# A RISK ASSESSMENT MODEL TO INFORM COVID-19 RETURN-TO-OPERATIONS DECISIONS

*Colin M. Coyne, Ed.D., M.M., Chief Strategy Officer, Samford University*

## I. Executive Summary

Pandemic related return-to-operations decisions present atypical challenges. Return-to-operations ("RTO") decisions following a COVID-19 induced closure -- or more accurately, the timing for *beginning* the process of returning to full-scale operations following such an event –are bounded by episodic variability, challenges in identifying and confirming patients infected by the virus, and factors unique to the institution. In the absence of certainty, a data-informed, rational model is required to reduce subjective bias; inform decision-making frameworks while promoting consistent application of a standard; and, minimize potential litigation. To date, no such decision model has been advanced to inform institution-level decisions or to encourage consistent decisions across institutions

By examining daily case data across 262 global and 3,255 US locations, this work provides both a foundation for insight and a specific tool to help institutions address the most pressing question of today: *On what date should the institution be able to return to operations with a prudent degree of risk?*

Based on the research findings and insight gained from manipulation of the model created, this paper advances twelve recommendations of policy and practice. A baseline copy of the model that allows customized RTO estimates unique to the user's institution is available to all interested parties by contacting Samford University care of Colin Coyne, Chief Strategy Officer (ccoyne@samford.edu).

## II. Context and Problem

There are no clearly defined protocols for pandemic related return-to-operations ("RTO") decisions. Unlike other emergencies such as hurricanes that have narrowly defined start and finish dates, pandemic response is shrouded in incomplete information of unknown duration. The relevant question no longer is a narrowly tailored, "When do we open?"

a. *Institutional Context.* Unknown characteristics related to the pathology, diagnosis and treatment of COVID-19 intersect with the nature of institutional settings. Institutions often serve more than a single purpose while catering to multiple audiences. In the case of a university, the institution serves both as a place of learning (and often living) for students and as host to wider public gatherings. Regarding the former, students often represent a widely dispersed geographic base. In the latter, gatherings may represent more discreet points of origin, but less is known about attendee backgrounds and experience.

b. *Episodic Variability.* From the outset, incidences of COVID-19 have presented themselves differently across variables that are beyond the institution's control. Examples include[1]:

[1] Note this is different than a discussion of fatality rates. For example, poverty levels and availability of Tier 1 and 2 hospitals within a close radius would be among complementary criteria.

i. Population Density: as a measure of unavoidable human-to-human interaction
ii. Large Group Attendance and Use of Mass Transit: what percentage of the population experiences *extremely* close proximity on a daily basis?
iii. The Epicenter Effect: A limited number of locations have a disproportionate effect on aggregate figures. One nursing home in Washington dominates that state's fatality rates; New York City alone accounts for nearly 20% of confirmed cases in the United States[2]. In China, the Hubei province accounts for 82% of all confirmed cases and 96% of all fatalities[3]. Moreover, a single case has the capacity to ignite a new wave of infection in previously dormant areas.
iv. Transitory Visitor Pattern: Prevention and containment is mitigated by an influx of visitors from unknown origins. This impacts tourist driven economies and individual retail store locations alike. It also subjects institutions to a much wider sphere of exposure.

The essential point is that no individual circumstance exactly mirrors another; COVID-19 is highly context specific. This challenges broad policy enactment at the federal, state or institutional level, either in response to COVID-19 outbreaks or for making RTO decisions.

c. *Definition of Problem.* A lack of homogeneous audience, coupled with as yet unknown variability in COVID-19 characteristics such as asymptomatic expression and time to diagnosis, renders certitude impossible. In the absence of certainty, a data-informed, rational model is required to reduce subjective bias; inform decision-making frameworks while promoting consistent application of a standard; and, minimize potential litigation. To date, no such decision model has been advanced to inform institution-level decisions or to encourage consistent decisions across institutions, be they related to higher education or otherwise. The last objective is especially germane as individual outcomes are co-dependent on the decisions of others.

## III. Study Questions

Framing Questions

Pandemic related RTO decisions may be framed by the following questions:

1) What level of risk is the institution willing to incur as a product of opening?
2) When will that risk fall below the acceptable threshold?
3) To what extent is timing impacted by stakeholder characteristics unique to the Institution?
    a. Who are the primary and secondary stakeholders?
    b. From which destinations and following what circumstance do stakeholders return to the institution?
    c. Does viral persistence vary among stakeholder home locations?
4) Under what circumstances do stakeholders come to the institution?

