VIRGINIA
COVID-19 MODELS

Initial Analysis

Carter C. Price, Ph.D. • April 13, 2020
Our work so far

We have reviewed the models being used by the Virginia Department of Emergency Management:

- University of Virginia model
- Penn Medicine’s CHIME model
- University of Washington’s IHME model

This analysis is preliminary:

- The models are being updated several times a week.
- New data become available daily and initial data may be biased due to the lack of testing.
- Documentation for some models is better than others.

We will continue to refine this assessment as models are updated and new data become available.
What constitutes a suitable model?

We won’t know how accurate a model is until after the fact

Models should behave in explainable ways
  - Policy changes should produce results that move in the direction we expect
  - The magnitude of the response to these changes should be based on data and analysis

Resource constraints are real but there is an asymmetric risk with modeling COVID-19
  - One too many ICU beds or ventilators costs a few thousand dollars; one too few costs lives
  - Assumptions and biases should reflect this concern
Models fell into two types

**Statistical Models**
- Projections based on curves that are fitted to historic data
- Include other factors as controls, such as policy responses
- IHME model is of this type

**Systems Dynamics Models**
- Assume exponential growth in the number infected
- Rely on estimates of the rate of spread
- UVA model and CHIME model are based on this
### Advantages of modeling approaches

<table>
<thead>
<tr>
<th></th>
<th>Systems Dynamics</th>
<th>Statistical</th>
<th>Alternative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Degree of a Threat</td>
<td></td>
<td></td>
<td>Surveillance</td>
</tr>
<tr>
<td>Rate of Spread</td>
<td></td>
<td></td>
<td>Surveillance</td>
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<tr>
<td>Extent of Spread</td>
<td></td>
<td></td>
<td>Experts</td>
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<tr>
<td>Timing of the Peak</td>
<td></td>
<td></td>
<td>Experts</td>
</tr>
<tr>
<td>Severity</td>
<td></td>
<td></td>
<td>Experts</td>
</tr>
</tbody>
</table>

- **Highly Suitable**
- **Suitable**
- **Somewhat suitable**
- **Not Suitable**

Penn Medicine’s CHIME Model

A Systems Dynamics Model where people transition between three states
- The population starts in the susceptible state, the infection spreads exponentially, and people recover (or die) at a defined rate
- Hospital bed and ICU bed utilization is based on fixed ratios

Each infected person is modeled as infecting some number of people (based on the rate) on average
- Conceptually, these methods reflect a realistic spread for the early to middle phase of an epidemic
- Easy to implement and fast to run

Because this model is simple, there are only a few ways to model policy responses
- See the case of social distancing
Choices about how to model policies can drive results

- For CHIME, social distancing is modeled as a reduction in the number of contacts
  - This lowers the rate of spread
  - Lowering the spread flattens the curve

- In practice, social distancing may be better modeled as a sequestration of a segment of the population that is no longer susceptible
  - This lowers the peak but doesn’t push the peak forward

- Which result you should believe depends on how you think social distancing functions in practice
  - The best option is likely in between
University of Virginia Model

**UVA uses PatchSim to model**

- Spread between geographic areas is explicitly modeled using travel data
- Disease dynamics inside an area are simulated with a variant of an SIR model that allows for a lag between exposure and onset of infection
- The model is calibrated on actual flu spread to refine model of spread

**The use of county data allows for detailed projections**

Calibration means that results are better tuned to different regions

**The results are sensitive to choices on how to model policy changes**
University of Washington’s IHME Model

IHME fits a statistical model for the trajectory of confirmed COVID-19 deaths and then projects it forward

- Hospitalization rates and the utilization of both ICU beds and ventilators are estimated using a simulation based on the estimated death rate
- Based on data not just from Virginia, but also China, Italy, Washington State, and other areas

This is not an SIR/SEIR-model and will behave independently from those
This model provides a different perspective from the other types of models

The model is likely biased though it should improve with more and better data

- Model results are not stable—the difference between the current and previous runs differ by 25% for VA
- Because of the lack of testing, many COVID-19 deaths may not be confirmed, which could bias the trends
- Policy interventions are treated equally (i.e., how many recommended policies does the locale implement?)
Key Take-Aways

CHIME may push the peak too far in the future because of how they model some policies such as social distancing.

