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The Application of the COVID-19 Global Economic Impact Simulator in China

Mario Arturo Ruiz Estrada[a] & Evangelos Koutronas[b]

Abstract: *This paper establishes conceptual foundations for analyzing the economic dimensions of regional or global emerging and endemic infectious disease events, such as the case of Covid-19. The Covid-19 Global Economic Impact Simulator attempts to identify the Covid-19 transmission parameters and forecast its trajectories. The model introduces seven basic indicators - (i) the Covid-19 contagious spread intensity rate (S.I.), (ii) the treatment level for Covid-19 infected cases rate (T); (iii) the number of Covid-19 causalities rate (-C); (iv) the economic wear from the Covid-19 epidemic rate (-Π); (v) the Covid-19 contagious cases multiplier rate (M); (vi) the total economic leaking from the Covid-19 epidemic rate ($-L_{total}$); and (vii) the economic desgrowth from the Covid-19 epidemic rate ($-\delta_{2019\text{-}nCoV}$). Findings show that Covid-19 exhibits parallel spatial and temporal conditions with the related R.N.A. virus family but carries distinct infection signatures and magnitude of virus replication. Covid-19 ferocity can trigger a severe public health emergency in China with significant impacts on the domestic and world economies.*

Keywords: Economic simulation; Contagious diseases; China; COVID-19; Policy modeling.
JEL Classification: C53, I15, I18

[a] Head of Centre for Latin American Studies University of Malaya, 50603 Kuala Lumpur, Malaysia & Full Visiting Professor, University of Economics and Human Sciences, Warsaw, Poland. *E-mail: marioruiz@um.edu.my*
[b] School of Mathematical and Data Sciences, West Virginia University, Morgantown, WV, United States. *Email: ekountro@mix.wvu.edu*, ORCID: 0000-0002-2647-025X

1. Introduction

In December 2019, an outbreak of respiratory illness emerged, caused by a novel coronavirus (named “Covid-19”) identified in the Wuhan City, Hubei Province, China, and has continued to expand. Chinese health officials have reported tens of thousands of Covid-19 infections in China, with the virus reportedly spreading from person to person in parts of the country. Covid-19 infections, most of them associated with travel from Wuhan, are also being reported in a growing number of international locations. At the time of this writing, Worldometer[1] reported 31,537 confirmed Covid-19 incidents, of which 4,826 are in critical condition, 638 died, and 1,170 recovered, affecting 28 countries and territories around the world (Worldometer, 2020).

The World Health Organization (WHO) estimates set the novel coronavirus’ case fatality rate at around 2%. The incubation period of the virus may be as few as two days or as long as 14 days (World Health Organization (WHO): 2-10 days; China’s National Health Commission (NHC): 2-14 days; The United States Center for Disease Control and Prevention (CDC) and 10-14 days), during which the virus is contagious, but the patient does not display any symptoms (asymptomatic transmission). Covid-19 can infect all population groups; however, seniors and people with preexisting medical conditions (such as asthma, diabetes, heart disease) appear to be more vulnerable to becoming severely ill (WHO, 2020).

Covid-19 belongs in the coronavirus category that can cause fever, breathing difficulties, pneumonia, and diarrhea. Some symptoms are potentially fatal, and others can cause relatively mild common cold symptoms. The Middle East Respiratory Syndrome (MERS) and the Severe Acute Respiratory Syndrome (SARS) are prominent examples (see Table 1). Since the etiology of a relatively large percentage of human and animal pathogens remains unidentified, it is possible that for a certain number of these illnesses, a yet unknown viral causative agent may be found. Screening for the presence of novel coronaviruses requires an integrated framework of subsequent biochemical, structural, and phylogenetic studies that can detect all corona and related viruses known at present.

Table 1: Common Characteristics and Differences of Well-Known Viruses

	Coronavirus disease 2019 (Covid-19)	**Middle East respiratory syndrome (MERS)**	**Severe acute respiratory syndrome (SARS)**
Origin	First reported in December 2019 in Wuhan, China.	First reported in 2012 in Saudi Arabia.	First reported in 2002 in southern China.
Transmission	Likely from touching or eating an infected yet unidentified animal. Human-to-human transmission occurs through close contact.	Often from touching infected camels or consuming their milk or meat. Limited transmission between humans through close contact.	Believed to have spread from bats, which infected civets. Transmitted mainly between humans through close contact.
Cases	Around 500 confirmed; 17 deaths as of Jan 22. Some victims were older males with preexisting conditions.	2,494 confirmed cases; 858 deaths (as of Nov 30, 2019). Mortality rate of 34%.	8,098 cases; 774 deaths. Mortality rate of about 10%.
Current status	Cases were reported mainly in Wuhan and other parts of China and Asia. One case reported in the U.S.	All cases are linked to Arabian Peninsula, with 80% in Saudi Arabia. Others in about two dozen countries, including U.S. Cases and deaths, have declined since 2016.	No new cases reported since 2004—87% of previous cases in China and Hong Kong.