[2] As of April 8, 2020.
[3] As of April 9, 2020.

5) To what extent does the return of a stakeholder group serve the central mission of the institution?
6) What unique stakeholder characteristics inform a hierarchy of timing for return to the institution?
7) What are the policy implications of this hierarchy?
8) How do specific mitigation and containment strategies influence our RTO decision?

Questions 1 is institutionally defined and this paper does not address the issue beyond the model's ability to accommodate user-defined risk parameters. Question 2 is addressed within the context of Questions 3(a), 3(b) and 3(c). Questions 4-8 are institutionally dependent, however this paper will address related policy implications.

Study Question

Ultimately, this paper seeks to answer one question above others, "*On what date should the institution be able to return to operations with a prudent degree of risk?*"[4]

## IV. Conceptual Framework

RTO decisions following a COVID-19 induced closure -- or more accurately, the timing for *beginning* the process of returning to full-scale operations following such an event –are bounded by episodic variability, challenges in identifying and confirming patients infected by the virus, and factors unique to the institution.

COVID-19 presents itself differently from location to location, sometimes extremely so. Episodic variability is a function of many factors, eight of which are considered here as influencing RTO decisions: 1) the duration from onset to remission, even assuming a common definition of remission; 2) the density of population generally or concentrations of forced proximity; 3) response strategies, particularly in response to "flattening the curve" to reduce strain on healthcare systems; 4) the amount of time before a coordinated response is implemented; 5) availability of, and access to, Tier 1 or 2 healthcare facilities; 6) onset intensity, or the extent and speed with which the virus "takes hold"; 7) the reliability of information and underlying data accuracy; and, 8) localized demographics in the area of infection.

Asymmetric infection and fatality rates among sub-populations confound cross-regional comparisons, potentially under-stating or over-stating risk. Five "at-risk" populations frequently are cited: the elderly, the poor, males, African Americans, and those with pre-existing conditions ranging from respiratory illnesses to auto-immune diseases.

Just as source populations differ, so does case identification. Risk assessment is inhibited when the number of infected individuals is suspect or difficult to ascertain. Even in the best of circumstances, some variability should be expected: COVID-19 is a previously unidentified virus; onset in the Hubei province of China where the virus is believed to have originated was swift; the speed with which the virus was identified and then communicated to world health

[4] The emphasis of this work is timing, not magnitude. This shapes the methodology employed. While data could be used to estimate total numbers of cases, that is not the challenge this study seeks to address.

officials is uncertain; and, as a new disease, standards for diagnosing and reporting lacked uniformity.

Setting aside issues of availability and reliability of test kits, the manner in which the virus presents itself adds to a complex landscape: some infected patients display symptoms while others do not; some symptoms mimic influenza and therefore lend themselves to misdiagnosis either before or after the patient is introduced to a healthcare system where they can be tracked; and, the rates of asymptomatic expression are not yet known. A central -- perhaps *the* central -- goal for return-to-operations decisions is not (re)introducing the virus to the institution's environment. Therefore, asymptomatic "lurking" should be weighted appropriately when trying to identify exposure risks.

Macro-considerations are essential to informing RTO decisions. However, existential threats frame an incomplete picture of the risk management challenge. Institutional specifics add complexity, define acceptable thresholds, and point the finger of responsibility back to those ultimately responsible for living with the consequences of the decision. While non-governmental institutions are bound by federal guidelines, state regulations or local ordinances, these merely provide outer-markers; they are not the relevant measure of assurance for reopening the institution. Rather, confidence is earned by thoroughly understanding what is happening in the location of the furthest stakeholder, further in this instance being defined as the location where COVID-19's viral spread has least progressed. That stakeholder carries the risk associated with the individual's local community when returning to the institution. Therefore, the institution is held captive to the last mover; it is not released by the first.

Institutional specifics include: 1) drawing radius from which stakeholders originate, with risk increasing significantly as the radius grows; 2) the number and individual circumstance of each location within this radius; 3) the proportion of stakeholders from each location; and 4) relative advantages and disadvantages of the institution's local market relative to the incidence of COVID-19 and the capacity to treat those infected. Pragmatics may limit market specificity to the state level. Nonetheless, state-level indexing of key variables provides greater granularity than using national averages and better captures the reality that every institution has its own discreet profile. Even then, institutions remain responsible for knowing whether their home states exhibit bifurcated tendencies requiring multiple response scenarios.

