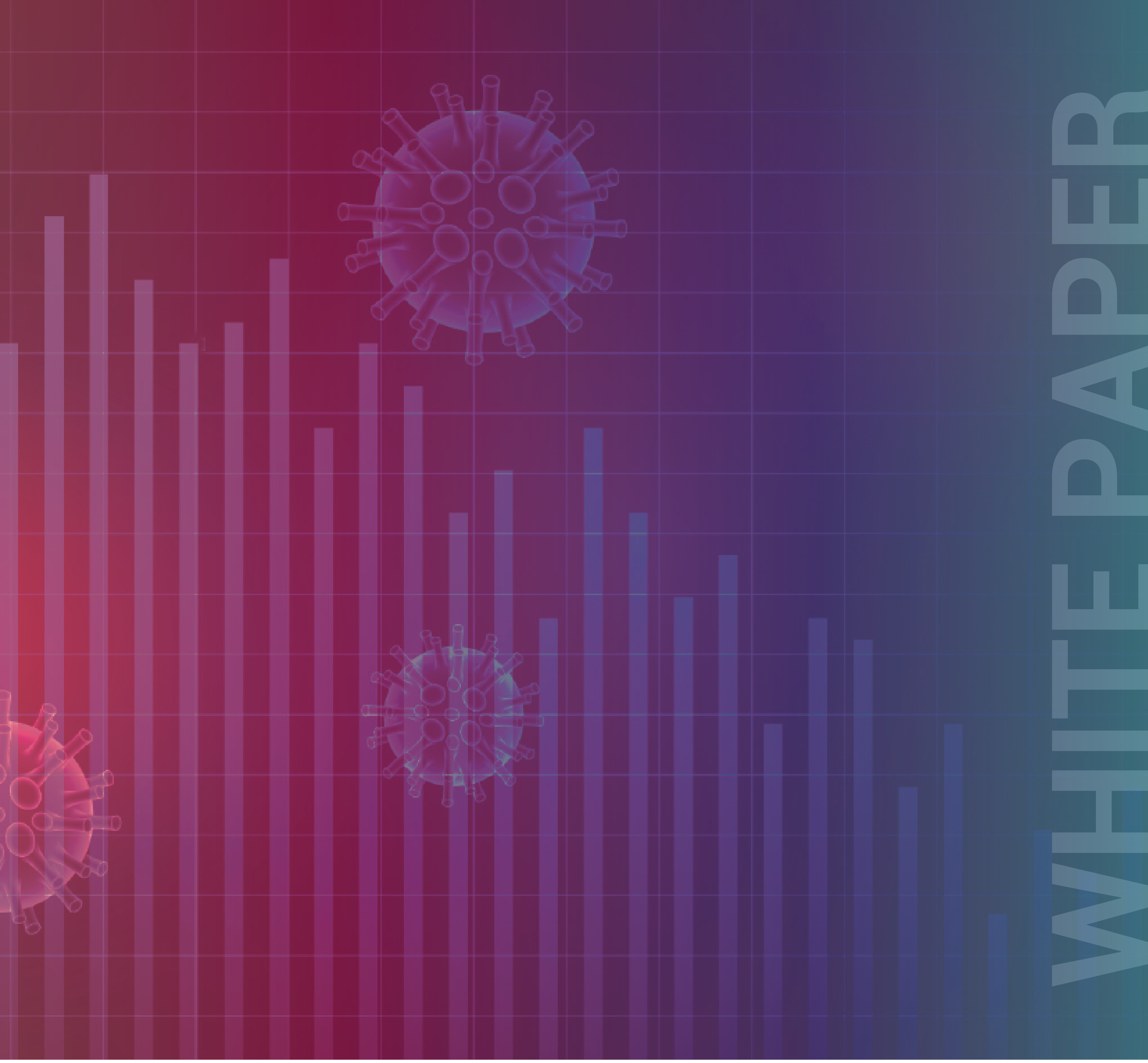

Business Impacts of Covid-19 on Production & Manufacturing

Authors: Yogesh Agrawal (Affine Analytics) and Tapas Ray (ABInBev)

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Contents

Abstract

The coronavirus outbreak is a human tragedy that has affected thousands of lives. The rapid outbreak of the coronavirus presents an alarming health crisis that the world is grappling with. The outbreak of the novel coronavirus **(COVID-19)** has been declared a pandemic by the World Health Organization (WHO). The growing impact of this pandemic has already sent several shocks to the global economy. Total loss on this pandemic could range from $2 trillion to $4.1 trillion, averaging from 2.3% to 4.8% of the world Gross Domestic Product (GDP). Countries like US, China, Germany, UK, France, and Italy, etc. are the worst hit by the pandemic so far.

This whitepaper intends to explain the designs of Susceptible, Exposed, Infected, Recovered and Death (SEIRD) models that can project real-world estimates to provide business leaders with perspective on the evolving situation and implications for their companies.

Introduction

Covid-19 originated from the Wuhan province of China. In the glimpse of time, it has spread over the globe, forcing the WHO to declare it as a Pandemic. It has disrupted the global economy by exponentially raising unemployment, crossing over all other viruses like the Ebola, Zika virus, SARS, MERS, etc. in terms of infections, mortality, and economic loss.

Flattening the curve by social distancing seems to be the only way to fight this pandemic. Many countries have been locked down for the past few weeks, people have been asked to strictly stay at home as a precautionary measure to slow the virus from spreading and reduce the pressure on the health care system.

This paper describes a model that determines the efficacy of quarantine measures to better predict spread of the virus. One interesting fact about the model is that unlike previous models, it does not rely on data from previous outbreak studies like SARS or MERS.
The SEIRD model is trained to capture the number of infected individuals under quarantine to measure the quarantine impact and spread of the virus in the region.

These modeling results could be used to analyze different viral phases (Pre-infection, limited transmission, Moderate, Severe, Critical, Post-peak, Recovery, Post-infection, Restriction Ease Date) in the key market.

