Quantified Easing of Social Distancing Restrictions:
Prediction of Covid-19 Disease Transmission Based on a Social Distancing Index

Ty Newell, PhD, PE
Emeritus Professor
Mechanical Science and Engineering
University of Illinois
tynewell@illinois.edu
May 6, 2020

Foreword

More the 7 weeks of social isolation, unemployment, fear, and general restrictions in one's activities are leading to "distancing fatigue". Active protests are occurring throughout the US. Messages providing a quantified rationale for continued distancing are not being coherently communicated to the public. Results from expert simulation models are referred to in vague manners that convey a complexity too difficult for the general public to understand, resulting in mistrust of government messages and policies.

We are at the very beginning of the spread of the SARS-CoV-2 virus. Total infections and fatalities in the US are at horrendous levels, however, things will get much worse if the general public continues backsliding in precautionary actions. The following report describes a means for connecting Covid-19 disease spread with quantifiable metrics (aka, social distancing index). The framework of this prediction method enables quantitative metrics for comparing the effectiveness of social distancing modifications with trends in disease transmission. An additional benefit of the prediction method is a straightforward basis for explaining intended policy goals to the general public.

Introduction

A relation coupling Covid-19 disease transmission to a social distancing index is presented in this report. Directly linking Covid-19 disease transmission to a social distancing index is important for predicting impacts of social distancing policy changes to disease infection growth trends. The relation provides a means to assess the effectiveness of social distancing reduction practices. Seasonal virus viability effects, facemask implementation, building ventilation operation, regional/cultural/social populace differences (eg, urban versus rural), and other disease transmission efficiency effects (reduced occupant density in restaurants and other public places) can be directly factored into the relation. One can also look backwards to determine the impact of delayed social distancing restriction guidelines. Finally, economic impact models based on the social distancing index can be used to investigate cost of Covid-19 management programs in relation to societal costs (hospitalizations, business activity reduction, travel reduction, etc).

Appendices at the end of this report provide modeling background assumptions and derivations.

Predicting Covid-19 Infection Growth

Prediction of disease transmission growth within a fully susceptible populace is straightforward given the exponential growth characteristic of infection spread. A single parameter, the Basic Reproduction number, R_0, defines infection growth characteristics. R_0 for Covid-19 is estimated to be in the range of 2 to 3, however, the actual value is dependent on many factors such as outdoor and indoor environmental factors (temperature, humidity), population characteristics (eg, density, interaction, health, age), built environment (ventilation air flow, air filtration, ventilation system design), and other factors that may be hidden or ill-defined (eg, unknown number of asymptomatic infection carriers).

Figure 1 is a plot of US Covid-19 infection data for the United States and 8 additional countries. [Worldometers.info] is used for infection data. Predictions for the US and South Korea, which are currently two orders of magnitude different in Covid-19 infections, are shown on the plot. An "Infection Parameter", IP, analogous to the basic Reproduction Number, R_0, is used to drive the infection growth model. The IP, further defined in an accompanying appendix, is a metric describing the number of infections per infected person over an assumed 14 day infectious period. IP levels as large as 50 to 100 occurred during early disease transmission for many countries, and currently range between 1.5 to 3 for the countries shown in Figure 1. An IP level of 1 indicates 0 infection spread.

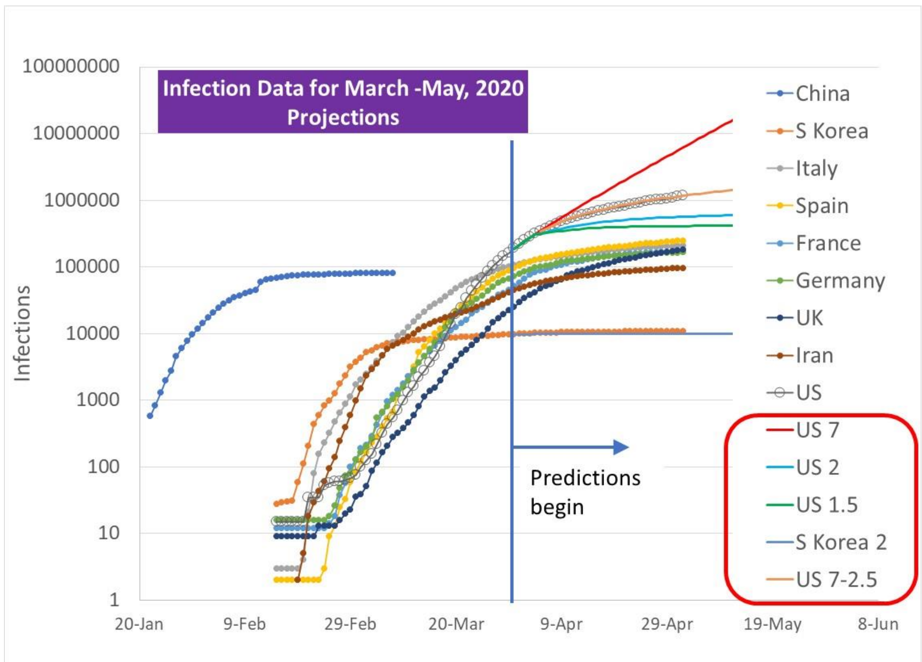

Figure 1 Reported total Covid-19 infections for 9 countries from January through April, 2020.

