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Health Interventions in a Poor Region and Resilience in the Presence of a Pandemic¹

by

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Abstract

We focus on a poor region and study the nexuses between health interventions undertaken by a regional authority (RA) and this region's Holling resilience in the presence of a pandemic such as Covid-19. First, we show how a health intervention by the RA probabilistically affects an appropriately defined health indicator. Second, we compute the chance that the health status of this region's population falls below a minimum acceptable level in the presence of the health intervention. Third, we solve an optimization problem in which the RA maximizes the likelihood that the health status of this region's population stays above a minimum acceptable level at a given economic cost. Our analysis demonstrates that there is a connection between a health intervention, a region's health status, and its Holling resilience by presenting two applications. Our analysis reveals that this paper's methodology can be used to compute a region's Holling resilience with a particular health intervention. The main policy implications of our analysis concern the need for a RA to pay attention to (i) a region's health infrastructure and financing, (ii) sufficient engagement with the region's population, (iii) regional heterogeneity, (iv) data collection, and (v) the likelihood that sicker regions are likely to require more health interventions at a higher cost.

Keywords: Cost, Pandemic, Regional Health Indicator, Resilience, Uncertainty

JEL Codes: R11, I18

1. Introduction

1.1. Preliminaries

Li Wenliang, a physician from Wuhan, China, commented in a group chat in December 2019 that he had observed a series of patients demonstrating signs of an illness that was similar to severe acute respiratory syndrome (SARS). As pointed out by Lango (2020), this illness was then reported to the World Health Organization (WHO) country office in China on 31 December 2019. On 12 January 2020, Chinese scientists published the genome of the virus and the WHO asked a team in Berlin, Germany to use the information provided to develop a diagnostic test to identify any active infection. Such a test was developed a few days later.

The work of Chaplin (2020) and that of many others tells us that the cause of the SARS-like illness that subsequently became known as Covid-19 was a novel coronavirus, in particular, the SARS-CoV-2. On 30 January 2020, Covid-19 was declared by the WHO to be a Public Health Emergency of International Concern (PHEIC). The first case of Covid-19 arising from local person-to-person spread in the United States (U.S.) was confirmed in mid-February 2020. On 11 March 2020, the WHO declared COVID-19 a pandemic.

Consider how Covid-19 has affected different *nations* and different *regions* within the same nation. For instance, China and Italy, the two nations in which the adverse impacts of Covid-19 were felt very strongly early on in the spread of the coronavirus---see Perez-Pena (2020)---are now doing much better as far as the management of the virus is concerned. In contrast, Londono (2020) points out that initially little affected nations such as Brazil are now seeing some of the worst outbreaks of the virus. There are substantial differences in the impacts of Covid-19 *within* individual nations. To see this, let us focus on some examples, first from the U.S. and then from Switzerland. In the U.S., northeastern states such as Connecticut, New Jersey, and New York were

all initially hit hard by Covid-19 but now have few new cases or deaths (Anonymous, 2020). In contrast and as noted by Findell *et al.* (2020), states such as Arizona, Florida, and Texas that were relatively untouched by Covid-19 during the early days of the outbreak in the U.S. are now seeing large increases in both new cases and deaths. Even if we focus on a single state such as California within the U.S., one can find regional differences. Blumenberg *et al.* (2021) have shown how the onset of Covid-19 has had differential impacts on the availability of food in three different metropolitan statistical areas (MSAs), namely, San Francisco-Oakland-Berkeley, Los Angeles-Long Beach-Anaheim, and Riverside-San Bernardino-Ontario. Finally, Seiler *et al.* (2021) have demonstrated that Covid-19 resulted in significant regional differences in the behavior of families arriving in pediatric emergency departments with concerns about their children and themselves in the north and the south of Switzerland.

