 0.0709      |
| Risk 4| 20-44 | BM<30     | Smoker      | No Comorbidity | 0.0307 | 0.0736      |
| Risk 4| 20-44 | 30<BM<40  | Non Smoker  | Comorbidity | 0.0238   | 0.1098      |
| Risk 5| 20-44 | 30<BM<40  | Non Smoker  | No Comorbidity | 0.0240 | 0.0757      |
| Risk 5| 20-44 | BM<30     | Non Smoker  | Comorbidity | 0.1055   | 0.0634      |
| Risk 5| 20-44 | BM<30     | Non Smoker  | No Comorbidity | 0.1401 | 0.0430      |
| Risk 5| 0-19  | BM<30     | Non Smoker  | No Comorbidity | 0.1463 | 0.0163      |
IFR varies widely across risk profiles within age groups

Scenario analysis: 1st and 2nd Epidemic Waves, March – October, 2020
Policies evaluated:
More moderate intervention via modifying $R(t)$
Policies evaluated:
Protection of at-risk populations

No (direct) protection of at-risk groups
• What actually happened

Protect those > 65 years old
• 17% of the LAC population

Protect those >65 years old AND/OR with highest health risk factors
• ~35% of the LAC population
Counterfactual Scenario Results

<table>
<thead>
<tr>
<th>More moderate Lockdown</th>
<th>Observed Lockdown</th>
</tr>
</thead>
<tbody>
<tr>
<td>No protection</td>
<td>No protection</td>
</tr>
<tr>
<td>Protect 65+</td>
<td>Protect 65+</td>
</tr>
<tr>
<td>65+ AND risks</td>
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</tr>
</tbody>
</table>

- Deaths
- In Hospital
- Infected

Actual interventions
1st and 2nd wave analysis – what went right

The strict initial lockdown period in LAC was effective because it both **reduced overall transmission** and **protected individuals at greater risk**

Moderate interventions + protection of 65+ alone would have overwhelmed healthcare capacity and doubled the death count
But what about the major 3rd epidemic wave?
November 2020 – February 2021
3rd wave dynamics:
Driven by major disparities in risk of infection
Different types of COVID-19 at-risk populations

At higher risk of exposure and infection
- Social and socio-economic factors:
  - Household crowdedness
  - Employment and ability to work from home
  - Income and ability to protect oneself
  - Access to healthcare

At higher risk of severe illness given infection, i.e. of hospitalization and death
- Biological / health-related factors:
  - Age
  - Comorbidities
  - Obesity
  - History of smoking
The Team

• USC Department of Preventive Medicine
  • Lai Jiang, MS Biostatistics PhD Candidate
  • Emil Hvitfeldt, MS Research Programmer
  • Wendy Cozen, DO, MPH Professor of Preventive Medicine
  • Kayla de la Haye Assistant Professor of Preventive Medicine

• USC School of Public Policy
  • Neeraj Sood, Professor and Vice Dean of Research

• Los Angeles County Department of Public Health (LACDPH)
  • Paul Simon, MD, MPH, Chief Science Officer
  • Will Nicholas, PhD, MPH Director, Center for Health Impact Evaluation, LACDPH
  • Faith Washburn, MPH Epidemiology Analyst
Big mobility data:
Informs risk of infection by neighborhood

- Big data from geolocation traces on smartphone devices

- A large and representative population sample (10% of US population)

- Spatial measures of:
  - Population able to stay at home
  - Population traveling in to work

- Aggregated individual-level patterns across neighborhoods
Measures from mobility data: who is able to stay at home

COVID-19 Incidence Rate

Population staying at home (ratio difference from pre-pandemic)
Measures from mobility data – by neighborhood

COVID-19 7-day Crude Incidence Rate  

Population able to stay at home

Crude Incidence Rate per 100,000

- 0 – 50
- 50 – 100
- 100 – 200
- 200 – 400
- 400 – 600
- 600 – 800
- 800 – 1,000
- 1,000 – 2,000
- 2,000 – 4,000
- 4,000 – 8,000
- 8,000 – 10,000

Ratio increase in stay-at-home proportion

- 0.0 – 1.0
- 1.0 – 1.5
- 1.5 – 2.0
- 2.0 – 2.5
- 2.5 – 3.0
- 3.0 – 3.5
- 3.5 – 4.0
- 4.0 – 4.5
- 4.5 – 5.0
- 5.0 – 10.0
Next steps:
Investigating 3rd wave with neighborhood model

Use the neighborhood model to do scenario analysis on the 3rd wave to investigate:

- How effective were policy measures to protect different populations from infection, hospitalization, and death?
- What would things have looked like if we had done a greater job to help more people stay at home or not go to work if sick?
Mobility data informing contact rates

• Incorporate mobility data. Ongoing.

(Ratio increase in staying at home, relative to pre-pandemic baseline)
Counterfactual Scenario Results

More moderate Lockdown

- No protection
- Protect 65+
- 65+ AND risks

Observed Lockdown

- No protection
- Protect 65+
- 65+ AND risks

Actual interventions

Horn et al. 2021, MedarXiv.