At the end of March, the US had reduced its IP to 7, with continuous reduction of IP to 2.5 as of the end of April. South Korea has maintained an average IP of 2 since the beginning of April. Predictive paths for the US and South Korea are extended to May 15, with model predictions beginning April 1.

Infection growth varies significantly with small changes in the Infection Parameter, IP. Figure 2 shows US Covid-19 infection trend predictions for March 1 to May 31, 2020 based on three levels of Infection Parameter. Currently, the US has maintained an IP of 2.5 to 3 with social distancing restrictions in place throughout most of the country. If relaxation of social distancing restrictions in May cause a reversion of IP to 7, accelerated growth of Covid-19 infections will increase US infections to nearly 7,000,000 with an estimated 4,000,000 active infections by the end of May.

Relaxing social distancing restrictions while simultaneously maintaining reduced IP levels is a desired objective. Ideally, Covid-19 recoveries outpace infection growth, resulting in a lowered number of active infection cases. Figure 2 shows that an IP of 3 maintained throughout May results in 2,000,000 total recorded infections with a level number of active cases (~850,000) throughout May. Reducing the US IP to 2 throughout May, lower than today's 2.5 to 3 IP range, would result in 1,500,000 total Covid-19 infections in the US, with estimated active infections decreasing to approximately 460,000.

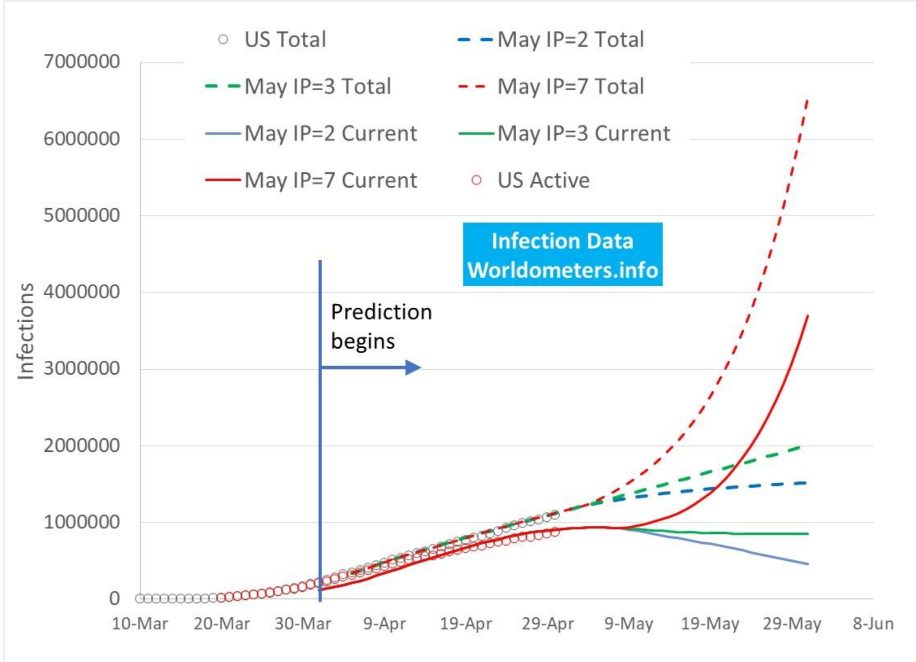

Figure 2 Covid-19 infection growth predictions through May, 2020 based on three levels of Infection Parameter. Infection data and estimates of active infections are also plotted.

<u>Social Distancing Index</u>

Today's technologies provide the capability to quantify social activities in anonymous manners. The [University of Maryland and Maryland Transportation Institute] have developed a social distancing index for the United States that strongly correlates to the Covid-19 Infection Parameter, IP. The UMD social distancing index (we will call the "Terp Parameter", TP) is a weighted parameter based on anonymous cell phone and vehicular gps data coupled with algorithmic processing for a scale that varies from 0 (maximum human social interaction) to 100 (minimum human social interaction). Note that state and county level data is also available from the UMD research group.

The ability to directly assess Covid-19 infection growth to a social distancing index provides a quantitative metric for assessing policy measures designed to reduce the infection parameter as social distancing restrictions are reduced.

Figure 3 shows daily trends in the UMD social distancing index for the US since the beginning of March. Daily social distancing index variations are significant, with weekends having higher levels of social distancing than weekdays. By the third week of March, much of the US enacted social interaction restrictions, causing a general increase of the social distance index. Social distance index values were approximately 20 for "normal" US activity levels and increased to 50 to 60 as restrictions were in place throughout most of the US.