We would now like to emphasize three points. First, the central conclusion we draw from the above discussion is that irrespective of whether we use the word region to refer to a nation or to a sub-national geographic entity, as far as the impacts of and the responses to a pandemic such as Covid-19 are concerned, there are clear *regional differences*. Second, this paper is part of a special issue that is broadly about the topic “sustainable resilience for smart spatial planning.” This explains why we focus on how health interventions affect a region’s Holling resilience in detail.⁴ In this regard, it should be noted that the use of a “resilience perspective” as developed in this paper is helpful not only because it permits the analyst to explicitly account for the ways in which stochastic events or shocks influence the behavior of socioeconomic systems in one or more regions but, in addition, this perspective explicitly recognizes the point that socioeconomic systems are non-linear and adaptive which means that they often exhibit complex and far-from-

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Section 5 explains how we measure the Holling resilience---on which more below---of a region in detail.

equilibrium dynamics. Third, we wish to *contribute* to the above-mentioned topic and to *fill* a lacuna in the spatial science literature by developing a theoretical model that can be used to quantify the impacts that health interventions undertaken by a regional authority (RA) in the presence of a pandemic such as Covid-19 have on a region's health status and ultimately on its Holling resilience.⁵ We now discuss this paper's specific goals in greater detail.

1.2. Our objectives

Our primary objective is to concentrate on an economically disadvantaged or poor region and analyze---to the best of our knowledge for the first time---the links between health interventions undertaken by a RA and this region's Holling resilience in the presence of a pandemic such as Covid-19. Note that how economically disadvantaged or poor a region is can be measured by, for instance, its gross regional product.⁶ Also, for the purpose of this paper, a region refers to a sub-national geographic entity.

Consistent with the work of Paul-Sen Gupta *et al.* (2007), Adler and Newman (2002), and Choksi (2018), we take it as given that the population of an economically disadvantaged or poor region also has poor health. In this setting, we first demonstrate how to connect the RA's health

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The term *resilience* was introduced into ecology in the post-World War II era by C.S. Holling (1973). Even so, this concept now has two meanings in ecology. First, we have *engineering or Pimm* resilience. Even though Holling (1996) came up with the term engineering resilience, resilience in this particular sense originates from the research of Pimm (1984). Second, we have *ecological or Holling* resilience. This second sense in which the notion of resilience is used in ecology is due to Holling (1973). It is important to comprehend that engineering and ecological resilience are *dissimilar* concepts and therefore, in general, we do not expect there to be any discernable relationship between these two ideas. To see the difference between these two notions of resilience, let us reflect on the prevailing definitions of these two concepts. Engineering resilience "concentrates on stability near an equilibrium steady state, where resistance to disturbance and speed of return to the equilibrium are used to measure the property..." (Holling, 1996, p. 33). In contrast, ecological resilience "emphasizes conditions far from any equilibrium steady state, where instabilities can flip a system into another regime of behavior---that is, to another stability domain" (Holling, 1996, p. 33). From these two definitions, it should be clear to the reader that engineering resilience is an "equilibrium-centered" view of a system and that ecological resilience is a "far-from-equilibrium" view of a system. We concentrate exclusively on the Holling resilience of a poor region in this paper and *not* on its Pimm resilience. Therefore, unless stated otherwise, it is understood that all mentions of resilience in this paper are to the notion of Holling resilience.

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Go to https://unstats.un.org/unsd/economic_stat/China/background_paper_on_GRP.pdf for additional details on this point. Accessed on 24 February 2022.

intervention or action⁷ to the evolution of a suitably defined regional health indicator in an environment of uncertainty. With this connection made, we then compute the probability that the health status of this region's population falls below a minimum acceptable level in the presence of a health intervention. Next, we use this probability to set up and solve an optimization problem in which the RA maximizes the likelihood that the health status of this region's population stays above the minimum acceptable level at a given economic cost.

Finally, we discuss the nexuses between a health intervention, our poor region's health status, and its resilience by presenting two applications of our theoretical model. These two applications explicitly account for the regional differences we have mentioned above and they also point out which parameters of the theoretical model a RA would need to have information about in order to operationalize our theoretical model in a particular circumstance. We now review four relevant topics in the existing literature to buttress our section 1.1 claim that we are, in fact, filling a lacuna in the literature with our contributions in this paper.