- Pre-Infection - No virus present
- Limited Transmission - Virus present, < 10 cases
- Moderate - < 10 cases per million
- Severe - 10 to 99 cases per million
- Critical - Over 100 cases per million
- Post-peak - Reduction in overall case number (recoveries > new cases)
- Recovery - Acceleration in reduced cases, < 10 cases per million people in recovery
- Post-Infection - Virus no longer present
- Restriction Ease Date - Based on research from Columbia University, one can expect Governments to ease restrictions after a period of 27 days from when the infection hits the peak

Viral Phases in China & South Korea based on model results

Country	Viral Phase	Markets Post - Peak Period	Markets Recovery Period
China	Post-Peak or Recovery	(~Mar 10)	~ May/June
South Korea	Post-Peak	(~Mar 12)	~ May

Initial findings

- Armed with precise data, it is noticed that the spread of virus follows a very similar pattern across countries with over 500 confirmed cases. (Refer below Fig. [1])

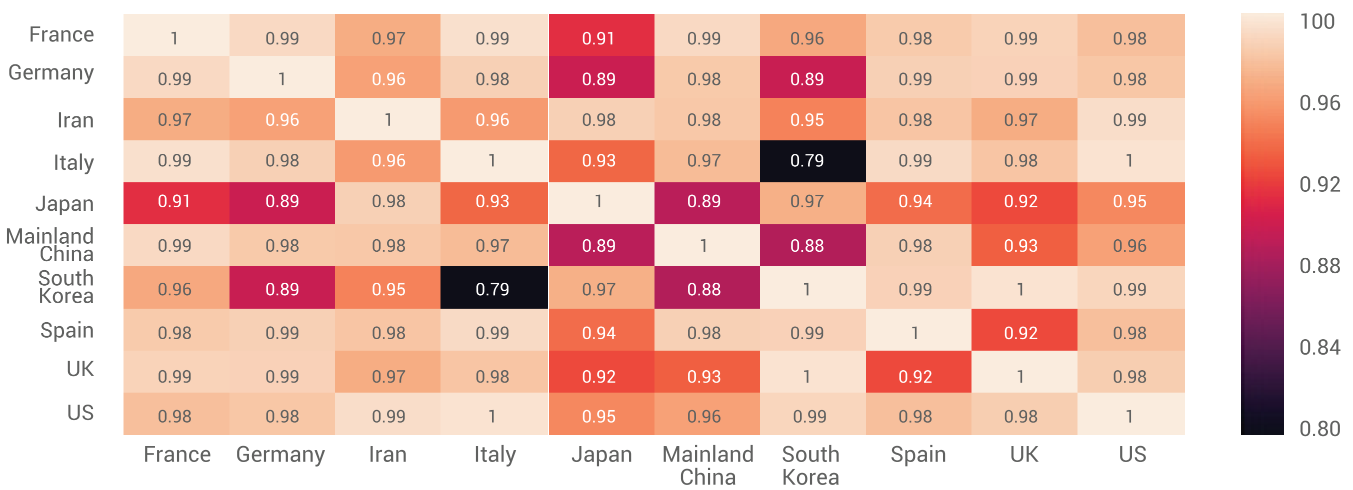


Figure 1. Correlation on confirmed cases with different geographies after 500 cases as on March 22nd 2020

- It is noticed that after the past epidemics like SARS, MERS, etc. discretionary purchases (e.g. liquor, apparel, personal care) follow a 'dip and recover' pattern. Refer Fig. [2]. Usually follows a quick recovery after the crisis, releasing demand squeezed during an epidemic.