Most essentially, each institution must define its unique risk tolerance and the degree of confidence it seeks before it is willing to resume operations. Given episodic variability and the number of incomplete datasets (i.e.: many locations have yet to reach their peak in reported cases and few have completed a full viral cycle with reliable data), one should expect wide confidence intervals in modeling scenarios. This is an important point as it opens the door to decisions makers seeing what they want to see in the data. Committing to a predefined standard is advisable and offers the best assurance of objectivity in addressing different, sometimes competing, stakeholder needs. Given how much remains unknown, committing to the most conservative thresholds seems prudent.

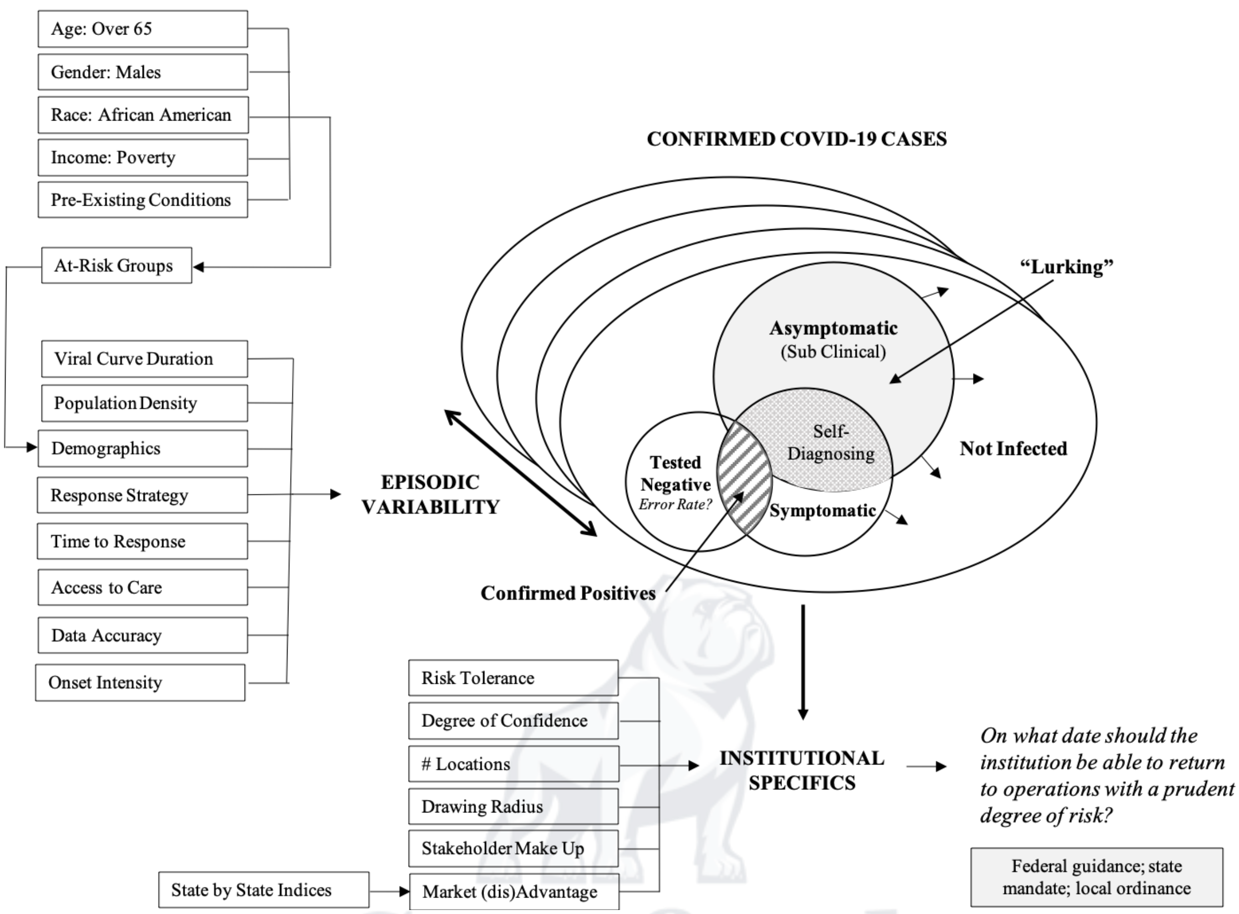


***Figure 1**:* *Conceptual Framework for returning to work on a risk adjusted basis after COVID-19 induced closures. Decisions are bounded by episodic variability, inconsistencies in case reporting and institutional specifics.*