1.3. Literature review

Since our paper is integrally concerned with decision-making under uncertainty, we begin this review by commenting on the work of researchers who have utilized a complementary approach to study alternate aspects of decision-making under uncertainty, namely, Bayesian models. To this end, Eibich and Ziebarth (2014) use hierarchical Bayes models to analyze spatial health effects in Germany. These researchers show that more than twenty years after the reunification of Germany, a clear spatial east-west health pattern exists that equals an age impact on health of up to five life-years for a 40-year-old individual. Dorfman and Mandich (2016) utilize a Bayesian estimation strategy to examine the phenomenon of migration for amenities by "later-

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In the remainder of this paper, we use the terms "action" and "health intervention" interchangeably.

life migrants.” Their analysis shows that there is a positive association between access to healthcare and the migration decisions of older individuals.

Second, since a health intervention, a key topic in the present paper, can be thought of as one kind of provision of healthcare, we now briefly consider this provision issue from the perspective of consumers or demanders and health professionals or suppliers. Focusing first on consumers, Alm and Enami (2017) study the Massachusetts healthcare reform of 2006. They ask whether governmental subsidies to low-income persons influences them to move to a state with better health subsidies. Their analysis reveals that the reform did not lead to a “global effect” meaning that there was no movement of low-income persons across all cities in Massachusetts. Even so, there was a “local effect” meaning that there was a noticeable movement of low-income persons into the border cities of Massachusetts. Moving on to the behavior of health professionals, Goodman and Smith (2018) look at the regional location of such individuals by examining 373 MSAs. They point out that spatial agglomerations raise factor productivity and therefore the rents paid and the wages earned by health professionals.

Third, since a pandemic such as Covid-19 can be thought of as a natural disaster, let us succinctly ponder the topic of natural disasters. In this regard, Skoufias *et al.* (2017) construct damage indices for individual districts in Indonesia and show how these indices can be used for budgetary planning. For instance, they contend that *ex ante* or before the occurrence of a natural disaster, these indices can be used to ascertain the size of the annual fiscal transfers that will need to be made from the central government to the affected sub-national governments. Looking at the impact of natural disasters on the growth of population densities across U.S. counties in 1960-2000, Wang (2019) finds no significant adverse long-term growth effects.

Finally, we come to the topic of resilience which is, as pointed out in section 1.1, a topic of great significance in the present paper. That said, the reader should note that our section 1.1 discussion of resilience and its two meanings notwithstanding, this concept has been used in many different ways in the social science literature. For instance, Longstaff and Yang (2008) contend that in the aftermath of natural disasters and health emergencies such as a pandemic, communicating crisis information effectively builds trust and that this buildup of trust makes individuals and groups more resilient. There is no gainsaying the point that Covid-19 has adversely affected the health of many families. Prime *et al.* (2020) increase our awareness of this point by first building an aggregative conceptual framework and then using this framework to show how shared family beliefs and close relationships help families deal with social disruptions and thereby enhance their resilience.⁸

This review of four topics in the extant literature leads us to a salient point. Consistent with our observation in sections 1.1 and 1.2, there are *no* theoretical studies in spatial science that analyze how a pandemic such as Covid-19 influences a poor region's health status and how policies adopted to combat the ill effects of the pandemic influence this same region's resilience. That said, the remainder of this paper is organized as follows. Section 2 delineates the theoretical model of an economically disadvantaged region that is adapted from Batabyal *et al.* (2003). Section 3 shows how to link the RA's health intervention to an appositely defined regional health indicator in an environment of uncertainty. Building on this linking exercise, section 4 first determines the probability that the health status of this region's population falls below an exogenously specified minimum acceptable level in the presence of the health intervention. Next,

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The ways in which the notion of resilience has been studied in the spatial science literature and some of the problems stemming from this kind of study have been discussed in detail by Batabyal (2021) and by Batabyal and Kourtit (2021). See Di Caro (2018) and Ezcurra and Rios (2019) for a discussion of related issues.

this section uses the above-mentioned probability to set up and then solve an optimization problem in which the RA maximizes the likelihood that the health status of this region's population stays above the exogenously given minimum acceptable level at a given economic cost. Section 5 comments on the connection between the RA's health intervention and this region's resilience by presenting two straightforward applications of our theoretical framework. Finally, section 6 concludes and then discusses three ways in which the research described in this paper might be extended.