IHME may have the peak too early and the resource requirements too low at the peak because of bias in the data.

UVA and IHME models should get more accurate in time as more relevant data become available.

- The dearth of initial testing may bias all of the models.
- Many of the parameters used in the models come from China studies that might not be as relevant.

CHIME is best used as a decision support tool for hospital level utilization rather than as a forecast.

A synthesis should produce more suitable results.

- A composite of the different models can reduce bias and produce more accurate estimates and ranges.
Questions and Discussion

Carter C. Price, Ph.D.
Senior Mathematician
price@rand.org
Estimation of COVID-19 Impact in Virginia

April 13, 2020
(data current to April 11, 2020)
Biocomplexity Institute Technical report: TR-2020-048
Who We Are

• Biocomplexity Institute at the University of Virginia
• Over 20 years of crafting and analyzing infectious disease models
  • Pandemic response and support for Influenza, Ebola, Zika, others
• COVID-19 researchers on today's panel

Bryan Lewis
Research Associate Professor

Chris Barrett
Executive Director

Madhav Marathe
Division Director
Overview

• **Goal**: Understand impact of COVID-19 mitigations in Virginia

• **Approach**:
  • Calibrate explanatory mechanistic model to observed cases
  • Project infections through the end of summer
  • Consider a range of possible mitigation effects in "what-if" scenarios

• **Outcomes**:
  • Ill, Confirmed, Hospitalized, ICU, Ventilated, Death
  • Geographic spread over time, case counts, healthcare burdens
Key Takeaways

Projecting future cases precisely is impossible and unnecessary. Even without precise projections, we can confidently draw conclusions:

• Current social distancing efforts have paused the growth of the epidemic.
• Under current conditions, Virginia as a whole will have sufficient medical resources for at least the next couple months.
• Lifting social distancing restrictions too soon can lead quickly to a second wave.
• Further modeling could elucidate the effectiveness of test-trace-isolate policies.
• The situation is changing rapidly. Models will be updated regularly.
Model Configuration and Data Analysis
Simulation Engine – PatchSim

- Metapopulation model
  - Represents each county’s population and its interactions in a single patch
  - 133 patches for Virginia
- Extended SEIR disease representation
  - Includes asymptomatic infections and treatments
- Mitigations affect both disease dynamics and population interactions
- Runs fast on high-performance computers
  - Ideal for calibration and optimization

Model Configuration

• **Transmission**: These parameters are calibrated to the observed case counts
  - **Reproductive number**: 2.1 - 2.3
  - **Infectious period** (time of infectiousness before full isolation): 3.3 to 5 days

• **Initial infections**: Start infections from confirmed cases by county
  - Timing and location based on onset of illness from VDH data
  - Assume 15% detection rate, so one confirmed case becomes ~7 initial infections

• **Mitigations**: Duration and intensity of mitigations into the future are unknowable, thus explored through 5 scenarios
Mitigation Scenarios

• Consider 5 possible futures
  • Two levels of intensity with two durations and one with no effect

• Start of social distancing: March 15th, as measured from VDH data

• Duration: Lift on April 30th or lift on June 10th

• Intensity of mitigation:
  Slowing growth vs. Pausing growth
  • Slowing – Social distancing slows the growth, but doesn’t fully stop it
  • Pausing – Social distancing pauses growth, keeping new cases steady
  • Pausing scenarios track the data better