Sources: (Huang, 2020) information based on the World Health Organization, U.S. Center for Disease Control and Prevention, and Wuhan Municipal Health Commission.

Beyond the public health impacts of regional or global emerging and endemic infectious disease events, lay wider socio-economic consequences that are often not considered in risk or impact assessments. Endemic infectious diseases set in motion a complex chain of events in the economy. Outbreaks and epidemics are rare, and extreme events, are highly diverse and volatile over time and geographical space. Estimating epidemic and pandemic risks depend on several factors that vary by activity type. The idiosyncratic nature of endemic infectious diseases is based, among others, on the magnitude and duration of the event, the size and state of the local economy, the geographical locations affected, the population density, and the period it occurs. Estimating direct medical and hospitalisation costs attributable to endemic infectious disease treatment is readily traceable. On the other hand, estimating the indirect costs in terms of trade, economic development, human movement, and cultural exchange can be an onerous task.

Indeed, it is estimated that the SARS outbreak caused more than US$50 billion of damage to the global economy (Candeias & Morhard, 2018), which knocked off an estimated 1% or more from China's growth rate (Johnson & Palmer, 2020). The MERS outbreak caused irreparable damage to South Korea's tourist industry, translating into US$2.6 billion in losses (Joo et al., 2019). Furthermore, empirical evidence on seasonal epidemics such as influenza, Dengue virus (DENV), Zika virus (ZIKV), Ebola virus (EBOV), have also a considerable economic impact in the affected areas. In the United States (US), the annual economic costs of influenza vary from US$13,900 to US$957.5 million across US counties, with a median of US$2.47 million (Liang, Yang, Youliang, & Yan, 2012). In the case of Dengue fever, the overall annual cost in 2013 amounted approximately up to US$8.9 billion spread across 141 countries (Shepard, Undurraga, Halasa, & Stanaway, 2016). Finally, the recent Zika outbreak caused socio-economic costs of approximately US$7-18 billion in Latin America and the Caribbean from 2015 to 2017 (United Nations, 2017). Finally, during the severe Ebola epidemic, an estimated $2.2 billion was lost in 2015 to the gross domestic product (GDP) of Guinea, Liberia, and Sierra Leone (CDC, 2020).

This paper formulates an analytical framework for estimating the economic consequences of endemic infectious disease in terms of immediate policy response in the aftermath of the disease and of medium-term policy implications for regulatory and fiscal policy. The Covid-19 Global Economic Impact Simulator (CGEI-Simulator) attempts to quantify potential epidemic and/or pandemic impact that can greatly increase morbidity and mortality over a wide geographic area and cause significant economic, social, and political disruption of any city or country based on selecting and combining risk indicators. The CGEI-Simulator develops methods for testing how the accuracy and distribution of risk from different estimates change concerning a wide range of assumptions about epidemic threats and capabilities and the dearth of information about how government agencies and policymakers might reduce risk. The model investigates the uncertainty and behavioural change under a new perspective within the framework of a dynamic imbalanced state (DIS) (Ruiz Estrada & Yap, 2013) and the Omnia Mobilis assumption (Ruiz Estrada, 2011).

This article is organised as follows. Section 2 offers an overview of the literature on the mathematical modelling of contagious diseases. Section 3 introduces the simulator. Section 4 establishes a simulation framework and presents model findings for the Chinese economy. Section 5 concludes.

2. Literature Review

Mathematical modelling provides a preliminary explanation and prediction of viral pathogenesis behaviour. It adds new theoretical information about the viral infection dynamics, the immune status, the *ex-post* and *ex-ante* evaluation of treatment, and the development of antibiotic resistance (Boianelli et al., 2015; Bonhoeffer et al., 1997; Ciupe & Heffernan, 2017; Perelson, 2002; Perelson & Guedj, 2015; Perelson & Ribeiro, 2013; Rong & Perelson, 2009). The development of an epidemiologic mechanism conceptualises the evolution time of an epidemic mathematically and shapes the interaction of agent, host, and environment. Satisfying all *a priori* conditions and constraints, the analysis of viral infection dynamics leads to the identification of an exceeded infection threshold where a unique endemic equilibrium exists, which is locally asymptotically stable (Hethcote & Thieme, 1985).