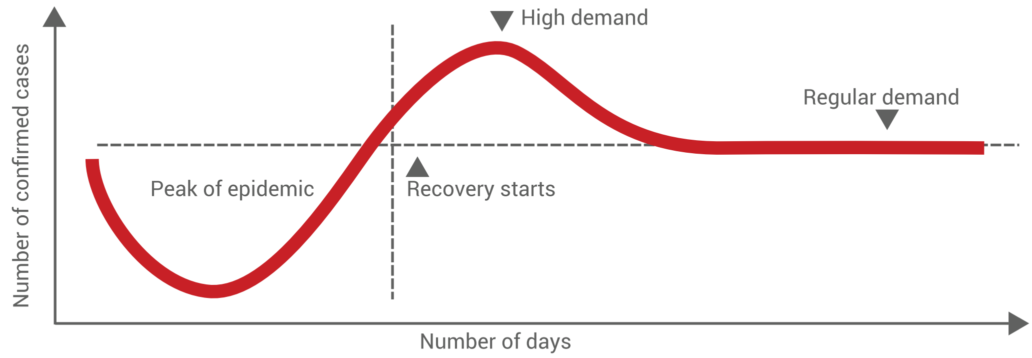


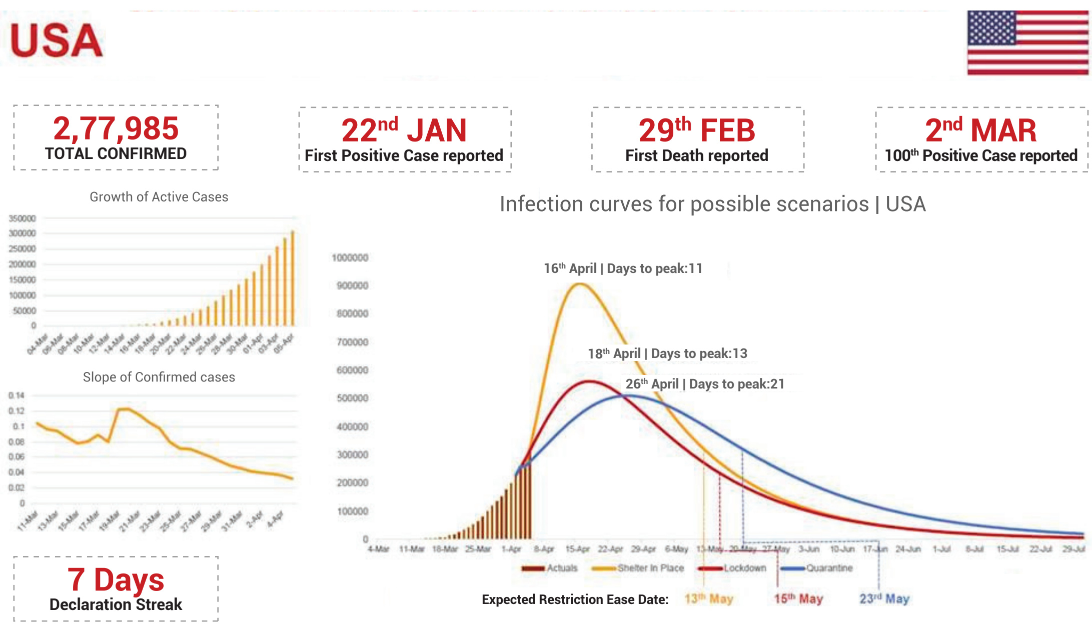
Figure 2. Peak and Recovery curve of an epidemic

Business problem

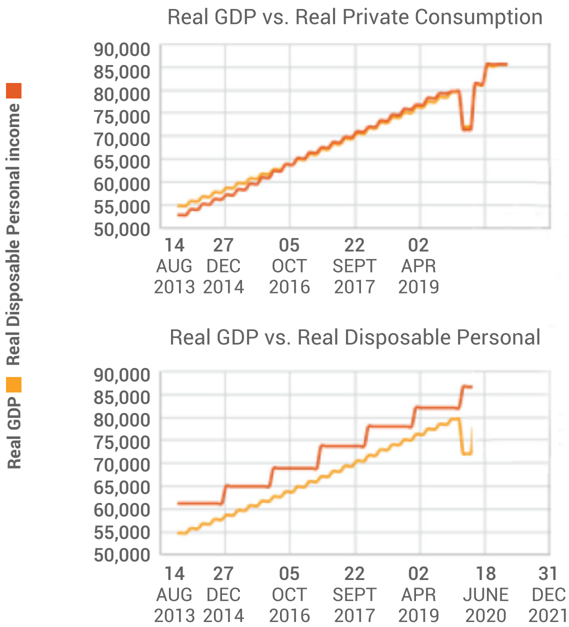
- To see when the market will reach peak and recovery based on the number of active cases.
- Translate that knowledge to predict shifting demand patterns while navigating the Coronavirus crisis.

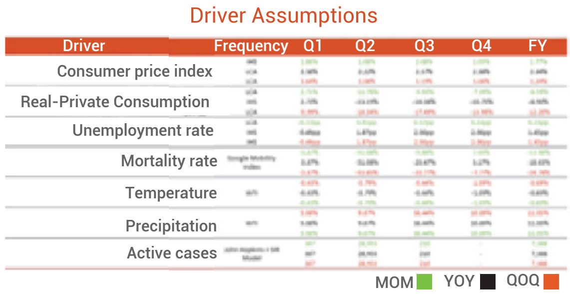
High level approach

Easing Infection Curves through Social Restrictions

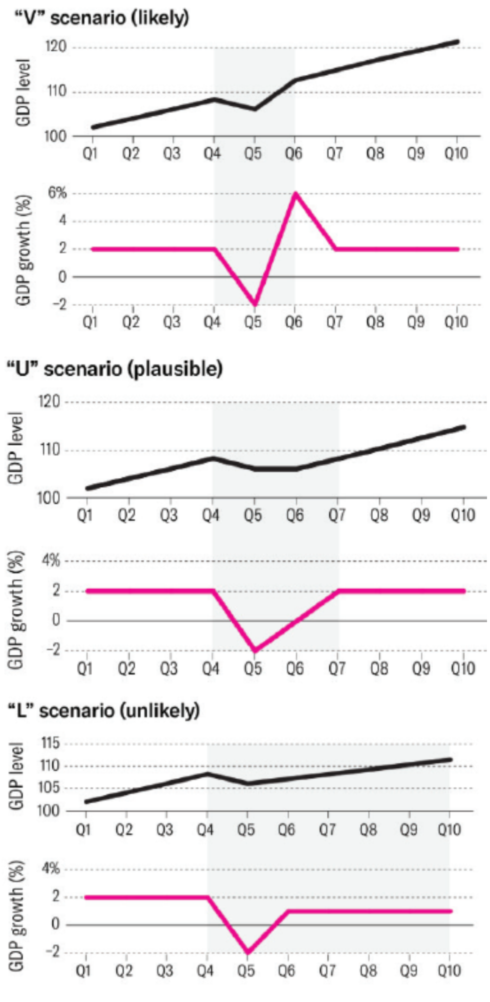


Projections: Macroeconomic Drivers
(GDP, Disposable Income, Unemployment, CPI, etc.)