## V. Study Design

### Source Data

Case data for this study originates from the Center for Systems Science and Engineering (CSSE) at John's Hopkins University. Time series data with daily cases from January 23, 2020 to April 15, 2020 was downloaded by country and/or protectorate (N=262 over 85 days) from the website https://github.com/CSSEGISandData/COVID-19 . Data used to construct and test the model was downloaded on April 7, 2020 and then updated on April 16, 2020 before making the model available for use. US data was downloaded from the same site and on the same dates (N=3,255 over 85 days.).

Sources for determining State Index Rates include:

| *Index* | *Source* |
|---|---|
| Population | https://worldpopulationreview.com/states/ |
| % Over-65 | https://www.prb.org/which-us-states-are-the-oldest/ |
| Poverty Rate | https://worldpopulationreview.com/states/poverty-rate-by-state/; |
| | https://datausa.io/profile/geo/puerto-rico/ |

| *Index* | *Source* |
|---|---|
| % African-American | https://www.governing.com/gov-data/census/state-minority-population-data-estimates.html; https://datausa.io/profile/geo/puerto-rico/#demographics |
| % Male | https://www.kff.org/other/state-indicator/distribution-by-gender/ ?currentTimeframe =0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D |
| Cases per Capita | https://www.nytimes.com/interactive/2020/us/coronavirus-us-cases.html |
| Fatality Rate | https://www.nytimes.com/interactive/2020/us/coronavirus-us-cases.html |
| Access to Care | https://www.beckershospitalreview.com/rankings-and-ratings/states-ranked-by-hospital-beds-per-1-000-population.html |

## Methodology Summary

Essentially all locations have continuing COVID-19 cases creating an infinite distribution tail, at least presently. Estimating a date-specific return to operations using case data therefore requires establishing a viral curve with onset and termination thresholds.

To do so, each location's daily rate was smoothed by calculating a three-day rolling average. Locations with fewer than 100 cases were removed from both the global and the US-Only datasets resulting in new N values of 174 and 484 cases respectively. The three-day average peak date was identified for each location (or if the peak rate was the last day of available data, that location was classified as "no-peak".)