A growing body of literature employs complex infectious disease models that span from the molecular scale of intracellular virus-host interactions, extracellular cell-to-cell infection at the population scale, to virus spread within organs or whole organisms (Kumberger, Frey, Schwarz, & Graw, 2016). Intracellular models were initially developed for bacteriophages (Buchholtz & Schneider, 1987; Eigen & Biebricher, 1991; Endy et al., 1997), Baculoviral (Dee & Shuler, 1997), and Semliki Forest Virus (Dee et al., 1995). In the context of cell-to-cell infection, early models for Human Immunodeficiency Virus (HIV) (Ho et al., 1995; Perelson et al., 1997; Perelson et al., 1996; Stafford et al., 2000; Wei et al., 1995) provided insights into the pathogenesis, treatment strategies, and virus control by the immune system. On the population scale, the target cell-limited model (Bonhoeffer et al., 1997; Nowak et al., 1996; Nowak & Bangham, 1996; Perelson, 2002; Wodarz & Nowak, 2002) has been extensively used to investigate the virus-host interaction of HIV, Hepatitis C Virus (HCV), and Influenza A Virus (IAV). Age-based multi-scale models have been used in order to study the modes of action of antivirals within a virus-infected cell (Clausznitzer et al., 2015; Guedj et al., 2013; Heldt et al., 2013; Nelson et al., 2004). Agent-based models help characterise viral spread in tissue, within organs, or in the whole human body (Bauer et al., 2009; Graw & Perelson, 2015; Kumberger et al., 2016)

Technological advancements in the last decades enable the development of more holistic, data-driven, and computer-intensive conceptual modelling frameworks. The new epidemic models have depicted a more sophisticated probability range, readily quantifying and approximating uncertainty. In addition, multi-dimensional computations of complex multi-scale disease phenomena are now within reach. Sophisticated nonlinear analysis deepens our understanding of the large-scale epidemic process. Multidimensionality discovers the level of (dis)similarity data as distances in a high dimensional space to make these data accessible to visual inspection and exploration. Computational results feedback into the modelling process and provide insight into detailed mechanisms that real-life experiments often cannot study.

The Global Epidemic and Mobility (GLEAM) model is a spatially structured framework. GLEAM employs metapopulation dynamics to explore population density and human mobility heterogeneity for estimating infection transmission parameters and forecasting epidemic trajectories. The use of real data worldwide allows GLEAM to perform numerous stochastic simulations, yielding the incidence and seeding events at a daily resolution for 3,253 subpopulations in 232 countries and dependent territories (Broeck et al., 2011; Meirelles, 2013; Piontti et al., 2019). Adopting a similar metapopulation approach, the Global Epidemic Model (GEM) investigates air travel's temporal and spatial trajectories, particularly air network topology, geography, traffic structure, and individual mobility patterns. The airline network comprises 155 major metropolitan areas in the world for the stochastic simulation of contagion dynamics (Bobashev et al., 2007, 2008; Broeck et al., 2011). In contrast, the Spatiotemporal Epidemiological Modeler (STEM) is based on an extensible software platform, which promotes the contribution of data and algorithms by users for the testing and validation of specific assumptions on the spread of a disease, the understanding of observed epidemic patterns, the study of the effectiveness and results of different intervention strategies, analysis of risk through model scenarios, forecast of newly emerging infectious diseases (IBM Research, 2020; Piontti et al., 2019; Zhang, 2009). Furthermore, an open-source software system for modelling infectious diseases and control strategies using census-based populations have been developed, dynamically evolved and adapted to actions taken by individuals and public health interventions, including FluTe (Basta et al., 2009; Chao et al., 2010; Chao et al., 2011; Yang et al., 2009), EpiFast (Kannan, 2015; Nisset et al., 2008; Piontti et al., 2019) and FRED (A Framework for Reconstructing Epidemiological Dynamics) (Daughton et al., 2017; Grefenstette et al., 2013; Public Health Dynamics Laboratory, 2020).

Infectious disease modelling is a broad and promising field. It possesses a range of problems, including fundamental theoretical work, understanding and capturing observed network data, and guiding network-based public-health interventions. However, even the simplest epidemic models present unanswered questions and the list of potential challenges is practically endless. A more general theory is needed to understand the impact of network structure on the dynamics and control of infection.

3. Simulator Setting

This paper intends to establish conceptual foundations for analyzing the economic dimensions of regional or global emerging and endemic infectious disease events. The CGEI-Simulator attempts to identify infection transmission parameters and forecast epidemic trajectories. The model introduces seven basic indicators - (i) the Covid-19 contagious spread intensity rate (SI), (ii) the treatment level for Covid-19 infected cases rate (T); (iii) the number of Covid-19 causalities rate (-C); (iv) the economic wear from the Covid-19 epidemic rate (-Π); (v) the Covid-19 contagious cases multiplier rate (M); (vi) the total economic leakage from the Covid-19 epidemic rate ($-L_{total}$); and (vii) the economic desgrowth from the Covid-19 epidemic rate ($-\delta_{2019\text{-}nCoV}$).