Figure 4 is a plot showing a correlation of the Infection Parameter, IP, to the UMD social distancing index, TP. A simple curvefit function is used to demonstrate the correlation of IP with TP. Two keys to relating IP and TP are described below. Appendix C describes the procedure in more detail.

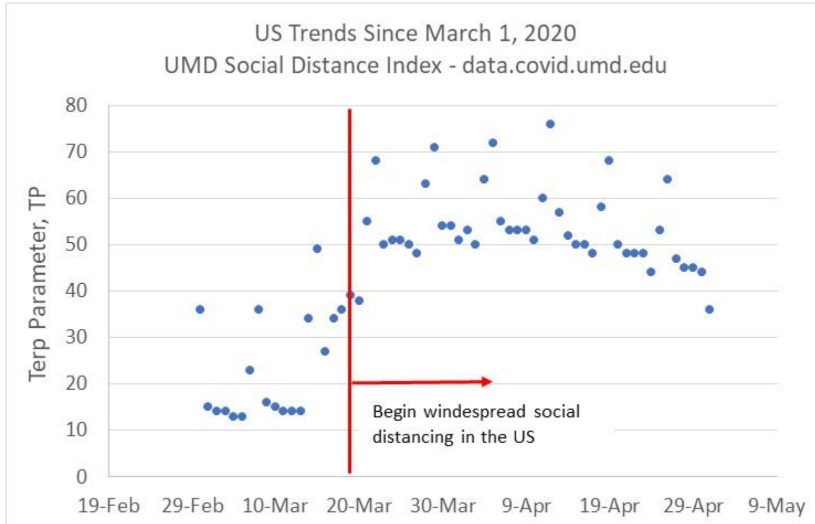

Figure 3 Daily trends of the University of Maryland social distancing index for the United States for March and April.

1) The social distance index is averaged with a 2 week moving window, reflecting the average estimated time length of SARS-CoV-2 infectious period.
2) A phase shift of 7 days between the social distance index and the infection parameter is assumed, approximately representing the incubation, infection realization period between social activities that resulted in infection, and the time when someone is infectious.

Figure 5 compares predictions for total US Covid-19 infections using the previously described Infection Parameter, IP, and the the Terp Parameter, TP. The social distancing model begins on March 22, although it uses data beginning on March 1 for the two week moving average window coupled with a 1 week incubation, phase shift period. No adjustments are made to model predictions from March 22 through May 2 simulation period shown.

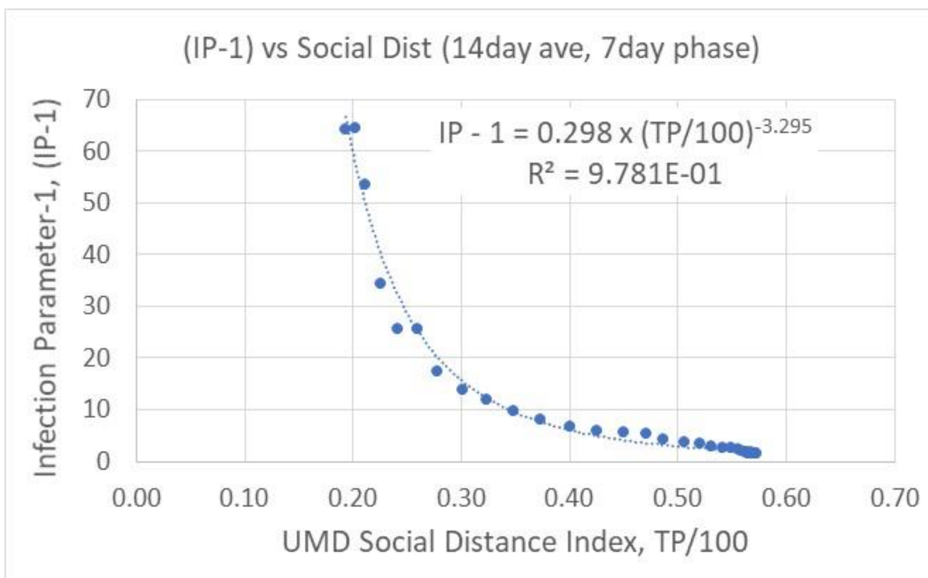

Figure 4 Correlation of the Infection Parameter, IP, with the UMD social distancing index, TP.

Figure 6 shows predicted versus actual reported total Covid-19 infections for the simulation period of Figure 5. Prediction error percentages are also shown on the plot. Initial prediction errors deviated by as much as 6 to 8% when total US infections were relatively low (75 to 24,000 reported infections from March 1 to 22, 2020). During early stages of US infection growth, data reporting uniformity and time shifting of data reporting are likely causes of error.

Error deviations are mostly within +/-2% as total US infections grow during the simulation period, with a systematic trend of negative error due to accumulating error over the simulation period. Based on these results, model predictions of 1 to 1 ½ months are reasonable for estimating future infection trends based solely on the social distancing index, TP.