<table>
<thead>
<tr>
<th>Duration (lift date)</th>
<th>Intensity</th>
<th>Short Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apr 30th</td>
<td>Slowing</td>
<td>Slow - Apr30</td>
<td>Slowing intensity, lift April 30th</td>
</tr>
<tr>
<td>June 10th</td>
<td>Slowing</td>
<td>Slow - Jun10</td>
<td>Slowing intensity, lift June 10th</td>
</tr>
<tr>
<td>Apr 30th</td>
<td>Pausing</td>
<td>Pause – Apr30</td>
<td>Pausing intensity, lift April 30th</td>
</tr>
<tr>
<td>June 10th</td>
<td>Pausing</td>
<td>Pause – Jun10</td>
<td>Pausing intensity, lift June 10th</td>
</tr>
<tr>
<td>None</td>
<td>Unmitigated</td>
<td>Unmitigated</td>
<td>No effect of social distancing</td>
</tr>
<tr>
<td>Parameter</td>
<td>Estimated Values</td>
<td>Description [Source]</td>
<td></td>
</tr>
<tr>
<td>---------------------------------</td>
<td>------------------</td>
<td>----------------------</td>
<td></td>
</tr>
<tr>
<td>Transmissibility (R0)</td>
<td>2.2 [2.1 – 2.3]</td>
<td>Reproductive number *</td>
<td></td>
</tr>
<tr>
<td>Incubation period</td>
<td>5 days</td>
<td>Time from infection to Infectious *</td>
<td></td>
</tr>
<tr>
<td>Infectious period</td>
<td>3.3 - 5 days</td>
<td>Duration of infectiousness *</td>
<td></td>
</tr>
<tr>
<td>Proportion asymptomatic</td>
<td>50%</td>
<td>Proportion of infections that don’t exhibit symptoms *</td>
<td></td>
</tr>
<tr>
<td>Proportion hospitalized</td>
<td>5.5% (~20% of confirmed)</td>
<td>Symptomatic Infections becoming Hospitalized *</td>
<td></td>
</tr>
<tr>
<td>Proportion in ICU</td>
<td>20%</td>
<td>Hospitalized patients that require ICU *</td>
<td></td>
</tr>
<tr>
<td>Proportion ventilated</td>
<td>70%</td>
<td>Proportion of ICU requiring ventilation *</td>
<td></td>
</tr>
<tr>
<td>Onset to hospitalization</td>
<td>5 days</td>
<td>Time from symptoms to hospitalization *</td>
<td></td>
</tr>
<tr>
<td>Hospitalization to ventilation</td>
<td>3 days</td>
<td>Time from hospitalization to ventilation *</td>
<td></td>
</tr>
<tr>
<td>Duration hospitalized</td>
<td>10 days</td>
<td>Time spent in the hospital</td>
<td></td>
</tr>
<tr>
<td>Duration ventilated</td>
<td>14 days</td>
<td>Time spent on a ventilator †</td>
<td></td>
</tr>
<tr>
<td>Infection detection rate</td>
<td>15%</td>
<td>One confirmed case becomes ~7 initial infections #</td>
<td></td>
</tr>
</tbody>
</table>

# Li et al., Science 16 Mar 2020:eabb3221 [https://science.sciencemag.org/content/early/2020/03/24/science.abb3221](https://science.sciencemag.org/content/early/2020/03/24/science.abb3221)
Calibration Approach

• **Data:**
  - County level case counts by date of onset (from VDH)
  - Confirmed cases for model fitting

• **Model:** PatchSim initialized with disease parameter ranges from literature

• **Calibration:** fit model to observed data
  - Search transmissibility and duration of infectiousness
  - Markov Chain Monte Carlo (MCMC) particle filtering finds best fits while capturing uncertainty in parameter estimates

• **Project** future cases and outcomes using the trained particles


Accessed 1pm April 12, 2020
Impact of Interventions
Estimating Effects of Social Distancing

- Anonymized mobility data shows Virginia greatly reduced activities
  - Google: -44% retail & recreation, -18% grocery stores, -39% workplaces
  - Cuebiq: 50% reduction of average person’s movement compared to Jan / Feb
- VDH data shows reductions in growth rate starting in mid-March
  - Weekly average growth rate by date of onset
    - Week before March 15 = 0.3
    - Week after March 15 = 0.03
  - Equivalent reproductive number change
    - 2.2 before March 15th
    - 1.1 after March 15th