3.1 Initial Covid-19 contagious stage

Infectious diseases are caused by pathogenic microorganisms, such as bacteria, viruses, parasites or fungi. Contagious diseases (such as the flu, colds, or strep throat) spread from person to person. The model classifies four root causes for the spread of both types of diseases, directly or indirectly, to the human population: (i) natural disasters – (C_1); (ii) humans disaster – (C_2); (iii) hybrid disasters – natural and humans' disaster together - (C_3); and (iv) unknown disasters – non-natural disasters or non-humans disaster - (C_4). These four factors directly affect "the Covid-19 contagious spread intensity rate (*SI*)"

$$SI = f(C_1, C_2, C_3, C_4) \tag{1}$$

Differentiate expression (1) will give the maximum level of the Covid-19 contagious spread intensity rate (SI)

$$f'(SI) = \frac{\partial SI}{\partial C_1} + \frac{\partial SI}{\partial C_2} + \frac{\partial SI}{\partial C_3} + \frac{\partial SI}{\partial C_4} \tag{2}$$

Thus,

$$f'(SI) = \sum \lim_{\Delta C_1 \to 0} \frac{\Delta SI}{\Delta C_1} + \lim_{\Delta C_2 \to 0} \frac{\Delta SI}{\Delta C_2} + \lim_{\Delta C_3 \to 0} \frac{\Delta SI}{\Delta C_3} + \lim_{\Delta C_4 \to 0} \frac{\Delta SI}{\Delta C_4} \tag{3}$$

The second differentiation of expression (2) determines the critical point (inflection point) of infection spread:

$$f''(C_1, C_2, C_3, C_4) = \frac{\partial^2_{SI}}{\partial^2_{C_1}} + \frac{\partial^2_{SI}}{\partial^2_{C_2}} + \frac{\partial^2_{SI}}{\partial^2_{C_3}} + \frac{\partial^2_{SI}}{\partial^2_{C_4}} \tag{4}$$

Expression (4) indicates the minimum spread of a potential epidemic outbreak, which equals [0,1]. Epidemic risk is considerably higher in geographical areas of high population density. The Jacobian determinant gives the magnitude of territorial dispute tension at the first level.

$$|J'| = \begin{bmatrix} \frac{\partial SI}{\partial C_1} & \frac{\partial SI}{\partial C_2} \\ \frac{\partial SI}{\partial C_3} & \frac{\partial SI}{\partial C_4} \end{bmatrix} \tag{5}$$

The model considers the assistance of health organisations and agencies at the local, $HO_{i = 1,2..n}$, regional, $HR_{j = 1,2..k}$, and international level, $HI_{m = 1,2..p}$ to cope with the epidemic. The second-order Jacobian determinant defines the *Pareto* optimal between the aforementioned organisations (P_1) and the infected population (P_2):

$$|J''| = \begin{bmatrix} \frac{\partial_{SI}^2}{\partial_{C_1}^2} & \frac{\partial_{SI}^2}{\partial_{C_2}^2} \\ \frac{\partial_{SI}^2}{\partial_{C_3}^2} & \frac{\partial_{SI}^2}{\partial_{C_4}^2} \end{bmatrix} \quad (6)$$

The Covid-19 contagious spread intensity rate (SI) determines the endemic threshold. The threshold is a unique endemic equilibrium that is locally asymptotically stable. The epidemic threshold has exponential growth; once the endemic equilibrium is exceeded, the infection spreads to the whole population constituting the treatment level of Covid-19 infected cases rate (T) as inefficient in the short run. Hence, the relationship between the Covid-19 contagious spread intensity rate (SI) and the treatment level for the Covid-19 infected cases rate (T). Its mathematical formulation is given by expression (7).

$$SI = x \log_2 T \ \Rightarrow \left\{ \frac{T}{T} : C \cap HO, HR, HI \right\} \quad (7)$$

3.2. Rapidly Covid-19 epidemic spread stage

The rapid Covid-19 epidemic spread stage consists of – (i) the national Covid-19 spread stage, and (ii) the worldwide Covid-19 spread stage.

3.2.1 National Covid-19 spread stage

In the national Covid-19 spread stage, both Players (P_1) and (P_2) have different levels of Response (R_d) and Safety (S_i):

$$P_1(R_d) \neq P_2(S_i) \quad (8)$$

And the Covid-19 contagious spread intensity rate (SI) proportions (Δ)

$$P_1(\Delta SI) \neq P_2(\Delta SI) \quad (9)$$

Which corresponds to their level of Response and Safety too:

$$P_1(\Delta SI^{respond}) \neq P_2(\Delta SI^{safety}) \tag{10}$$

When the Covid-19 contagious spread intensity rate (SI) reaches its maximum limit, the treatment level for Covid-19 infected cases rate (T) success will be

$$SI = f'(T) = \frac{\partial x \log_2(SI)}{\partial T} > 0 \tag{11}$$

With inflection point

$$SI_{max} = f''(T) = \frac{\partial_x^2 \log_2(SI)}{\partial_T^2} > 0 \tag{12}$$

3.2.2 Worldwide Covid-19 spread stage

The number of 2019-nCoV causalities rate (-C) is based on nine main variables: (i) the late mass media information systems to the general public (v_1); (ii) the limited hospital infrastructure access (v_2); (iii) the limited antibiotics diversity access (v_3); (iv) the limited social security access (v_4); (v) the higher water pollution levels (v_5); (vi) the higher air pollution (v_6); (vii) temperatures (v_7); (viii) the limited international health cooperation (v_8); and (ix) basic knowledge of health education (v_9). The number of 2019-nCoV infected cases and causalities rate (-IC) is the $\langle t + 1\rangle$ event period and $\langle t - 1\rangle$ a pre-event period at the first level given by the Jacobian determinant (see expression 13).