Estimating macro-recovery curves (*V*, *U*, *L*) and long-term volume projections



Source: BCG Center for Macroeconomics analysis

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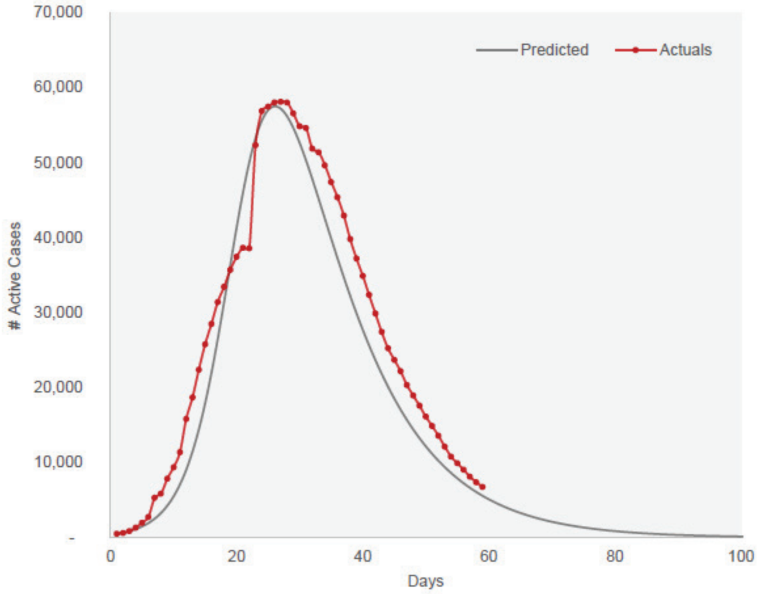
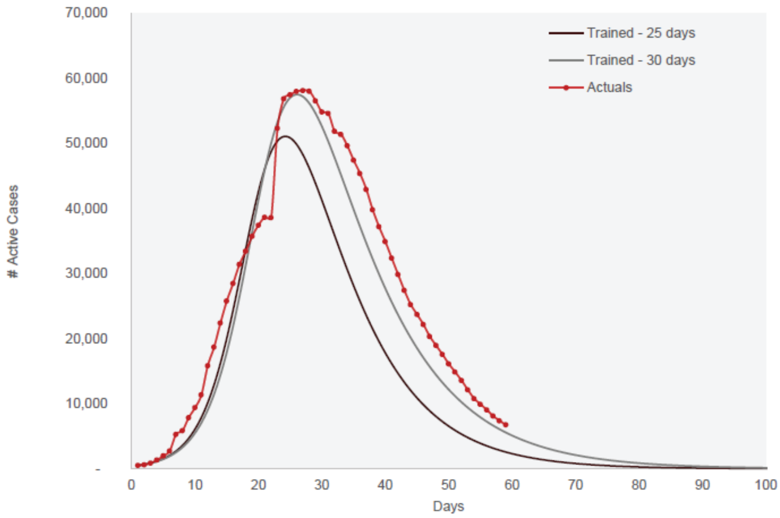
Initial results from the SEIRD model



According to the model for China:

- Active Cases Reduced <1000 on 14-04-2020
- Active cases Reduced <100 on 12-05-2020

Model results for trained data for different time periods



This chart explains the model predictions based on how much data was used to create the model. This illustrates the need to refresh the model frequently to update impact of goverment actions in order to predict the future more accurately.

SEIRD model has been applied to fit the historical data of the spread of COVID-19 in South Korea and China. As said earlier, we will use the historical data to find the optimal parameters of the SEIRD model. This objective will be achieved through a mono-objective optimization. The objective function is the mean squared error between the prediction of the active cases from the model and historical data.

The model accurately captures active cases in China during 9 weeks since the lockdown. Progressively supplying information on a daily basis improves the modeling.

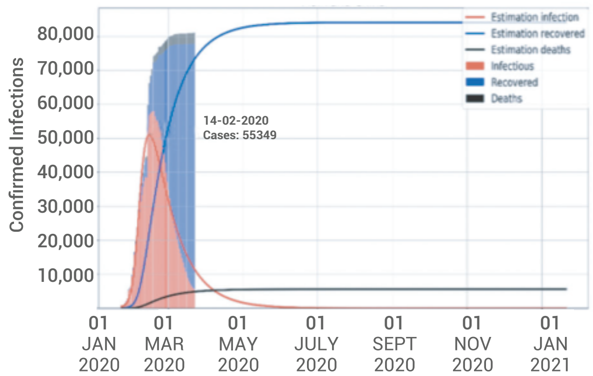
We assess the effective reproduction number, R0, which quantifies the time-dependent variations in the average number of secondary cases generated per case during an outbreak due to intrinsic factors (decline in susceptible individuals) and extrinsic factors (behavioral changes, cultural factors, and the implementation of public health measures).

Model Results for China - Mainland

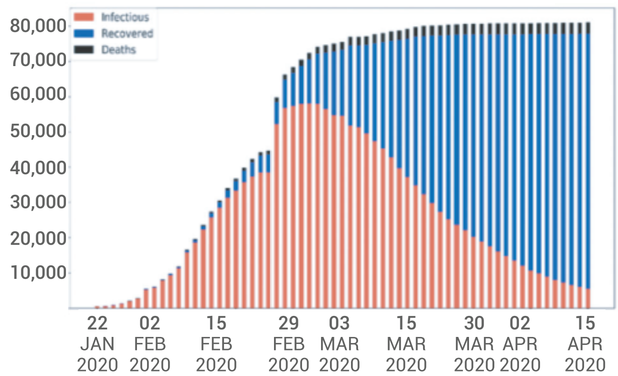
Actual Active Cases peak: 17th Feb
Pred. Active Cases peak: 14th Feb

Beta: 1.248086 | Kappa: 0.172414 | Gamma: 0.048303
Tau: 0.015333 | The estimates of R0 lies in the range <2.5-4>