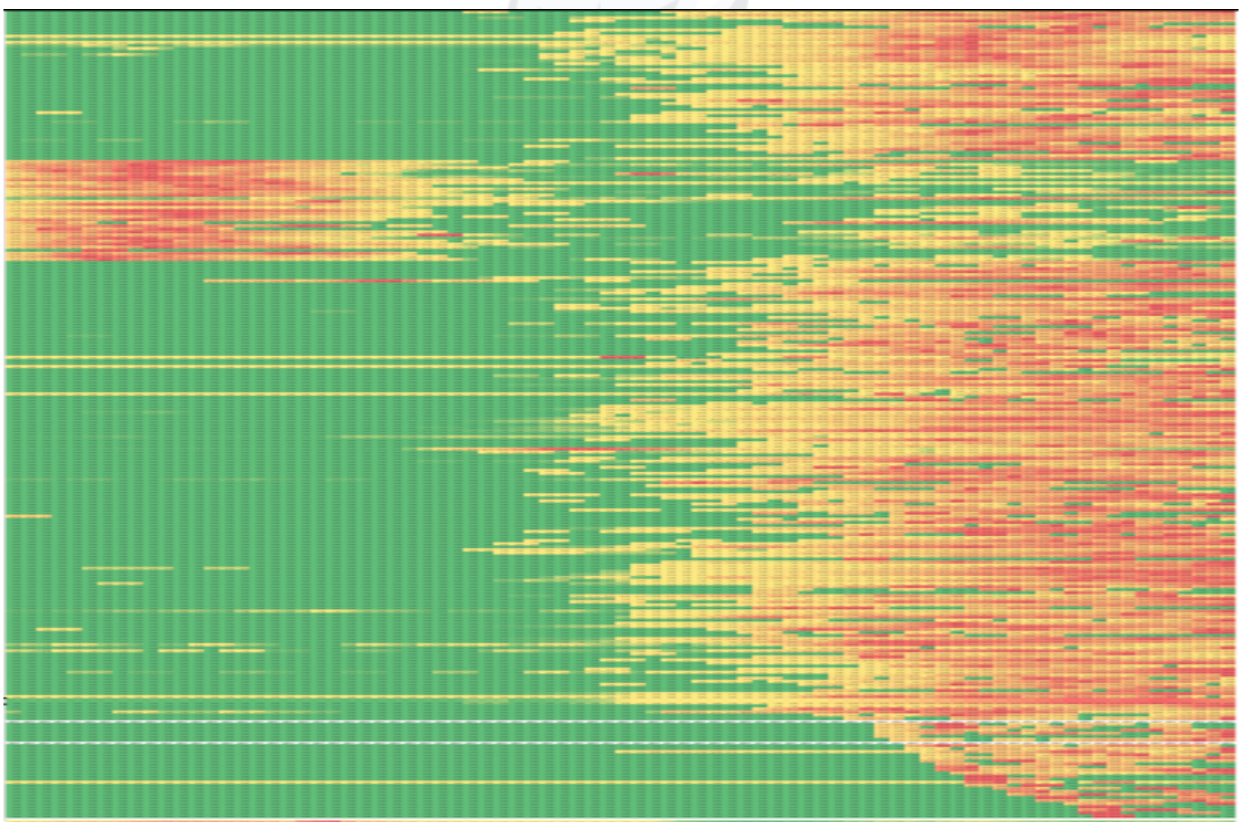

***Figure 2:*** *Global heat map of COVID-19 Incidence Rates illustrating all case curves as of April 15, 2020. Red indicates peak date. Days are on the horizontal axis; each row of the vertical axis represents a different country..*

At 1%, 5% and 10% of the three-day rolling average peak, the number of days to peak was calculated for all cases with an identifiable peak (N=148 globally; N=436 US-Only, at the 5% threshold). Using only cases where a complete viral curve is identified (N=34 in the global dataset; N=14 in the US-Only), the average number of days between the peak and the end of the viral curve was determined. Confidence intervals (95%) were established for the pre-and post-peak ranges. The high ranges for each were added together to establish an estimated total viral curve. The pre-peak and post peak correlation coefficients using all cases and only full-cycle cases were measured for both the global and US-Only data.

Based on higher percentages of full-cycle locations and higher correlation coefficients, the Global dataset was used to calculate a normalized estimate of time from first case to peak. Adjusting all cases to a common start date allows for estimating the number of days from first identified case to the first viral threshold. Descriptive statistics were calculated with corresponding confidence intervals and again, the highest range was applied. The sum of the average normalized first-case-to-peak plus the peak-to-post-peak-threshold yields an estimated time to resuming operations on a mean average basis.

## Pragmatic Adjustments

Exclusively applying global Mean Averages as the basis for making US-based RTO decisions offers limited utility due to a host of confounding factors including: wide episodic variability in general; differing societal norms; multiple containment timeframes and strategies employed across different states; intentional efforts to lengthen duration to mitigate stress on healthcare systems ("flattening the curve"); and limited post-peak data from US locations. Estimation complexity is compounded by undertesting in some areas and the extent to which misdiagnosed or asymptomatic patients do not appear as confirmed cases ("lurking").

An applied model should accommodate curve-flattening, lurking, stakeholder variations, and institution specifics, including leadership's assessment of acceptable risk. Without surrendering empirical foundations of the model, institutional priorities and first-hand knowledge allows the model to inform decisions rather than prescribe them. Therefore, the model allows users to control the following parameters at their discretion:

| # | Parameter | Purpose | Options |
|---|---|---|---|
| *1* | Viral Threshold | User defined risk tolerance | Infinite. Default Rate = 5% |
| *2* | Confidence Interval Alpha | Determines range of confidence interval (ie: 99%,95%, 90%, etc.) | Infinite. Default Rate = 5% |
| *3* | Institutionally Specific Profile | Applies weighted average indexing based on demographic makeup (by state) of stakeholders | On / Off |
| *4* | Curve Lengthening | Adjusts duration by applying US average days to peak indexed to global average | On / Off |
| *4(a)* | Curve Lengthening: *Local Variation* | Allows partial over-ride of US index if local area displays different characteristics from US averages | Infinite. Logical range -100% to +100% |