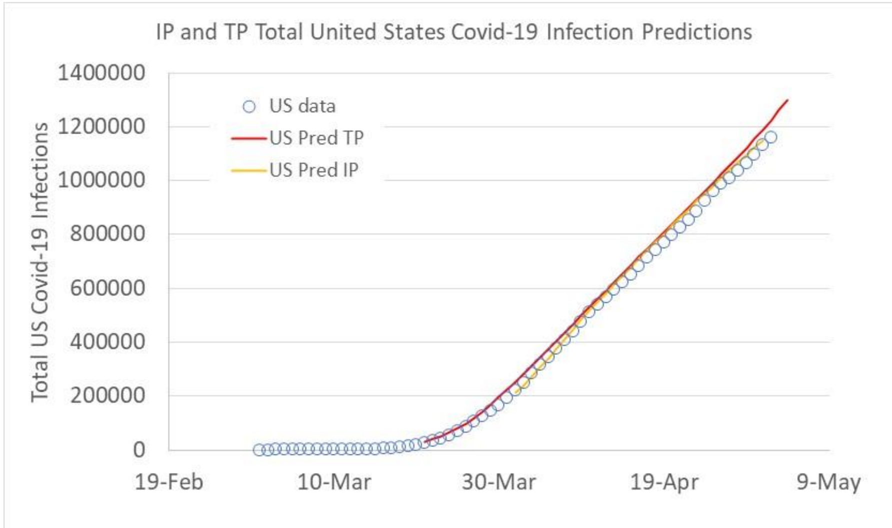

Figure 5 Comparison of predictions models based on the Infection Parameter (IP) and the UMD social distancing index, Terp Parameter (TP) to actual reported US Covid-19 infection data (Worldometers.info).

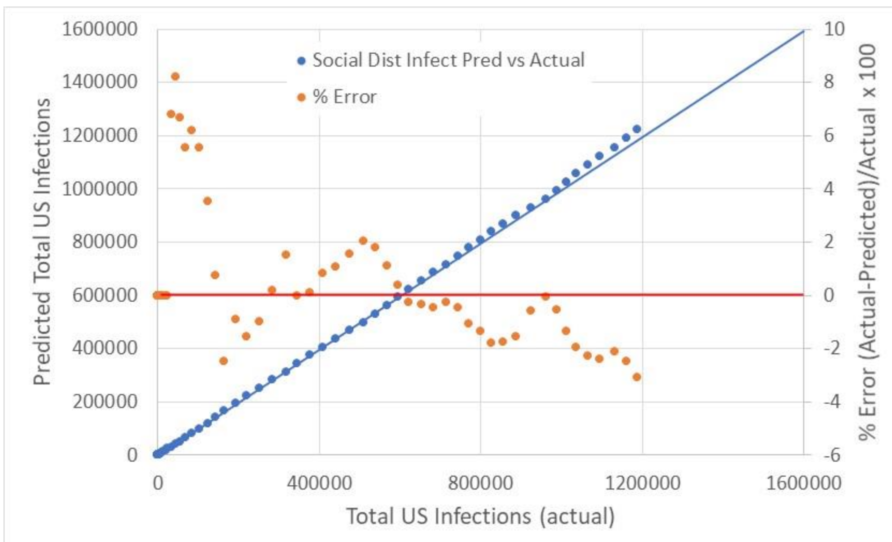

Figure 6 Comparison of predicted and reported total Covid-19 US infections and an error estimate between predicted and actual data.

Reducing Infection Growth While Reducing Social Distancing

Our objective in fighting the spread of Covid-19 is to allow social interactions to increase in a manner that minimizes the infection parameter. The relation between the Infection Parameter, IP, and the UMD social distance index, TP, provides a method to quantify variations of IP as social protection measures are implemented.

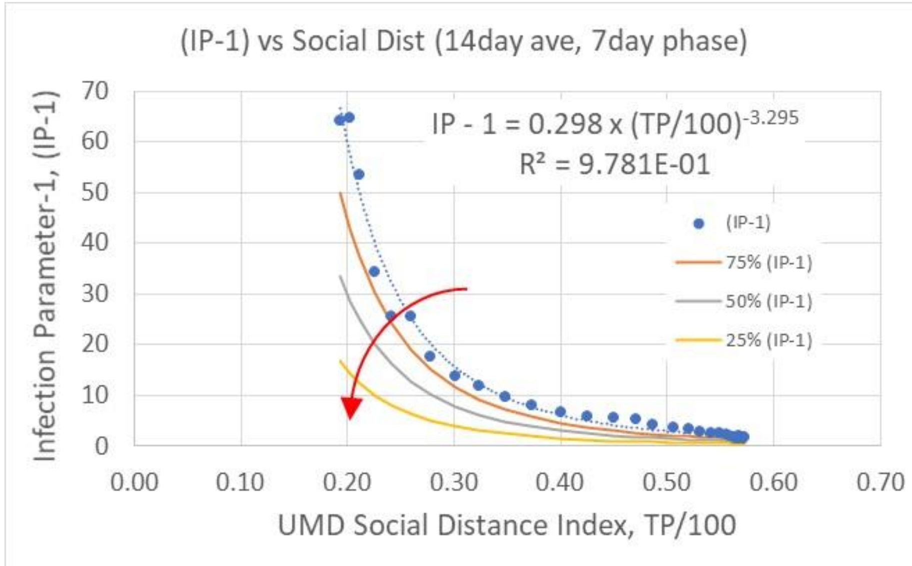

Figure 7 Parametric reductions of IP relative to the social distancing index, TP.