Infections of a new coronavirus in Mainland China



Infections of a new coronavirus in Mainland China



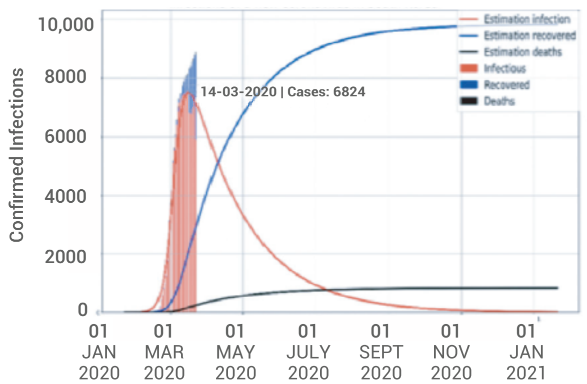
Model Results for South Korea

Actual Active Cases peak: 15th March
Pred. Active Cases peak: 16th March

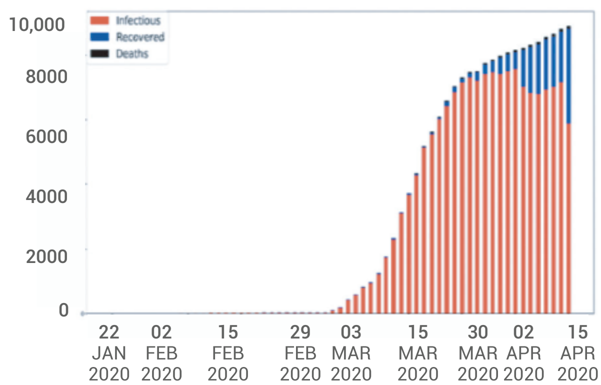
Beta: 0.631545` | Kappa: 0.172414 | Gamma: 0.027653
Tau: 0.001464 | The estimates of R0 lies in the range <1.5-2.0>

These findings support the range of social distancing interventions and active contact tracing that the Korean Government put in place to bring the outbreak under control as soon as possible .

Infections of a new coronavirus in South Korea



Infections of a new coronavirus in South Korea



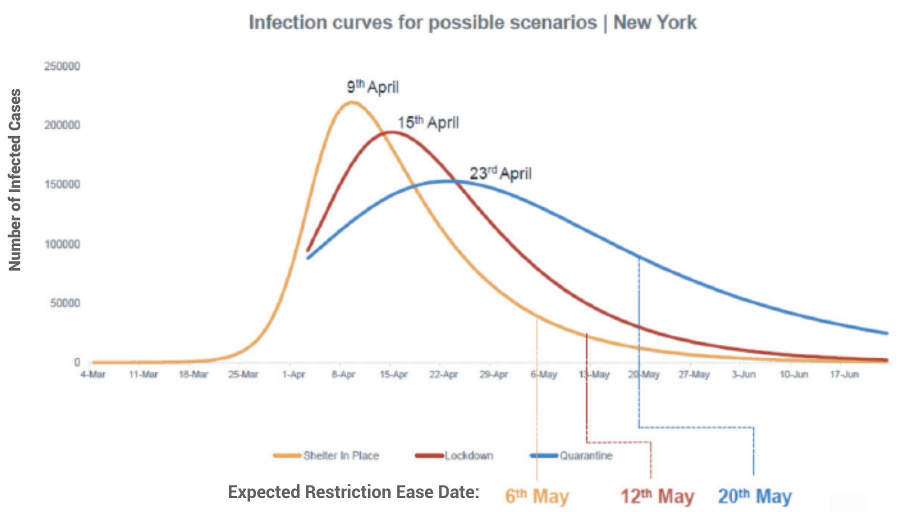
The above image shows the initial model results as on March 22nd 2020

Business application

Part 1

Scenario planning for other countries using learnings from the model built for China and South Korea.

Using the learnings from China and South Korea curves we were able to build three different scenarios per region that tries to mimic different government actions to flatten the curve



Part 2

Impact on Beverage Industry divided into 2 channels:

1. On-trade Assumptions

Pubs, Restaurants, Night-life will be permanently closed during the lockdown as it turned out in China. Replicate what happened in China basis the lockdown percentage in respective countries.

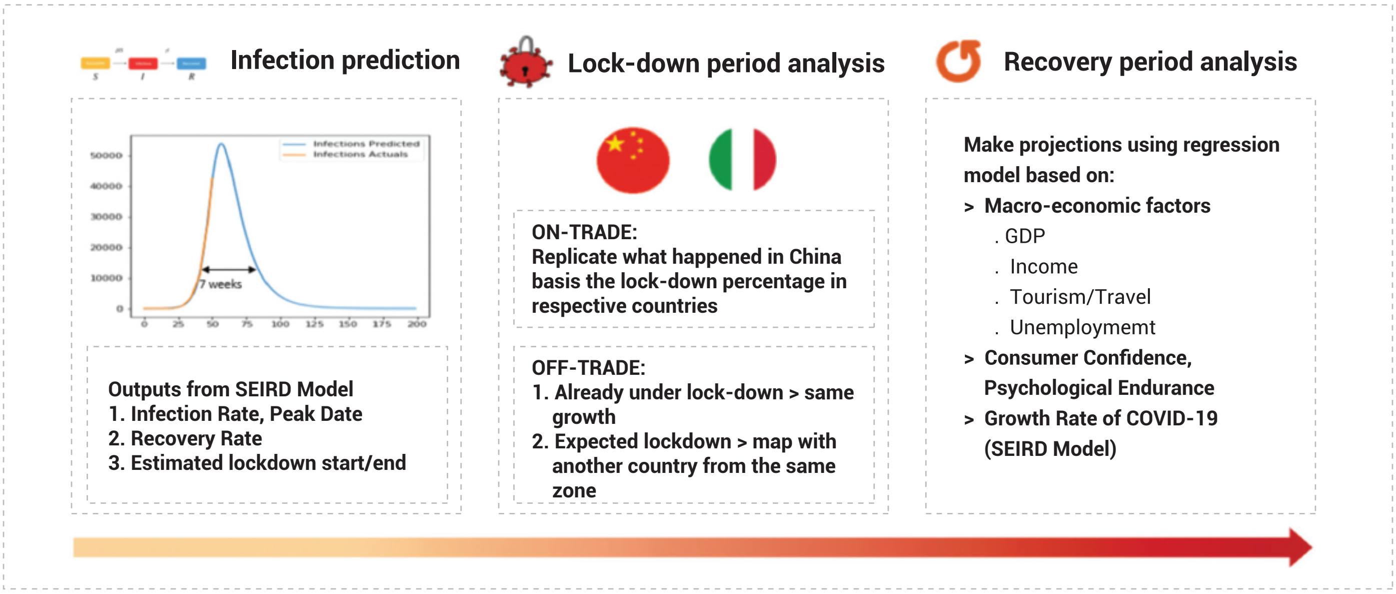
2. Off-Trade Assumptions

Off-Trade will occur in higher income markets with modern channels.