2. The Theoretical Framework

Consider a poor region in a particular country. Why focus on a poor region? This is because a lot of research---see Marmot (2005) and Anonymous (2021)---convincingly shows that impoverished and marginalized communities residing in economically disadvantaged regions are disproportionately affected by diseases and pandemics. People living in such regions are more likely to become sick because they tend to earn low wages, have few employment protections, live in hazardous environments, and receive low-quality education. In contrast, people living in wealthy regions tend to face very few of these same problems. Therefore, in the presence of a pandemic, from the standpoints of both equity and fairness, it is particularly important for a RA to provide the necessary health interventions and thereby ensure that the health status of a poor region's population does not fall below a minimally acceptable level. Examples of the kinds of regions we are interested in include, but are not limited to, the state of Chattisgarh in India, the state of Mississippi in the U.S., and, looking within a state, the San Joaquin Valley in California.

In practice, it is common to find one or more health indicators that provide a researcher with information about the health status of those residing in this region. So, for instance, if the region under consideration is New York State in the U.S. then we know that there exist "The New

York State Community Health Indicator Reports (CHIRS)” that are annually updated to consolidate and provide information regarding health indicators in the so called County Health Assessment Indicators (CHAI) for all communities in New York.⁹ The CHIRS dashboard tracks about 350 indicators organized by 15 health topics and hence an analyst can easily obtain information about the incidence of, for instance, cancer, cardiovascular disease, and communicable diseases.

Similarly, if we were to focus on what the WHO calls the “European region,” then we could use information published by this organization in the “Core Health Indicators” to monitor progress towards the attainment of specific health targets in the 53 member states of the WHO European region.¹⁰ Finally, the Ministry of Health and Family Welfare in India, in cooperation with the World Bank, publishes information about different health indices for states in India.¹¹

Since we are interested in studying the effects of a pandemic such as Covid-19 on the health of people living in our economically disadvantaged region, suppose that a relevant health indicator (H) tells us the proportion of the regional population with *no* respiratory disease. We suppose that H has a stable, steady-state value denoted by H_0 . When the stochastically arriving coronavirus begins to spread in our region, *ceteris paribus*, the virus tends to *lower* the value of the health indicator (H) to some fraction below H_0 . Note that this lowering of the indicator means that the proportion of the regional population that now has a respiratory ailment of some sort has *risen*.

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Go to <https://www.health.ny.gov/statistics/chac/indicators/> for more information about these indicators. Accessed on 24 February 2022.

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Go to <https://www.euro.who.int/en/data-and-evidence/evidence-resources/core-health-indicators-in-the-who-european-region> for more information. Accessed on 24 February 2022.

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Go to https://smartnet.niua.org/sites/default/files/resources/healthy-states-progressive-india-report_0.pdf for more details. Accessed on 24 February 2022.

To combat this insalubrious state of affairs, a RA takes action (A) to raise the value of the health indicator from H_0 to $H_0 + \beta A$, where $\beta > 0$ is a parameter. Taking action is costly and therefore we suppose that the cost of taking action A can be described by the cost function $c(A)$. We assume this cost function is both strictly increasing and strictly convex. In terms of the derivatives of the cost function, we have $c'(A) > 0$ and $c''(A) > 0$.

Examples of an action A taken by the RA include, but are not limited to, a lockdown, a mandatory mask wearing requirement, an increased level of testing, a decision to quarantine visitors and those testing positive for Covid-19, and contact tracing. The action A can be viewed as a single action or it can also be viewed as a set of actions. When viewed as a set, we would let A_i denote the i th possible action, N denote the total number of actions that may be taken by the RA, and the composite action A would be, for instance, a linear combination of the individual actions. Mathematically, we would then have $A = \sum_{i=1}^N \alpha_i A_i$ where the weights $\alpha_i \in (0, 1)$ would denote the relative importance the RA assigns to each of the individual actions.¹² We now demonstrate how to connect the RA's action A to the behavior of our regional health indicator H in an environment of uncertainty.