Figure 7 shows parametric reductions in Infection Parameter versus the social distancing index, TP. Reducing IP is essential as social distancing restrictions are relaxed. Equally important is the ability to determine the impact of actions taken to reduce IP. For example, relaxation of social distancing restrictions that lower TP to 30 without infection transmission management would increase IP to 15. Some combination of public face masks (with an eventual supply that may provide a level of protection in both directions for users), alternating work schedules, decreased seating density in public spaces, incorporation of increased ventilation air flow with enhanced filtration (MERV 13 and greater) and upper room UVGI (Ultraviolet Germicidal Irradiation), and other methods might reduce IP to 25% or lower of "normal" social interaction IP, resulting in an IP of 3 or less.

Relaxing social distancing to an average TP of 30 with infection control policies that only reduce the IP in half (IP ~ 7) will cause accelerated growth of infections throughout the US with excessive strain on medical personnel and equipment. Policies must be established that lower IP to much less than 3 in order to gain ground on active infection cases and accelerated growth of new infection cases. Ideally, maintaining an IP of 2 or less, as demonstrated by several countries such as South Korea and now Spain and Italy, would significantly lower active infection cases in the US.

Maintaining IP at 2 or less for a sustained period would allow US communities to transition to testing, tracking and isolation control as practiced in South Korea and Czechia. As shown in Figure 2, a reduction in social distancing parameter with an increase of IP to 7 (~50% reduction of IP with TP of 30), would grow total infections to nearly 7 million by the end of May with nearly 4 million active cases. A 25% decrease of IP to 3 with TP of 30 would grow total infections to 2 million while keeping active infection cases nearly constant at 850,000 cases. An effective reduction of IP to 15% of its normal value at TP of 30 would limit total infections to 1.5 million and reduce active infection cases to 460,000.

We do not yet know SARS-CoV-2's seasonal dependence, however, one can anticipate the impact of the virus based on assumed seasonal changes to the IP parameter. Seasonal variation of SARS-CoV-2 virus potency can be included in the social distancing model by adding a time varying function, climate (temperature and humidity) dependent function, utility data parameters, or other measures indicative of IP seasonal dependencies. Finally, note that IP can increase above the level shown in Figure 7 with poorly constructed policies or ill-advised actions undertaken by an angry populace.

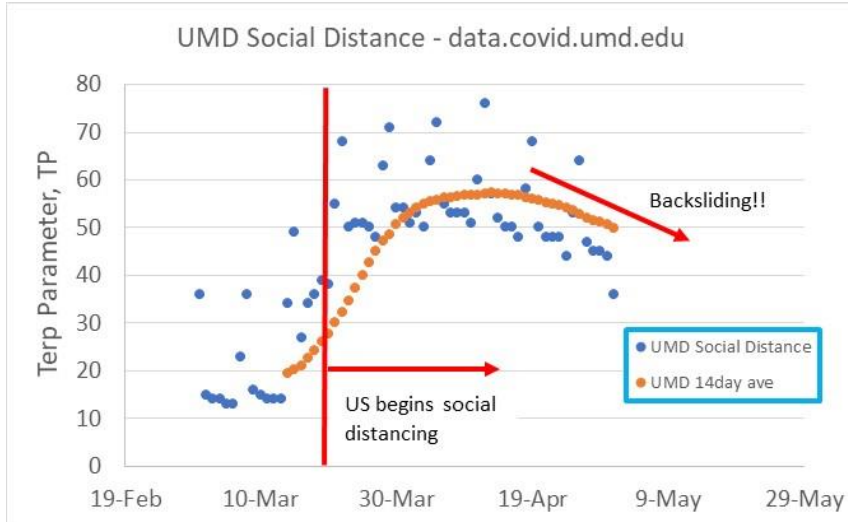

Figure 8 Two week moving average values of the daily TP plotted with daily TP values.

Figure 8 shows the daily UMD social distancing index along with the 2 week moving average index used for correlation with the Infection Parameter, IP. The 2 week average index clearly shows backsliding of TP for various reasons including ill-advised lifting of restrictions in various states, angry citizens refusing to distance, and desperate citizens needing to work. If backsliding linearly continues to a TP of 30 by the end of May without implementation of effective IP reducing policies, the US will return an IP level of 15 with devastating, accelerating infection transmission across the country. The long incubation time and long infectious period of SARS-CoV-2 predetermines a path of illness before its impact is felt.