| # | Parameter | Purpose | Options |
|---|---|---|---|
| *5* | Asymptomatic Lurking | Estimates extent of unknown positive cases in population. Index based on third party estimates ranging from 25-50%. | On / Of |
| *5(a)* | Asymptomatic Lurking: *Local Variation* | Allows partial over-ride of US index if local area displays different characteristics from US averages | Infinite. Logical range -100% to +100% |
| *6* | Access to Care | Adjusts duration based on reduced risk afforded by available hospital beds | On / Off |
| *6b* | Access to Care – *State Code* | If Access to Care is activated, a two-character state code must be entered (ex: AL) | Official two-letter state code |
| *6c* | Access to Care – *County Beds / 1,000 residents* | If known, allows more granular application of access to care as intrastate variability can be significant. If unknown, the variable can be blank when Access to Care is activated. | On / Off |
| *7* | State Variability Adjustment: Age | Allows user to suppress impact of high-risk group when Institutionally Specific Profile is activated. Should be applied if population is under-represented among stakeholder group. | On / Off. Weighting can be adjusted but is not encouraged. |
| *8* | State Variability Adjustment: *Poverty* | Allows user to suppress impact of high-risk group when Institutionally Specific Profile is activated. Should be applied if population is under-represented among stakeholder group. | On / Off. Weighting can be adjusted but is not encouraged. |
| *9* | State Variability Adjustment: *Race* | Allows user to suppress impact of high-risk group when Institutionally Specific Profile is activated. Should be applied if population is under-represented among stakeholder group. | On / Off. Weighting can be adjusted but is not encouraged. |
| *10* | State Variability Adjustment: *Gender* | Allows user to suppress impact of high-risk group when Institutionally Specific Profile is activated. Should be applied if population is under-represented among stakeholder group. | On / Off. Weighting can be adjusted but is not encouraged. |
| *11* | State Variability Adjustment: *Confirmed Cases* | Applies state rate indexed to national average | On / Off. Weighting can be adjusted but is not encouraged. |
| *12* | State Variability Adjustment: *Fatality Rate* | Applies state rate indexed to national average | On / Off. Weighting can be adjusted but is not encouraged. |
| *13* | Date of Last Reported First Case: Local / Employee Area | Commences viral cycle to estimate final RTO date as adjusted by other settings. The date of last reported breakout within the local area should be used. | Date of first case in local area |

| # | Parameter | Purpose | Options |
|---|---|---|---|
| *14* | Date of Last Reported First Case: Institution Drawing Area | Commences viral cycle to estimate final RTO date as adjusted by other settings. The date of last reported breakout within the total stakeholder drawing radius should be used. This may vary significantly from the local / employee area. | Date of first case in local area |

Based on user-defined parameters, the mean average durations will be adjusted and the model returns two suggested dates:

**Return to Public Operations**: the earliest date when the institution should *begin* the process of allowing external and/or distant stakeholders to return subject to institutionally defined priorities as suggested in framing questions 5-7 above. Institutions with broad constituent bases (ex: universities, concert arenas, etc.) have broader risk exposure and therefore require a longer period of time to attain acceptable risk thresholds.

**Return to Local / Employee Operations:** the earliest date to *begin* the process of reintroducing employees or local stakeholders to the institution. Where an institution's stakeholder base is well known and highly localized (ex: restaurant, fitness studio), this better approximates risk. However, the institution will remain subject to random introduction of COVID-19 from local visitors traveling to other places.