In mature markets, off-trade will stabilize at levels seen prior to Government restrictions and stock up. Off-trade alcohol bans will not last longer than 30 days due to economic pressure and social unrest.

As per the model, behavior of recovery will be different for off-trade channels across countries that can be captured by macro-economic drivers such as GDP, Income, Travel & Tourism, Unemployment, Growth rate of COVID 19 cases.

Examples showing methodology to model COVID-19 impact on Beverage Industries



Analytical Approach

Output requirement

Part-1: To build the Mathematical SEIRD Model:

Data (confirmed cases, fatalities, recovery)

The below figure provides a glimpse of datasets before any pre-processing:

Date	Confirmed	Fatalities	Recovery
22-01-2020	548	17	0
23-01-2020	643	18	0
24-01-2020	920	26	0
25-01-2020	1406	42	1

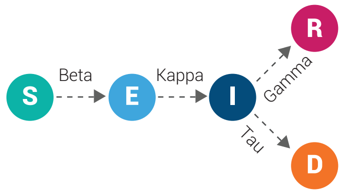
Figure 3. China sampled data which is used for analysis (Source JHU)

Part-2: To predict shifting demand patterns using information from the model:

Drivers such as Market maturity/disposable income, on/off trade weights (modern/traditional split), Government actions, vulnerable employment, Covid-19 tests available per million, hospital beds available per million, etc.

Part 1 deep dive:

In this whitepaper, we have tried infectious disease modeling, like SEIRD which stands for Susceptible, Exposed, Infected, Recovered and Death.



Susceptible
Exposed
Infected
Recovered
Died

Beta: Infection rate (S2E)
Kappa: Incidence rate (E2I)
Gamma: Recovery rate (I2R)
Tau: Mortality rate (I2D)

Definition of Epidemiology Parameters used:

Parameter	Name	Units	Meaning
S	Susceptible Individuals	No. of Individuals	Individuals susceptible to infection who can contract the disease when exposed.
E	Exposed Individuals	No. of Individuals	Individuals exposed to infection who are infected but have not yet become infectious.
I	Infected Individuals	No. of Individuals	Infected individuals capable of transmitting the infection to susceptible individuals.
R	Recovered Individuals	No. of Individuals	Individuals recovered from infection who are temporarily immune from the infection.
D	Dead Individuals	No. of Individuals	Individuals dead from infection due to weakened immunity.

Parameter	Name	Units	Meaning
b	Birth Rate	Births per day	Birth rate of newborns each year.
$\frac{1}{\tau}$	Death Rate	Day^{-1}	Death rate of susceptible, exposed, infected, and recovered individuals.
$\frac{1}{\alpha}$	Transmission Rate (Recovered to Susceptible)	$Days^{-1}$	Rate at which recovered individuals lose temporary immunity and leave recovered class and enter susceptible class.
$\frac{1}{\beta}$	Transmission Rate (Susceptible to Infected)	$Days^{-1}$	Rate at which susceptible individuals become exposed by infected individuals and leave susceptible class and enter exposed class.
$\frac{1}{\gamma}$	Recovery Rate (Infected to Recovered)	No. of Individuals	Rate at which infected individuals leave infected class and enter recovered class.

- $\frac{1}{\alpha}$ is the mean latent period for the disease, it is found that it is about 5.2 as virus shows symptoms between 2-14 days.
- $\frac{1}{\gamma}$ is the mean infectious period. Recovery rate can be calculated as :

$$\sum_{i=0}^{N}\left(\frac{\left(\frac{R_{\text{till today}} - R_{\text{till previous day}}}{I_{\text{till Previous day}}}\right)}{\text{length}(N)}\right) \qquad (1)$$

- $\frac{1}{T}$ is mortality rate, which is calculated similarly as:

$$\sum_{i=0}^{N}\left(\frac{\left(\frac{D_{till\,today} - D_{till\,previous\,day}}{I_{till\,Previous\,day}}\right)}{length(N)}\right) \tag{2}$$

Where: R – Recovered, D – Death, I – Infectious, N – Total number of days.

Terminology:

- Confirmed cases – Sum of all the active, dead, recovered cases.
- Active cases – Currently infectious from the virus and present either in hospital or at home.
- Recovered cases – Fully recovered from the infection.
- Dead cases – Died during this infection.

***Note – All the above cases numbers are cumulative.**

Reproductive number (R0) - The epidemiological definition of R0 is the average number of secondary cases produced by one infected individual introduced into a population of susceptible individuals, where an infected individual has acquired the disease, and susceptible individuals are healthy but can acquire the disease.

$$R_0 = \frac{\beta S_0}{\gamma} \qquad \text{when, } R_0 < 1 \tag{3}$$

$$R_0 = \frac{k*\beta S_0}{(d+k)*(d+\gamma)} \qquad \text{when } R_0 > 1 \tag{4}$$

Infection rate:

$$IR = e^{\log\left(\frac{N_{tD}}{N_{t0}}/D\right)} \tag{5}$$

Where:

N_{tD} is the day of calculation (till date).

N_{t0} is the date when first case is identified.

D is difference between $N_{tD} - N_{t0}$

Error term - This is the rate of error while forecasting active cases to the actual active cases. Which is given as follows - the error is calculated as Mean squared log error:

$$L(y,\hat{y}) = \frac{1}{N}\sum_{i=0}^{N}\left(\left(\log\left(y^i+1\right)-\left(\log\left(\hat{y}^i+1\right)\right)\right)^2 \quad (6)$$

Where:

*Y– Actual active cases, $\hat{y}$ – Predicted active cases

In order to achieve good accuracy, error needs to be minimized.