<u>What If?</u>

What would be the current state of infection in the US if social distancing policies had been established by March 7 rather than March 21?

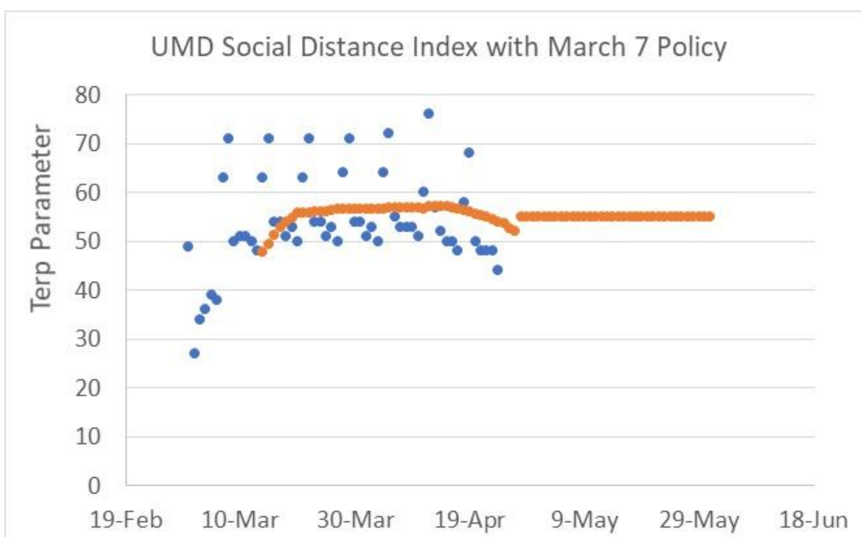

Figure 9 Social distance index shifted two weeks earlier in March with no backsliding of distancing in May.

We can historically reconstruct the infection path of earlier implementation of social distancing restrictions by shifting the UMD social distance index by two weeks from March 21 to March 7 as shown in Figure 9. The two-week moving average social distance parameter is assumed constant through May at 55 with no backsliding as observed in Figure 8.

Infection growth is drastically reduced by restricting infection spread early while infection cases are few. Figure 10 shows that the US could have kept infection levels to 150,000 as of May 2, rather than 1,200,000 infections. Active infections as of May 2 would be 95,000 rather than 920,000, and fatalities would be less than 10,000 instead of 70,000 with deaths expected to surpass 100,000 by the end of May.

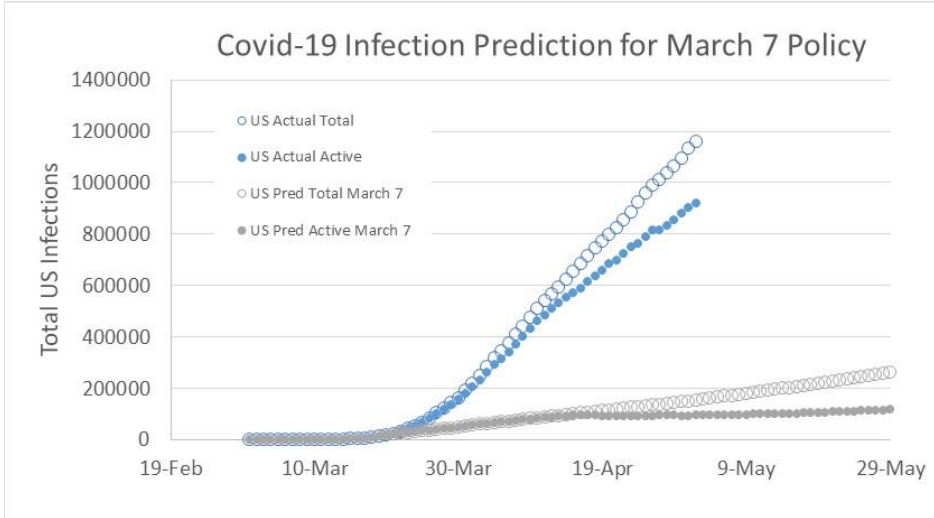

Figure 10 Comparison of actual Covid-19 infections and predicted infections based on implementing social distancing policies by March 7.

Summary

Covid-19 infection growth can be predicted directly with the UMD social distancing index. Correlating an infection parameter to the social distancing index creates a metric that helps quantify policy efforts to reduce infection spread relative to relaxation of social distancing. Additionally, relating infection spread to social distancing provides a mechanism for quantitatively describing the expected effectiveness of policies and guidelines to the general public.