*Regardless of the date or combination of dates applied, appropriate mitigation strategies should be employed in all RTO decisions from the first day of reopening.*

## VI. Findings

Findings most relevant to developing a pragmatic RTO model are summarized below. Additional and significant findings embedded in the dataset are not included in this summary. All findings are as of April 15, 2020.

| GLOBAL VIRAL CURVE at 5% Viral Threshold and Alpha = .05** | | | N=174 |
|---|---|---|---|
| Full Cycle Locations: | 34 | 20% | |
| Ongoing Tail Locations: | 114 | 66% | |
| No Peak Locations | 26 | 15% | |

**Viral Curve Duration**

| N = | | Low | Mean* | High |
|---|---|---|---|---|
| **148** | Pre-Peak (*using Full Pre-Peak Cycle locations*) | 17.31 | 18.61 | 19.91 |
| **34** | Post-Peak (*using Full Post-Peak Locations*) | 15.20 | 18.91 | 22.62 |
| | | 32.51 | 37.52 | 42.53 |

| | |
|---|---|
| Pre-Peak/Post-Peak Correlation Coefficent - All Cases | (0.66) |
| Pre-Peak/Post-Peak Correlation Coefficent - Full Cycle Cases Only | (0.60) |

** Significant difference in means between global and US Pre-Peak Durations ($p < .05$)*
*** $p < .001$ at all risk thresholds and alphas (1% - 10%; .01 - .10)*

UNITED STATES VIRAL CURVE at 5% Viral Threshold and Alpha = .05** N=484

| | | |
|---|---|---|
| Full Cycle Locations: | 14 | 3% |
| Ongoing Tail Locations: | 422 | 87% |
| No Peak Locations | 48 | 10% |

**Viral Curve Duration**

| N = | | Low | Mean* | High |
|---|---|---|---|---|
| **148** | Pre-Peak (*using Full Pre-Peak Cycle locations*) | 16.76 | 17.22 | 17.68 |
| **34** | Post-Peak (*using Full Post-Peak Locations*) | 3.00 | 5.93 | 8.86 |
| | | 19.75 | 23.15 | 26.54 |

| | |
|---|---|
| Pre-Peak/Post-Peak Correlation Coefficient - All Cases | (0.63) |
| Pre-Peak/Post-Peak Correlation Coefficient - Full Cycle Cases Only | (0.11) |

** Significant difference in means between global and US Pre-Peak Durations (p < .05)*
*** p < .001 at all risk thresholds and alphas (1% - 10%; .01 - .10)*

# CASES AS A PERCENT OF TOTAL*

**Descriptive Statistics**

| | |
|---|---|
| MEAN | 40.62% |
| Standard Deviation | 20.15% |
| Count | 34.00 |
| Alpha | 0.05 |
| Confidence Interval | 6.8% |
| MEDIAN | 40.61% |
| HIGH | 47.39% |
| MEAN | 40.6% |
| LOW | 33.85% |

DAYS TO PEAK

**Descriptive Statistics**

| | |
|---|---|
| MEAN | 31.91 |
| Standard Deviation | 17.07 |
| Count | 174.00 |
| Alpha | 0.05 |
| Confidence Interval | 2.54 |
| MEDIAN | 28.50 |
| HIGH | 34.45 |
| MEAN | 31.91 |
| LOW | 29.38 |

Extracting from the tables above:

At the Global Mean Average, 40.62% of cases occur prior to the highest peak with the peak occurring 31.91 days after the first reported case or 8.61 days after reaching a threshold of 5.0% of the peak number of cases. At global rates, 493,387 additional cases will appear in the United States after reaching its peak date on April 10, 2020 when 337,512* confirmed cases were recorded since the first US case on January 23, 2020. At the Global Mean Average, cases fall below the viral threshold 18.91 days after the peak date or 50.83 days after first onset. On that date and at that rate, an estimated 3,028 newly confirmed cases would present themselves in the US, representing 0.91 cases per 100,000 residents.

At the Global Mean Average, 33.85% of cases occur prior to the highest peak with the peak occurring 34.45 days after the first reported case or 19.91 days after reaching a threshold of 5.0% of the peak number of cases. At global rates, 659,688 additional cases will appear in the United States after reaching its peak date on April 10, 2020 when 337,512* confirmed cases were recorded since the first US case on January 23, 2020. At the Global Mean Average, cases fall below the viral threshold 22.62 days after the peak date or 57.07 days after first onset. On that date and at that rate, an estimated 3,028 newly confirmed cases would present themselves in the US, representing 0.91 cases per 100,000 residents.

As previously noted, exclusively applying Global Mean Averages as the basis for making US-based RTO decisions offers limited utility due to a host of confounding factors.

## VII. Recommendations of Institutional Policy and Practice

Based on the research findings and insight gained from manipulation of the model created, this paper advances twelve recommendations of policy and practice.