3. Link between an Action and the Health Indicator

At any time t , let $Z(t) = \{H(t) - H_0 - \beta A\}$ denote the deviation in the value of our health indicator from the steady-state value H_0 when the RA's action or control variable is A . To account for the point that a pandemic such as Covid-19 almost certainly affects the value of the health

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In what follows, in order to avoid algebraic clutter and to keep the mathematical analysis tractable, we shall proceed with the assumption that the action A is a single action and not a set of actions. That said, the reader should understand that an analysis of the "set of actions" case would proceed in a manner that is very similar to what we illustrate in the subsequent sections of this paper.

indicator H stochastically, we model the evolution of the $Z(t)$ deviations with a stochastic differential equation.¹³

The next question concerns what kind of stochastic differential equation we ought to use to model the $Z(t)$ deviations. Here, we are guided by two considerations. First, because there is no evidence to suggest otherwise, we assume that a linear approximation around the steady-state is valid. Second, because of the way in which we have defined the deviation random variable, we expect this variable to display some degree of mean reversion over time. Putting these two considerations together, we contend that it is reasonable to model the evolution of $Z(t)$ with the Ornstein-Uhlenbeck process.¹⁴ This means that $Z(t)$ satisfies the linear stochastic differential equation

$$dZ = -\zeta Z dt + \sigma dW, \quad (1)$$

where $\zeta > 0$ is the speed of reversion, $\sigma > 0$ is the variance parameter, and dW is the increment of a standard Brownian motion or Wiener process.

We wish to analyze the steady-state behavior of the deviation in the value of our health indicator from the steady state value H_0 . From Proposition 5.1 in Karlin and Taylor (1981, p. 219), it follows that the steady-state probability distribution function of $Z(t)$ is given by

$$f_{SS}(z) = \sqrt{\frac{\zeta}{\pi\sigma^2}} \exp\left(\frac{-\zeta z^2}{\sigma^2}\right). \quad (2)$$

¹³

Here Z denotes the deviation random variable and z denotes a particular realization of this random variable.

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See Karlin and Taylor (1981, pp. 170-173) or Taylor and Karlin (1998, pp. 524-534) for more on the Ornstein-Uhlenbeck process.

When we study nutritional health indicators, particularly those for children, we find that the notion of a “Minimum Acceptable Diet (MAD)” is one of eight core indicators developed by the WHO. Other similar indicators include the related concepts of “minimum dietary diversity (MDD)” and “minimum meal frequency (MMF).” In fact, the MAD indicator itself is a composite indicator that is constructed by using the MDD and the MMF indicators.¹⁵ In addition, Xing and Batabyal (2019) tell us that in the natural resource and environmental economics literature, it is now understood that when uncertainty and irreversibility are issues in natural resource and environmental management, the management function ought to pay attention to the notion of a “safe minimum standard (SMS).” The idea here is to manage an ecological–economic system¹⁶ so that this system's ability to provide humans with a flow of ecosystem services does not fall below a particular level, namely, the SMS.

This discussion suggests that it would be reasonable for our RA to focus on some *minimally* acceptable value of the health indicator H when pondering how it might combat the onset of a pandemic such as Covid-19 in our poor region. Since $H(t)$ tells us the proportion of the population in our region that has *no* respiratory disease at time t , concentrating on a minimum value of H is equivalent to taking an action A so that the fraction of people in our region with no respiratory disease does *not* fall below this minimum acceptable threshold. Let us denote this threshold by H_M . Note that the threshold does *not* depend on time. By making H_M be time-independent, we are seeking to capture the idea that when combating a pandemic such as Covid-19 in a region where the population has poor health, the choice of the *threshold* proportion of the population in our

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Go to <https://index.nutrition.tufts.edu/data4diets/indicator/minimum-acceptable-diet-mad> for more details. Accessed on 24 February 2022.