Appendix A – Covid-19 Infection Growth Model

A simple, early-stage infection growth model is used to demonstrate infection growth based on social distancing. The model assumes infection growth rate to be proportional to the number of infectious cases in a fully susceptible populace:

$$dI/dt = a \times [I_t - I_{t-\Delta t}]$$

where I = number of infections

t = time

dI/dt = infection growth rate

a = infection growth rate parameter

I_t = infectious cases at time "t"

$I_{t-\Delta t}$ = infectious cases at time "t-Δt"

Δt = average period of infectiousness, 14 days for Covid-19 assumed

Future infections can be predicted with a forward time step algorithm.

$$I_{t+1} = I_t + a \times [I_t - I_{t-\Delta t}]$$

The infection growth parameter can be determined from empirical data as:

$$a = (dI/dt) / [I_t - I_{t-\Delta t}]$$

A daily growth parameter can be numerically computed as:

$$a = [I_t - I_{t-1}]/\{ [I_t - I_{t-\Delta t}] \times 1 \text{ day}\}$$

Appendix B - Infection Parameter, IP

The growth parameter, a, can be scaled to produce a more descriptive parameter for understanding infection growth. We define the infection parameter, IP, as the ratio of current infections to infections two weeks prior:

IP = exp(a x 14days)

Where IP = Infection Parameter

IP ranges from 1 (no infection growth) to much greater than 1, as shown in Figures B1 and B2 for 8 countries. For example, for a daily growth factor of 0.1 per day, IP is 4. During the latter part of March, caused by delayed social distancing restrictions, IP values in the US soared to greater than 50, primarily driven by uncontrolled infection growth in New York. By April 7, New York and other states (eg, Michigan, Illinois, New Jersey) with high infection spread were able to implement restrictions that dropped IP below 7. Unfortunately, today's "distancing fatigue" in the US is preventing IP from dropping below 2, where Covid-19 recoveries could outpace new infections.

IP qualitatively describes the number of infections incurred over a 14 day period per infectious person. Contained within IP, as in the Basic Reproduction number, R_0, are many factors related to the transmission efficiency of a disease including social contacts, asymptomatic carriers, seasonal/climatic effects, indoor environmental factors, age, and other conditions.

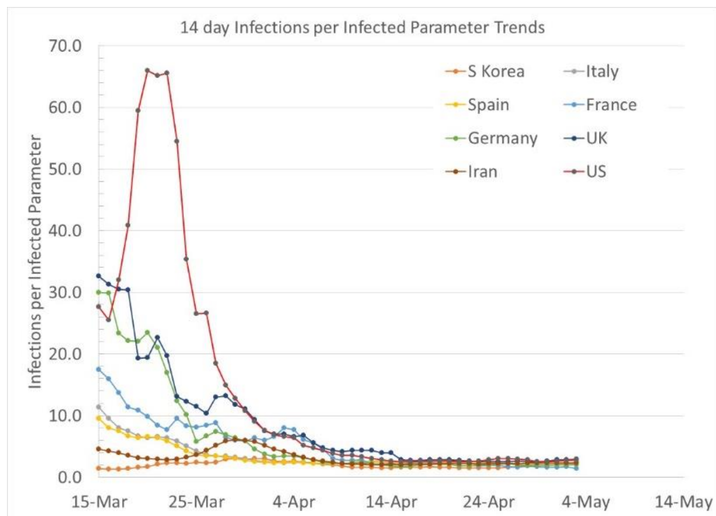

Figure B1 Infection Parameter, IP, trends for 8 countries since March 15, 2020

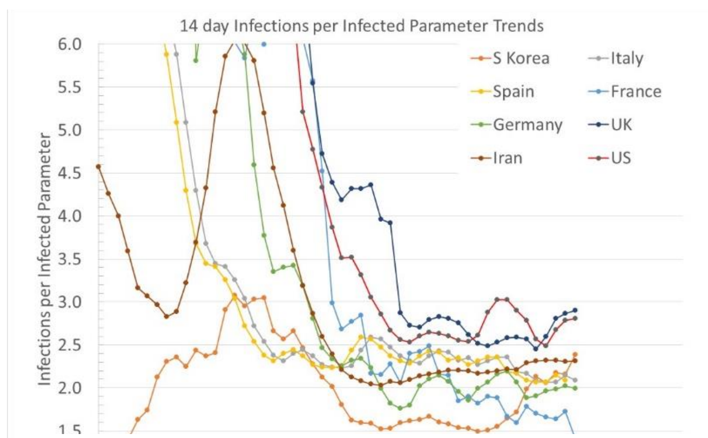

Figure B2 Infection Parameter, IP, trends at lower IP values for 8 countries.

Appendix C – Correlation of Infection Parameter and Social Distancing Index

The purpose of defining the Infection Parameter, IP, is solely for a quantitative description of infection spread. That is, the infection growth parameter, "a", with decimal level values does not have a descriptive value that is easily grasped by the general public, whereas IP's "whole number" scaled values can more readily convey a conceptual idea of infection spread.