Note that the variables give the fraction of individuals, i.e., we have normalized them so that:

$$S + E + I + R + D = 1 \quad (7)$$

$$S = -\left(\left(\frac{R_t}{t_{infectious\ time}}\right) * I * S\right) \quad (8)$$

$$E = \left(\left(\left(\frac{R_t}{t_{infectious\ time}}\right) * I * S\right) - \left(\frac{E}{t_{incubation\ time}}\right)\right) \quad (9)$$

$$I = \left(\left(\left(\frac{1}{t_{incubation\ time}}\right) * E\right) - \left(\left(\frac{1}{t_{infectious\ time}}\right) * I\right)\right) \quad (10)$$

$$R = \left(\left(\frac{1}{t_{infectious\ time}}\right) * I\right) \quad (11)$$

$$D = (\tau * I) \quad (12)$$

The initial R_0 derived from the data is constant and gradually decreases with Government measures such as lockdowns and mobility restrictions. See the below Fig. [4]

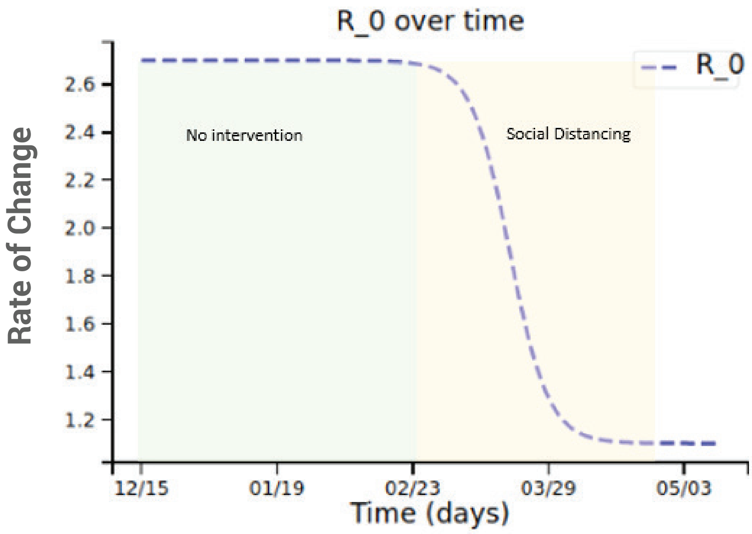


Figure 4. showing R_0 variation with time affected by govt. initiatives

To capture the time varying effect of R_0, Hill's Decay method was used. This model requires 2 additional parameters to be optimized, k & L. See the below Fig. [5]

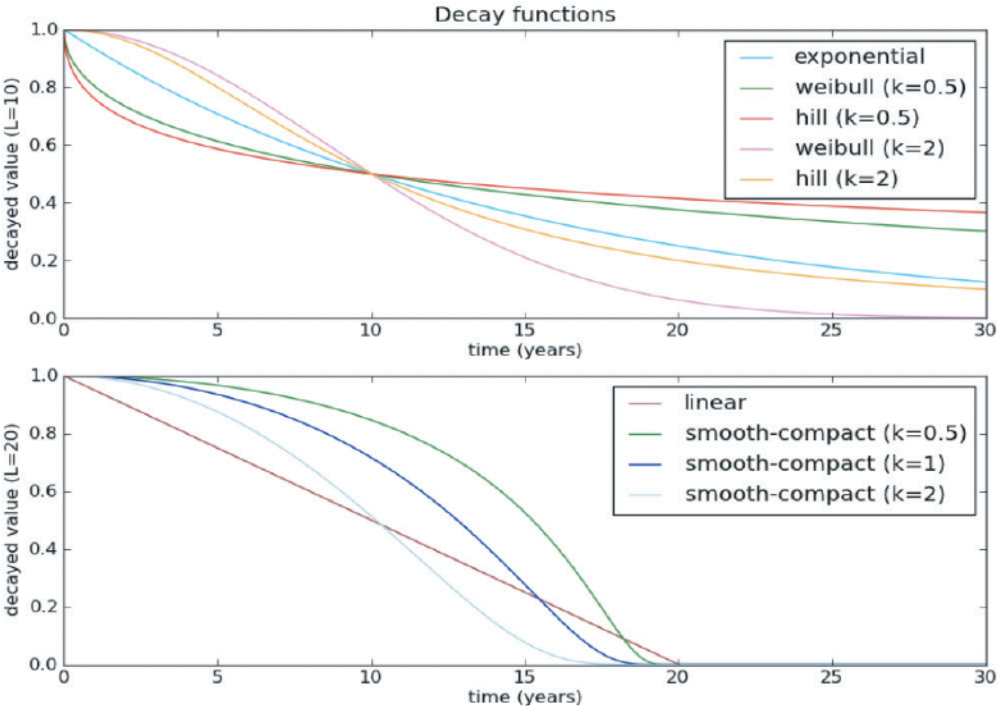


Figure 5. Hill's decay method hyperparameter

$$R_t = \frac{R_0}{\left(1+\left(\frac{t}{L}\right)^k\right)} \tag{13}$$

Where:

*L - is a description of the rate of decay, K- is a shape parameter with no dimensions.

Variation of epidemiology parameters with govt. actions:

In practical terms, the duration and shape of the infection curve is a function of both Beta(infection rate) and Gamma(recovery rate), with the former being a more dynamic parameter, i.e., affected by govt. actions.

BETA describes the effective contact rate of the disease: propotional to population. β indicates how many other indivduals will be in contact with infected individual per unit time. It is reduced by Govt. measures such as lockdowns and mobility restrictions and increased by mobility, density of population and big gathering events.