Virginia-wide results

Confected cases

Hospitalizations

Ventilations
Course of Action Analysis
Confirmed Cases – Many Possible Futures

Virginia - Daily Confirmed cases - Comparison

Weekly New Confirmed Cases

<table>
<thead>
<tr>
<th>Week ending</th>
<th>Unmitigated</th>
<th>Slow Jun10</th>
<th>Pause Jun10</th>
</tr>
</thead>
<tbody>
<tr>
<td>4/12/20</td>
<td>11,846</td>
<td>5,518</td>
<td>2,469</td>
</tr>
<tr>
<td>4/19/20</td>
<td>25,712</td>
<td>8,502</td>
<td>2,599</td>
</tr>
<tr>
<td>4/26/20</td>
<td>53,562</td>
<td>13,076</td>
<td>2,742</td>
</tr>
<tr>
<td>5/3/20</td>
<td>101,876</td>
<td>19,881</td>
<td>2,944</td>
</tr>
<tr>
<td>5/10/20</td>
<td>164,527</td>
<td>29,567</td>
<td>3,151</td>
</tr>
<tr>
<td>5/17/20</td>
<td>200,184</td>
<td>42,312</td>
<td>3,345</td>
</tr>
<tr>
<td>5/24/20</td>
<td>182,818</td>
<td>57,679</td>
<td>3,558</td>
</tr>
<tr>
<td>5/31/20</td>
<td>136,652</td>
<td>73,380</td>
<td>3,770</td>
</tr>
<tr>
<td>6/7/20</td>
<td>84,016</td>
<td>85,874</td>
<td>3,962</td>
</tr>
<tr>
<td>6/14/20</td>
<td>46,350</td>
<td>89,390</td>
<td>4,144</td>
</tr>
<tr>
<td>6/21/20</td>
<td>23,363</td>
<td>85,226</td>
<td>4,470</td>
</tr>
<tr>
<td>6/28/20</td>
<td>11,366</td>
<td>91,648</td>
<td>7,850</td>
</tr>
</tbody>
</table>
Hospital Demand and Capacity by Region

Assumes average length of stay of 10 days
COVID-19 capacity ranges from 80% (dots) to 120% (dash) of total beds

Date ranges when regions are estimated to exceed surge capacity

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Date Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slow – Apr30</td>
<td>Early May – Early June</td>
</tr>
<tr>
<td>Slow – Jun10</td>
<td>Early May – Mid June</td>
</tr>
<tr>
<td>Pause – Apr30</td>
<td>Mid June – Late July</td>
</tr>
<tr>
<td>Pause – Jun10</td>
<td>Mid July – Late August</td>
</tr>
<tr>
<td>Unmitigated</td>
<td>Late April – Mid May</td>
</tr>
</tbody>
</table>

Social Distancing postpones the time when capacity is exceeded 1 to 2.5 months

Timing estimates can be used for planning to augment existing capacities if needed
Ongoing Efforts and Improvements

• Incorporate age structure into transmission dynamics and stratify outcomes by age in these projections

• Incorporate Virginia-specific outcomes and durations which will better tailor these analyses to our Commonwealth

• Assess evidence for the role of seasonality, and incorporate if warranted

• Analyze Test-Trace-Isolate mitigations

• Connect forecast demand to VDH dashboard
Key Takeaways

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• Further modeling could explore the effectiveness of test-trace-isolate policies.
• The situation changes rapidly. Models will be updated regularly.
References


Questions?

Biocomplexity COVID-19 Response Team

Aniruddha Adiga, Hannah Baek, Chris Barrett, Golda Barrow, Richard Beckman, Parantapa Bhattacharya, Andrei Bura, Jiangzhuo Chen, Clark Cucinell, Allan Dickerman, Stephen Eubank, Arindam Fadikar, Joshua Goldstein, Stefan Hoops, Sallie Keller, Ron Kenyon, Brian Klahn, Gizem Korkmaz, Vicki Lancaster, Bryan Lewis, Dustin Machi, Chunhong Mao, Achla Marathe, Madhav Marathe, Fanchao Meng, Henning Mortveit, Mark Orr, Przemyslaw Porebski, SS Ravi, Erin Raymond, Jose Bayoan Santiago Calderon, James Schlitt, Aaron Schroeder, Stephanie Shipp, Samarth Swarup, Alex Telionis, Srini Venkatramanan, Anil Vullikanti, Jim Walke, Amanda Wilson, Dawen Xie

Points of Contact

Bryan Lewis
brylew@virginia.edu

Srini Venkatramanan
srini@virginia.edu

Madhav Marathe
marathe@virginia.edu

Chris Barrett
ChrisBarrett@virginia.edu