¹⁶

Examples of ecological-economic systems include fisheries, forests, and rangelands.

region that has no respiratory disease ought not to depend on how virulent the pandemic is at any particular point in time. Our next task is to compute the probability that the health status of this region's population falls below the minimum acceptable level H_M in the presence of the health intervention.

4. A Likelihood Function and an Optimization Problem

To compute the above probability, let

$$f(h)dh = Prob\{steady - state health status value \in (h, dh)\}. \quad (3)$$

The probability on the right-hand-side (RHS) of equation (3) can also be written as

$$f(h)dh = Prob\{steady - state deviation value \in (h - H_0 - \beta A, h - H_0 - \beta A + dh)\}. \quad (4)$$

Now, using equation (2), the probability on the RHS of equation (4) can be simplified. This simplification gives

$$f(h) = \sqrt{\frac{\zeta}{\pi\sigma^2}} \exp\left\{\left(\frac{-\zeta}{\sigma^2}\right) (h - H_0 - \beta A)^2\right\}. \quad (5)$$

Note that equation (5) provides us with an explicit way of calculating the probability density function of the deviation from the raised health indicator value $H_0 + \beta A$. We are now in a position to state and then solve an optimization problem in which the RA maximizes the likelihood that the health status of this region's population stays above the minimum acceptable level H_M at a given economic cost $c(A)$.

The RA chooses the control (action) A , incurs cost $c(A)$, and maximizes the probability that the health status of our region's population stays above the minimum acceptable threshold H_M . The reader will note that this is an unconventional objective function in the sense that it is partly focused on public health and partly on economic considerations. We say this because the

probability part of the objective function is a public health criterion whereas the cost part is clearly an economic yardstick.

Using equation (5) and the cost function $c(A)$, mathematically, our RA solves

$$\max_{\{A\}} \int_{H_M}^{\infty} \left[\sqrt{\frac{\zeta}{\pi\sigma^2}} \exp \left\{ \left(\frac{-\zeta}{\sigma^2} \right) (h - H_0 - \beta A)^2 \right\} \right] dh - c(A). \quad (6)$$

Let us now make the substitution $k = h - H_0 - \beta A$. Using this substitution, the RA's maximization problem in (6) can be written as

$$\max_{\{A\}} \int_{H_M - H_0 - \beta A}^{\infty} \left[\sqrt{\frac{\zeta}{\pi\sigma^2}} \exp \left\{ \frac{-\zeta k^2}{\sigma^2} \right\} \right] dk - c(A). \quad (7)$$

Differentiating the maximand in (7) with respect to the control variable A , the first-order necessary condition for an optimum is

$$\beta \left[\sqrt{\frac{\zeta}{\pi\sigma^2}} \exp \left\{ \left(\frac{-\zeta}{\sigma^2} \right) (H_M - H_0 - \beta A)^2 \right\} \right] = c'(A), \quad (8)$$

and the second-order sufficiency condition is

$$\sqrt{\frac{\zeta}{\pi\sigma^2}} \exp \left\{ \left(\frac{-\zeta}{\sigma^2} \right) (H_M - H_0 - \beta A)^2 \right\} \left\{ \left(\frac{2\beta^2\zeta}{\sigma^2} \right) (H_M - H_0 - \beta A) \right\} - c''(A) \leq 0. \quad (9)$$

The first-order necessary condition in equation (8) tells us that optimality requires the RA to choose the action A so that the marginal economic cost to the poor region from the use of this action designed to fight the pandemic's ill effects (the RHS of equation (8)) is equal to the marginal increase in the likelihood that the health status of our region's population will be above the minimum acceptable level H_M (the left-hand-side (LHS) of the same equation). We now proceed to show how our analysis thus far can be used to figure out the resilience of the region under study and to demonstrate the connection between the RA's action and the resilience of this region.