1. Institutions display unique characteristics and RTO decisions should reflect those specific circumstances to the greatest extent possible. Private and public policy needs to recognize COVID-19's wide degrees of situational variability. This may result in bifurcated reopening schedules.
2. RTO decisions require a deep understanding of stakeholder composition, points of origin, and varying potential for COVID-19 exposure. Exposure risk is multi-dimensional.
3. Competing stakeholder demands inject bias to the decision-making process. RTO decisions are best made with objective, data-informed and *pre-defined* standards. (Ex: "Once we have achieved the following, we will reopen.")
4. RTO timing is not a bivariate decision (i.e.: open or stay closed). A clear hierarchy of stakeholders is required, should be guided by mission centrality, and will result in a series of returns.
5. Institutions must acknowledge ongoing exposure and articulate an acceptable risk threshold;
6. Institutions impact, and are impacted by, other institutions, some of which may be thousands of miles away. Balancing individual wants against collective well-being is required and will fall to public policy.
7. Because institutions with wide stakeholder radii are captive to the last mover, they should not rely on local ordinances as a proxy for decisions that remain exclusive to the institution.
8. Before opening, a contingency plan for reinfection (at the institution or within its drawing radii) is strongly advised as data suggests a "bounce effect". Implementation decisions should incorporate a new normal based on lessons learned to date.
9. Public policy needs to reflect this same discipline as the option of "shutting down" a second time is far less likely. Just as institutions must prioritize stakeholders, public policy should prioritize protecting those at greatest risk and measures that have been shown to yield the greatest impact. Social distancing strategies are supported by the data as among the most effective means of limiting spread.
10. Public policy should reflect situational variability and mitigate risk accordingly. "When" becomes secondary to "how" and gradual easing of restrictions is strongly supported by this research.
11. Public policy should not wait for unproven unavailable technologies. Decisions should be made on what is known at the time. For example, behavior modification remains the

single most effective strategy and relentless promotion of these strategies is warranted. Similarly, redoubling efforts to increase supplies of personal hygiene products (sanitizer, disinfectant wipes, masks) seems a better allocation of financial resources while testing efficacy is proven.

12. Time matters in two ways. First, delayed responses to known outbreaks have significantly disproportionate consequences. Policy decisions should anticipate a "cut early and deep" response to future upticks. Second, knowing what decisions do not require immediate response also holds consequence. Decision makers should resist pressure, political or otherwise, to remove restrictions too quickly or too broadly.

## VIII. Limitations

Limitations of this research and study include:

- Due to time constraints and an urgent need for objective measures to inform pressing RTO decisions, this work lacks many academic conventions, most notably rigorous peer review and a robust literature review. As such, additional insight is encouraged and welcome.
- The dataset for the United States is still forming; while the model is adaptive to individual preferences to mitigate some of the known variances between global and domestic patterns, this accommodation allows bias into the model.
- This paper is temporal and rarely offers insight as to the potential magnitude of cases or fatalities associated with COVID-19. While data could be used to offer such insights (for example, if the date of peak cases is determined by the number of cases, surely we know what 5% of that number is), case estimation would necessitate a different line of reasoning.

## IX. Recommendations for Future Research

- Additional analyses might prove helpful in gaining predictive capacity or narrowing estimated timeframes. Examples include developing a deeper understanding of the relationship between duration and a) severity and/or b) location characteristics. Policy recommendations could be improved by delving deeper into local versus regional implications.

## X. Conclusion

The intent of this work is to provide an empirically grounded tool for *informing* decision-making. It does not purport to provide definitive conclusions and relieve decision makers of their obligation. Were this research to suggest such, it would reflect more than hubris. To do so would dramatically undercut the work's most fundamental finding: RTO decisions are quintessentially unique to each institution. Both private and public policy needs to address this.

Public health policy ensures collective well-being is not sacrificed to individual wants. Once that threshold is met, however, decision authority is and should remain with individual institutions as they absorb the risk and bear the consequence. Hopefully, this work lends much needed support to that process without supplanting it.

**Appendices**

A separate document accompanies this paper featuring a dashboard printout of the decision model developed as part of this research. A baseline copy of the model that allows customized RTO estimates unique to the user's institution is available to all interested parties by contacting Samford University care of Colin Coyne, Chief Strategy Officer (ccoyne@samford.edu).