$$|J'(\Delta v)| = \begin{bmatrix} \frac{\partial v_{1(t+1)}}{\partial v_{1(t-1)}} & \frac{\partial v_{2(t+1)}}{\partial v_{2(t-1)}} & \frac{\partial v_{3(t+1)}}{\partial v_{3(t-1)}} \\ \frac{\partial v_{4(t+1)}}{\partial v_{4(t-1)}} & \frac{\partial v_{5(t+1)}}{\partial v_{5(t-1)}} & \frac{\partial v_{6(t+1)}}{\partial v_{6(t-1)}} \\ \frac{\partial v_{7(t+1)}}{\partial v_{7(t-1)}} & \frac{\partial v_{8(t+1)}}{\partial v_{8(t-1)}} & \frac{\partial v_{9(t+1)}}{\partial v_{9(t-1)}} \end{bmatrix} \tag{13}$$

The final calculation is shown in expression (14)

$$-C = \frac{1}{|J'(\Delta v)|} \tag{14}$$

The outbreaks and epidemics' aftermath impose disproportionate repercussions on economic activity. The economic wear from the Covid-19 epidemic rate (-Π) depends on the changes of the SI and -C:

$$-\Pi = f(SI, -C) \tag{15}$$

The calculation of the economic wear from the Covid-19 epidemic rate (-Π) is

$$-\Pi = \iint_{00}^{11} -C(SI)dtdt \tag{16}$$

The next step is to specify the limits of each variable involved in calculating -Π – i.e., ensure that the limit is between 0 and 1.

$$-\Pi = \int_0^1 -IC(SI)^{-nt}dt = \lim_{Y\to 1} -IC(SI)^{-nt}dt \tag{17}$$

Where n refers to the discount rate of -Π under a uniform SI and -C rate per year. The first and second derivatives give the maximum –Π' and the inflection point –Π", respectively:

$$-\Pi' = \frac{\partial - \Pi_{(t)}}{\partial - \Pi_{(t+1)}}, \qquad -\Pi'' = \frac{\partial^2 - \Pi_{(t)}}{\partial^2 - \Pi_{(t+1)}} \tag{18}$$

Hence, the boundary conditions for the –Π' are given by

$$-\Pi' = \frac{\partial y - {\Pi_i}'}{\partial T}|t = 0 = 0, -\Pi' = \frac{\partial y - {\Pi_i}'}{\partial T}|t = 1 = 1, \ldots -\Pi' = \frac{\partial y - {\Pi_i}'}{\partial T}|t = \infty = \infty \tag{19}$$

3.3 Post-Covid-19 disease recovery

The rise in the number of Covid-19 infected individuals over time, followed by a fall to low levels, can be graphically depicted as an "epidemic curve," which usually represents days, weeks, months, even years. Infectious diseases fluctuate in pervasiveness and intensity, wreaking havoc in developing and developed economies alike when an outbreak (a sharp increase in prevalence in a relatively limited area or population), an epidemic (a sharp increase covering a larger area or population), or a pandemic (an epidemic covering multiple countries or continents) occurs. The recovery period of 2019-nCoV is intrinsically related to the country's development status. Developed countries have effective public institutions, strong economies, and adequate investment in the healthcare sector. They have built specific competencies critical to detecting and managing 2019-nCoV outbreaks, including surveillance, mass vaccination, and risk communications. Less developed countries may suffer from political instability, weak public administration, inadequate resources for public health, and gaps in fundamental 2019-nCoV outbreak detection and response systems.

In the long run, the recovery of all patients suffering from Covid-19 can experience different magnitudes (Δ). At the same time, this recovery highly depends on the reduction of -C. Additionally, the recovery of all sick patients from Covid-19 depends on their integral health system, civil society cooperation, military and emergency forces, and political support until the -C is equal to or close to zero.

$$-C = 0 \tag{20}$$

3.4 Covid-19 disease cases multiplier rate

The Covid-19 contagious cases multiplier rate (M) refers to the post magnitude effect of the Covid-19:

$$M = \frac{1}{[(\Delta P_{Annual}) - (\Delta - C_{Annual})]} \tag{21}$$

Where ΔP_{Annual} and $\Delta\text{-}C_{Annual}$ correspond to the annual population growth rate and the number of Covid-19 causalities rate (-C), respectively.