If β is decreased (strategy of many Governments)

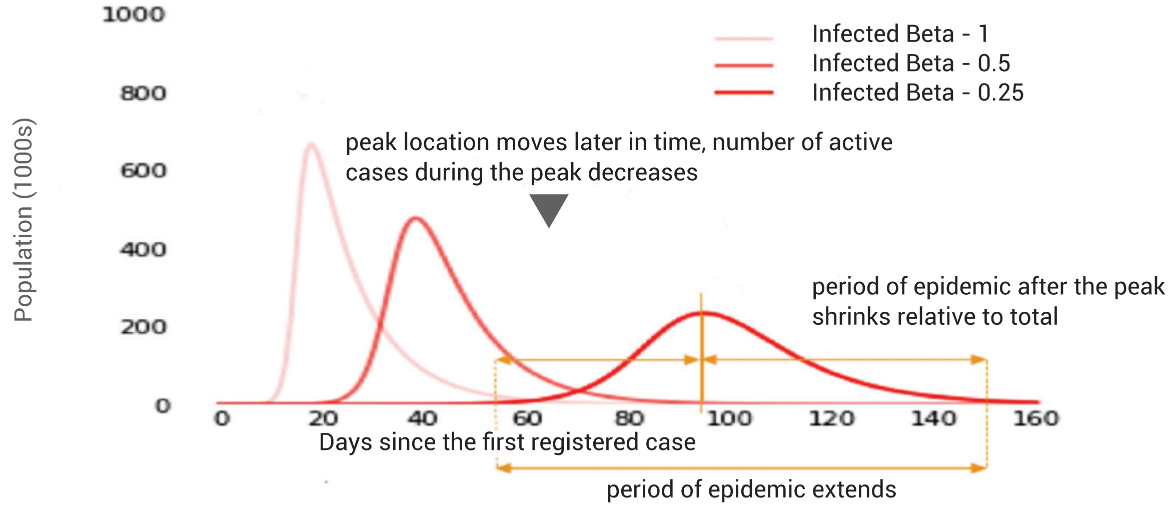


Figure 6. Beta decay when Government applies restriction

GAMMA is the mean recovery rate. Alternatively, $\frac{1}{\gamma}$ is the mean period of time during which an infected individual can pass the disease on. It is disease-specific and therefore harder to control. Improving medical care can push gamma upwards while widening the availability of tests (assuming that the disease is easier to treat in earlier phases).

If γ is increased (desirable, but harder to achieve)

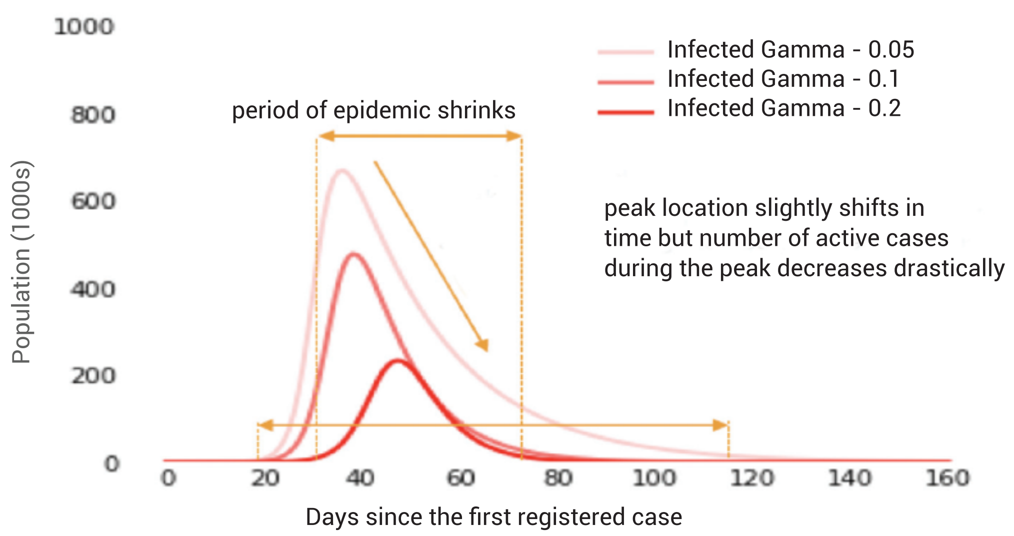


Figure 7. Gamma increase when Government applies restriction

Conclusion

To accurately model an emerging outbreak of a new disease, we must first have a thorough understanding of its parameters. Systems of ODEs are susceptible, even the slightest change to initial settings result in broad differences in output.

An understanding of what R_0, β, γ, etc. means allow you to tweak parameters to design, refine, and extend your models. Countries that were slower in implementing Government lockdowns, like Italy and USA witnessed an exponential spread in the actual reproductive number (R_0) of COVID-19.

We find that in places like South Korea, where there was prompt Government interference in implementing strong quarantine measures, the virus spread plateaued more quickly. India would have observed ~16% higher confirmed cases by the end of May without partial lockdown measures.

A robust study estimating intervals of confidence by considering the effect of bias introduced in historical data with the testing policy will substantially improve the model for further studies.

References

- Age-structured impact of social distancing on the COVID-19 epidemic in India [Rajesh Singh1, *and R. Adhikari1] https://arxiv.org/pdf/2003.12055.pdf
- https://www.researchgate.net/publication/260518034_A_SEIR_Model_for_Control_of_Infectious_Diseases_with_Constraints
- https://www.researchgate.net/publication/260518034_A_SEIR_Model_for_Control_of_Infectious_Diseases_with_Constraints
- Modelling Post-death Transmission of Ebola: Challenges for Inference and Opportunities for Control [https://www.nature.com/articles/srep08751]
- https://www.kaggle.com/anjum48/seir-hcd-model
- https://www.kaggle.com/yamashin/estimation-of-infection-with-seir

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