5. A Health Intervention and Regional Resilience

Let A^* be the solution to equation (8). To find an analytic or closed-form expression for A^* and to compute our region's resilience in the face of a pandemic, it will be necessary to impose more structure on the problem by positing explicit values for (H_0, H_M) and by working with a specific functional form for the cost function $c(A)$. Before we do this, let us emphasize three points.

First, we shall focus on two applications of our analysis thus far. In both applications, we shall make use of a key finding in the extant literature---see Paul-Sen Gupta *et al.* (2007), Adler and Newman (2002), and Choksi (2018)---that the residents of economically disadvantaged regions also tend to have poor health. This means that the population of the region we are studying is unhealthy as far as the proportion of the population that has one or more respiratory diseases is concerned.

Second, in the first (second) application, the region under study is more (less) healthy. We model this feature by supposing that $H_0 = 0.6$ (0.5) in the first (second) application. In words, when $H_0 = 0.6$ in the first application, when a pandemic such as Covid-19 hits this region, 60 percent of the region's population has no respiratory ailments of any kind and hence 40 percent do have one or more respiratory ailments. Similarly, when $H_0 = 0.5$ in the second application, upon

the onset of Covid-19, 50 percent of the regional population has no respiratory ailments and therefore 50 percent of this population is afflicted with some kind of respiratory disease.

Finally, we would like to point out that the optimization exercise that we have just gone through in section 5 is general in the sense that, in principle, this modeling approach can be applied to study health related issues in any---poor or rich---region. That said, a point of these two applications is to demonstrate one convenient way in which we can explicitly account for the *heterogeneity* between different poor regions by altering the steady-state value of the health indicator H_0 . So, in this way of looking at the problem, the region in the first application can be thought of as being less poor and thus healthier than the region in the second application which is more poor and therefore sicker.

Note that the purpose of the RA's health intervention is to act forcefully to improve the health status of the relatively unhealthy regional populations. As such, in both the following applications, we suppose that the RA's goal is to determine a stationary or constant value of the action A to maximize the likelihood that the health status of our region's population is above the minimum acceptable threshold or $H_M = 0.8$, at minimum cost. Finally, the cost of taking action A is represented by the exponential cost function.

5.1. Application 1: Healthier region

Suppose that the cost function $c(A) = \exp(A)$. Clearly, this means that $c'(A) = \exp(A)$. Let us now substitute $c'(A) = \exp(A)$ in equation (8). After several steps of algebra, equation (8) can be simplified to give

$$\beta \sqrt{\frac{\zeta}{\pi\sigma^2}} \exp \left\{ \left(\frac{2\zeta H_0 H_M - \zeta H_M^2 - \zeta H_0^2}{\sigma^2} \right) + \left(\frac{2\beta\zeta H_M A - \beta^2 \zeta A^2 - 2\beta\zeta H_0 A}{\sigma^2} \right) \right\} = \exp(A). \quad (10)$$

Taking the natural logarithm of both sides of equation (10) and then rewriting the resulting expression gives us a quadratic equation in the control variable A . That equation is

$$\left[\frac{\beta^2 \zeta}{\sigma^2}\right] A^2 + \left[\frac{2\beta\zeta H_0 + \sigma^2 - 2\beta\zeta H_M}{\sigma^2}\right] A + \left[\left\{\frac{\zeta H_M^2 + \zeta H_0^2 - 2\zeta H_0 H_M}{\sigma^2} - \log\left(\beta \sqrt{\frac{\zeta}{\pi\sigma^2}}\right)\right\}\right] = 0. \quad (11)$$