3.5 Economic desgrowth from Covid-19 epidemic rate

The concept of economic desgrowth from the Covid-19 epidemic rate ($-\delta_{2019\text{-}nCoV}$) (Ruiz Estrada et al., 2014) plays an essential role in the construction of the Covid-19 CGEI-Simulator. The $-\delta_{2019\text{-}nCoV}$ analyses how controlled and non-controlled shocks can adversely affect full potential GDP ($GDP_{potential}$) in the short run. The $-\delta_{2019\text{-}nCoV}$ is defined "as an indicator that can show different leakages that is originated from the total final number of contagious plus causalities cases from the 2019-nCoV epidemic that can affect the performance of the full potential gross domestic product in real prices ($GDP_{potential}$) formed in one year". The model shares the view that the world economy is in a chaotic state susceptible to butterfly effects of initial-condition sensitivity (Gleick, 1988; LeBaron, 1994; Wilmott, 2009). The $-\delta_{2019\text{-}nCoV}$ employs systematic sampling to assess the systemic risk of macroeconomic events. Lorenz's transformation assumptions also facilitate the analysis of $-\delta_{2019\text{-}nCoV}$. The calculation of $-\delta_{2019\text{-}nCoV}$ is based on total economic leaking from Covid-19 ($-L_{total}$) under the *Omnia Mobilis* assumption (Ruiz Estrada, 2011).

The $-L_{total}$ is based on nine variables: (i) ε_{11} is equal to x_1 (food quality consumption) to the power of α_1 (income growth rate); (ii) ε_{12} is equal to x_2 (exports volumes) to the power of α_2 (exports volume dynamicity growth rate); (iii) ε_{13} is equal to x_3 (imports volumes) to the power of α_3 (imports volume dynamicity growth rate); (iv) ε_{14} is equal to x_4 (airways and tourism volumes) to the power of α_4 (arrives of passengers to the country growth rate); (v) ε_{21} is equal to x_5 (exchange rate) to the power of α_5 (depreciation rate growth rate); (vi) ε_{22} is equal to x_6 (government spending in health) to the power of α_6 (public health spending growth rate); (vii) ε_{23} is equal to x_7 (sells of commodities online) to the power of $v\alpha_7$ (customers demand growth rate); (viii) ε_{24} is equal to by x_8 (financial service infrastructure) to the power of α_8 (stock market performance volumes growth rate); (ix) ε_{31} is equal to x_9 (public services supply –electricity, water, education) to the power of α_9 (public services volumes demand growth rate). The final measurement of $-L_{total}$ is derived by applying a large number of multi-dimensional partial derivatives on each variable (9 variables) to evaluate the changes of each variable (9 variables) based on the first derivative (between the present year (t+1) and the previous year (t-1) (see expression 22).

$$\Delta x_i = \sum \frac{\partial x_{i\ (t+1)}^{\varepsilon_i}}{\partial x_{i\ (t-1)}^{\varepsilon_i}} \tag{22}$$

The *ex-ante* and *ex-post* conditions are given by

$$\begin{matrix} \alpha_1|_{t-1=0} = 0 & \alpha_2|_{t-1=0} = 0 & \alpha_3|_{t-1=0} = 0 \\ \alpha_4|_{t-1=0} = 0 & \alpha_5|_{t-1=0} = 0 & \alpha_6|_{t-1=0} = 0 \\ \alpha_7|_{t-1=0} = 0 & \alpha_8|_{t-1=0} = 0 & \alpha_9|_{t-1=0} = 0 \end{matrix} \tag{23}$$

$$\begin{matrix} \alpha_1|_{t+1=0} = \infty & \alpha_2|_{t+1=0} = \infty & \alpha_3|_{t+1=0} = \infty \\ \alpha_4|_{t+1=0} = \infty & \alpha_5|_{t+1=0} = \infty & \alpha_6|_{t+1=0} = \infty \\ \alpha_7|_{t+1=0} = \infty & \alpha_8|_{t+1=0} = \infty & \alpha_9|_{t+1=0} = \infty \end{matrix} \tag{24}$$

The CGEI-Simulator needs to run nine first partial derivatives simultaneously to evaluate all possible changes in each total economic leaking from the Covid-19 epidemic rate ($-L_{total}$) in a fixed period (one year). The first derivative of the inverse Jacobian determinant in expression (25) gives us the $-L_{total}$.