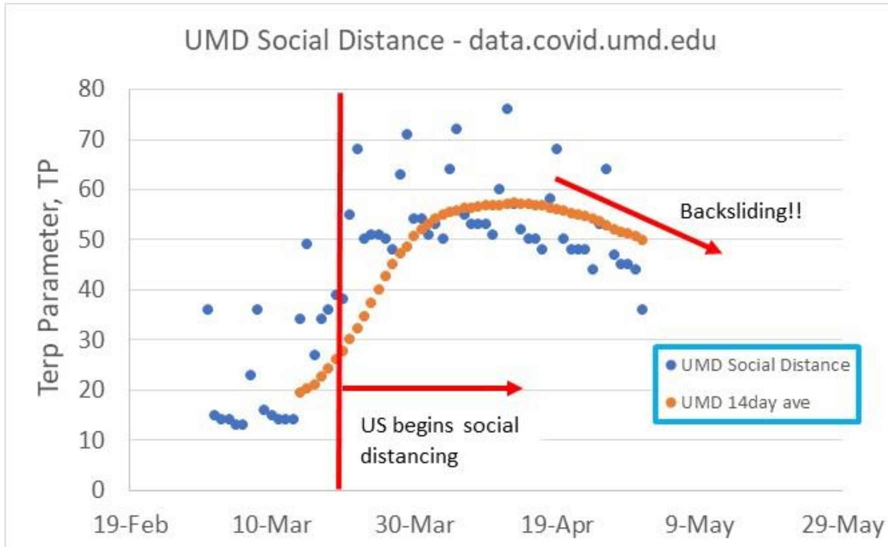

Figure C1 Daily and 14 day moving average UMD social distancing index values.

The University of Maryland social distancing index, TP (Terp Parameter), is scaled between 0 (maximum social interaction) and 100 (minimum social interaction). TP provides a quantitative scaling similar to IP that conveys a conceptual measure of social interactions. "Normal" weekday values, prior to social distancing in the US, were somewhat less than 20. Social distancing restrictions implemented around the 3rd week of March, increased weekday TP to 50 with weekends reaching 70.

Relating TP to IP consists of two operations:

a) Computing a 14 day moving average of daily TP values, as shown in Figure C1
b) Correlating IP and TP with a 7 day phase shift

The 7 day phase shift correlates a daily IP value with the moving average TP value 7 days prior to the IP value (ie, the IP value fore March 21 paired with the 14 day moving average value of TP from March 14). The phase shift between today's IP value and the TP value from a previous day perhaps accounts for incubation of the disease. The surprisingly strong correlation between IP and TP based on the moving average and phase shift provides a simple computational platform predictive modeling of Covid-19 transmission:

$$I_{t+1} = I_t + \ln[1 + 0.298 * (TP_{t-7}/100)^{-3.295}] \times [I_t - I_{t-14}] / 14\text{days}$$

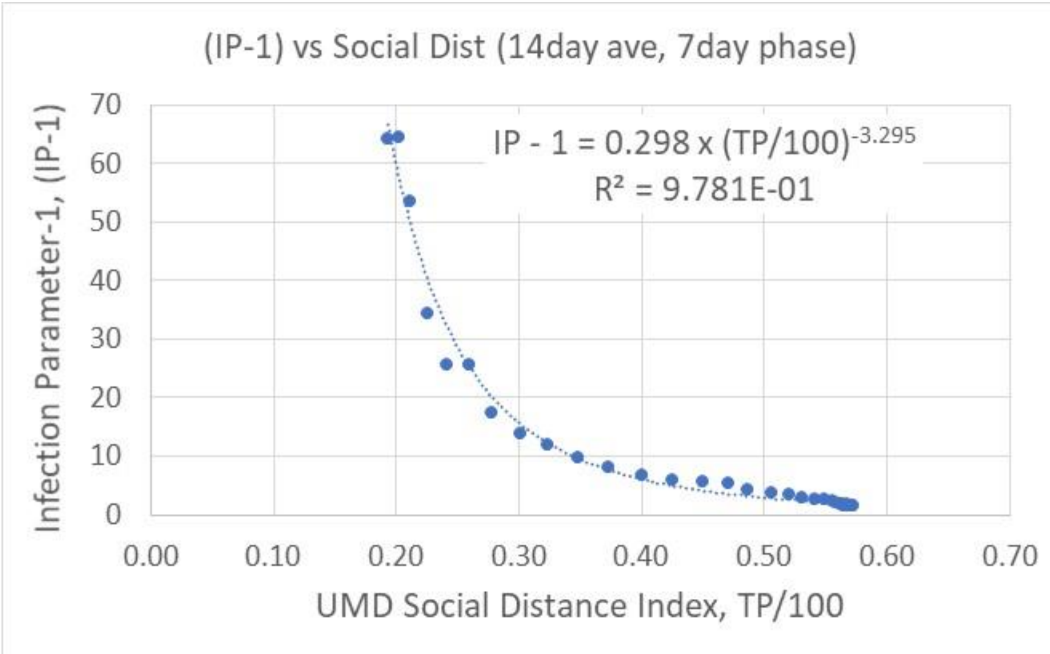

Figure C1 Correlation of Infection Parameter, IP, and UMD social distance index, TP.