$$J^{-1} = \begin{bmatrix} a'_{11} & a'_{12} & a'_{13} \\ a'_{21} & a'_{22} & a'_{23} \\ a'_{31} & a'_{32} & a'_{33} \end{bmatrix}^{-1} = \begin{bmatrix} \varepsilon'_{11} = \dfrac{\partial x_{1\ (t+1)}^{\alpha_1}}{\partial x_{1\ (t-1)}^{\alpha_1}} & \varepsilon'_{12} = \dfrac{\partial x_{2\ (t+1)}^{\alpha_2}}{\partial x_{2\ (t-1)}^{\alpha_2}} & \varepsilon'_{13} = \dfrac{\partial x_{3\ (t+1)}^{\varepsilon\alpha_3}}{\partial x_{3\ (t-1)}^{\alpha_3}} \\ \varepsilon'_{21} = \dfrac{\partial x_{4\ (t+1)}^{\alpha_4}}{\partial x_{4\ (t-1)}^{\alpha_4}} & \varepsilon'_{22} = \dfrac{\partial x_{5\ (t+1)}^{\alpha_5}}{\partial x_{5\ (t-1)}^{\alpha_5}} & \varepsilon'_{23} = \dfrac{\partial x_{6\ (t+1)}^{\alpha_6}}{\partial x_{6\ (t-1)}^{\alpha_6}} \\ \varepsilon'_{31} = \dfrac{\partial x_{i\ (t+1)}^{\alpha_i}}{\partial x_{7\ (t-1)}^{\alpha_7}} & \varepsilon'_{32} = \dfrac{\partial x_{8\ (t+1)}^{\alpha_8}}{\partial x_{8\ (t-1)}^{\alpha_8}} & \varepsilon'_{33} = \dfrac{\partial x_{9\ (t+1)}^{\ \alpha 9}}{\partial x_{9\ (t-1)}^{\alpha_9}} \end{bmatrix}^{-1} \tag{25}$$

To determine the $-L_{total}$:

$$-L_{total} = \frac{1}{(J^{-1})^2} \tag{26}$$

And calculate the economic desgrowth from the Covid-19 epidemic rate ($-\delta_{2019\text{-nCoV}}$):

$$-\delta_{2019-\mathrm{nCoV}} = \sqrt{GDP_{potential}\left(\frac{1}{-L_{total}}\right) - 1}, \quad 0 \geq -\delta_{2019-\mathrm{nCoV}} \leq -1 \tag{27}$$

It is plausible to expect the aftermath of the Covid-19 outbreak to cause widespread economic disruption. The CGEI-Simulator suggests the likelihood and magnitude of economic desgrowth from the Covid-19 epidemic rate ($-\delta_{2019\text{-nCoV}}$).

Boundary conditions for economic desgrowth from the Covid-19 epidemic rate ($-\delta_{2019\text{-nCoV}}$) is equal to

$$-\delta'_{2019-\mathrm{nCoV}} = \frac{\partial(-\delta_{2019-\mathrm{nCoV}})}{\partial T}\Bigg|_{t=0}^{0} = 0, -\delta'_{idc} = \frac{\partial(-\delta_{2019-\mathrm{nCoV}})}{\partial T}\Bigg|_{t=1}^{1} = 1, \ldots - \delta'_{idc}$$

$$= \frac{\partial(-\delta_{2019-\mathrm{nCoV}})}{\partial T}\Bigg|_{t=\infty}^{\infty} = \infty \tag{28}$$

The annual final GDP in real prices (GDP_{final}) is given by

$$GDP_{final} = [[(GDPnominal) - [(GDPnominal) * (CPI)]] \times 100\% \tag{29}$$

Where GDP_{final} corresponds to the $GDP_{potential}$ under the impact of the Covid-19

$$GDP_{final} = \left(-\delta_{2019-\mathrm{nCoV}} + GDP_{potential}\right) \tag{30}$$

The $GDP_{potential}$ calculation in expression 31.

$$GDPpotential \ = f(Labor, Capital, Land, Technology]\text{full } maximum\ output \tag{31}$$

In *Omnia Mobilis* setting, the $-\delta_{2019\text{-nCoV}}$ generates the relaxation of the ($-L_{total}$) calculation (non-controlled and controlled events) and the full potential $GDP_{potential}$.

4. Application of CGEI-Simulator to China

This section examines the impact of the recent Covid-19 epidemic identified in China. The model employs qualitative and quantitative data from the Chinese Ministry of Health. The 12-variable model algorithm performs one main and 35 sub-random and fuzzy simulations based on different infection disease scenarios across China to identify the drivers of the potential magnitude of the disease outbreak given the current 12-day data availability of the 2019-nCoV Coronavirus and the extended Chinese government's coronaviruses database (1995–2020). All equations in this model were transformed in a large algorithm by using the Mathematica Wolfram version 12 programming language that allows us to generate a large pool of possible results to the problem at hand.

The model's findings indicate that the 2019-nCoV triggers a serious public health emergency crisis in China, with significant impacts on the economy. The SI of China's Covid-19 is 0.77, affecting 10 out of every 1,000 people, substantially higher than SARS's 0.53, affecting only three out of 1,000 people in Hong Kong during the 2003-04 period. The spatial patterns of Covid-19 are also alarming: It is expected to accelerate at a greater rate than internationally, with contagion rates of 0.77 and 0.35, respectively. In contrast, SARS was internationally-prone with domestic and international contagion rates of 0.37 and 0.49, respectively. In the case of the level of T, the Covid-19 rate is 0.39 corresponding to two hospital beds for every 1,000 people compared to SARS 0.82, which corresponds to six hospital beds for every 1,000 people. This indicator provides a measure of the resources available for delivering services to inpatients in hospitals in terms of the number of beds that are maintained, staffed, and immediately available for use. It seems that Hong Kong was more prepared due to its strengthened public healthcare system to handle an infectious disease rather than the Wuhan district. Indeed, the Chinese government built a mega-hospital in just 10 days at Wuhan to attend to more Coronavirus cases. Furthermore, the -IC for Covid-19 is 0.73 with a causality probability rate of three out of 1,000 people, substantially higher than the SARS infection rate of 0.43 with a casualty probability rate of 1 out of 1,000 people.

The -Π of Covid-19 is 0.64, about three times the rate of SARS, 0.24. Subsequently, the M of Covid-19 is 0.75, more than three times the rate of SARS, 0.35. The -L_{total} of Covid-19 is -0.45, about three times the rate of

SARS, -0.15. Intuitively, by each one per cent of the $GDP_{potential}$ of China in the present year, China can easily lose approximately -0.45 per a unit of growth rate. In particular, x_1 = -0.40; x_2 = -0.30; x_3 = imports = +0.35; x_4 = airways and tourism = -0.85; x_5 = exchange rate = -0.45; x_6 = government spending = +0.65; x_7 = sells online = -0.35; x_8 = financial service = -0.65; and x_9 = public services = +0.45. Finally, the $-\delta_{2019\text{-}nCoV}$ for China for the year 2020 will be -0.45 compared to 2003/2004 Hong Kong's -0.17. In monetary terms, China's economy can drop its $GDP_{(year\ 2019)}$ = US$14.30 trillion ($GDP_{final}$ = 6.2%) to $GDP_{(year\ 2020)}$ = US$10.00 trillion ($GDP_{final}$ = 4.3%). We predict that China can lose at least 1.9% to 2% of GDP_{final}.

Suppose that the SARS outbreak caused losses of US$12.9-28.4 billion and an estimated GDP decrease of 1% in the Chinese economy (Qiu et al., 2018). In that case, it is a plausible conjecture that the economic consequences of Covid-19 for the Chinese economy will be substantially higher. The exponential growth of Covid-19 through droplets and surfaces, whereas it has not been confirmed yet whether is airborne or not, will cause severe economic and market dislocation igniting a supply-side and demand-side shocks. In January, the Chinese CPI rose 5.4%, the highest monthly rate since October 2011, while the manufacturing PMI hit a three-month low of 50%. The reason that inflation is rising today when it fell in 2003 is because both supply and demand are falling but supply is falling faster (He, 2020). As long as a known transcriptional mechanism of the immune system pathway has not been developed, Covid-19 can be an epidemic of unprecedented proportions, and a new virus mutation can appear at anytime.

Finally, the CGEI-Simulator also investigates coronavirus stability, whether T is susceptible to temperature differentials affecting SI. Daily data analysis shows an inversely proportional correlation between SI and temperature, indicating that Covid-19 depends on temperature seasonality. As temperature intervals rise, the number of SI cases decreases given a threshold temperature level of 24ºC. In particular, an increase of 1ºC in air temperature is associated with an average reduction of 11.64 out of 100 new patients. The above research findings are consistent with previous studies on the SARS virus presented surprisingly similar results: temperature seasonality, the threshold temperature level of 24.6ºC, and an increase of 1ºC in air temperature is associated with an average reduction of 2 to 8 out of 100 new patients (Chan et al., 2011; Lin et al., 2006). These two coronaviruses exhibit parallel spatial-temporal initial conditions but distinct infection signatures and magnitude of virus replication. Based on the current data, Covid-19 will have a substantially higher health, social, and economic impact than SARS.

There is currently a vaccine to prevent Covid-19. The seasonality information has important implications for health services planning, the timing of respiratory virus passive prevention, and the strategy of Wuhan 2019-nCoV virus and future respiratory virus vaccination. Till then, a series of preventive actions can be taken including (i) use of CCTV cameras in highly congested areas; (ii) consumption of vitamin C; (iii) extended exposure to sunlight (iv) a constant routine of exercises in green areas and a balanced diet (v) the use of masks, and constant washing of hands and face with soap, and less use of sanitisers.

5. Concluding Remarks

It is plausible to expect that the aftermath of Covid-19 has the potential to cause widespread economic disruption. The CGEI-Simulator findings suggest that the likelihood and magnitude of an epidemic are associated with the economic dynamics of the corresponding region. Epidemics are classified as rare events, so-called “new risks”. Infectious diseases occur randomly and asymmetrically. Assessing an epidemic is inherently challenging due to many factors, many of which are unique among natural disasters. However, it is possible to assess vulnerability regarding the likelihood of occurrence. Unlike most other natural disasters, epidemics do not remain geographically contained, and prompt intervention can mitigate damages. As a result, there are strong ethical and global health imperatives for building the capacity to detect and respond to epidemic threats, particularly in countries with weak preparedness and high spark and spread risk.

Notes

[1] Our sources include the United Nations Population Division, World Health Organization (WHO), Food and Agriculture Organization (FAO), International Monetary Fund (IMF), and World Bank.

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