Inspecting equation (11), if we denote the coefficient of A^2 by Γ , the coefficient of A by Δ , and the constant term by E , then the solutions to equation (11) are given by

$$A_i^* = \frac{-\Delta \pm \sqrt{\Delta^2 - 4\Gamma E}}{2\Gamma}, i = 1, 2, \quad (12)$$

with $\Delta^2 \geq 4\Gamma E$ for obvious reasons. Which of these two values¹⁷ of the action A makes most sense for the maximization problem that we are analyzing depends on the parameters of the stochastic differential equation describing the evolution of the $Z(t)$ deviations and on the exogenously given levels of the two health indicators H_0 and H_M . We already know that in this first application, $H_0 = 0.6$ and that $H_M = 0.8$. Therefore, to illustrate the working of our model, suppose that $\beta = \zeta = 2$, and $\sigma^2 = 4$. In this case, tedious but straightforward computations show that the quadratic equation in (11) has two real roots given by $A_1^* = 0.1191$ and $A_2^* = -0.1691$. To see which of these two solutions maximizes the objective function in equation (7), we substitute the above two candidate maximizers into equation (7) and then perform the necessary computations.¹⁸ This tells

¹⁷

It is understood that there will only be one value if $\Delta^2 = 4\Gamma E$.

¹⁸

We used the tables in Beyer (1991, p. 486) and the complementary error function calculator given in <https://keisan.casio.com/exec/system/1180573449> to perform the necessary computations. Accessed on 24 February 2022.

us that when $\beta = \zeta = \sigma^2 = 2$, $H_0 = 0.6$, and $H_M = 0.8$, $A_1^* = 0.1191$ maximizes the RA's objective function.

To see the link between the RA's maximization problem and the notion of resilience that we have discussed in section 1.1, note that one way to think about the resilience of a socioeconomic system is to say that it is "the capacity of [this] system to absorb disturbance and reorganize while undergoing change so as to still retain essentially the same function, structure, identity, and feedbacks" (Walker *et al.*, 2004). The socioeconomic system that we have been studying is the poor region and our specific focus has been on the health status of the population in this poor region. The disturbance alluded to in the definition above is the onset of a pandemic such as the Covid-19. So, we now ask the following question. When will our poor region be able to withstand the Covid-19 induced disturbance and still retain its function, structure, identity, and feedbacks? We contend that this will happen if, as a result of the RA's health intervention, the health status of our region's population is *above* the minimum acceptable threshold $H_M = 0.8$. However, since we are analyzing a stochastic environment, we *cannot* be sure about whether the RA will succeed in enhancing the regional population's health status to at least $H_M = 0.8$. That said, in the stochastic environment that we are studying, we can compute the *probability* that the RA's health intervention will improve the regional population's health status to at least $H_M = 0.8$. This probability is given by the integral in the first part of the maximand in equation (7). Using $A_1^* = 0.1191$ and the other parameter and indicator values given in the preceding paragraph, we can evaluate this integral and determine that the probability we seek is 0.5215.

In words, the probability that the RA's action will succeed in maintaining the health status of the population in our poor region above the threshold $H_M = 0.8$ is 52.15 percent. Put differently, the likelihood that our poor but healthier region will be resilient when faced with an adverse

stochastic shock from the Covid-19 pandemic is 52.15 percent. Since our analysis is long-run in nature, consistent with the previous work of Batabyal (1999) and Batabyal and Beladi (1999), we can think of the resilience of our poor region as a probability and, more specifically, as the probability 0.5215. This way of thinking about resilience has two distinct advantages. First, since it is a probability, resilience is bounded from above and below. Second, it is integrally tied to our RA's health intervention and this is as it should be because we are studying a socioeconomic or social-ecological¹⁹ system whose behavior in the presence of a pandemic is governed partly by natural and partly by human forces. We now proceed to discuss the second application of this paper.

5.2. Application 2: Sicker region

In this instance, $H_0 = 0.5$. This means that only 50 percent of our poor region's population has no respiratory ailments and therefore 50 percent do when a pandemic such as Covid-19 strikes the region. This is the sense in which the population of this region is *sicker* than the region studied in section 6.1. The cost function and the remaining parameter and threshold values are all as discussed in section 6.1. Hence, we have $c(A) = \exp(A)$, $\beta = \zeta = \sigma^2 = 2$, and $H_M = 0.8$. Also, the methodology we employ in this section is identical to that employed in section 6.1.

Let us plug the various values given in the preceding paragraph into equation (11) and then solve the resulting quadratic equation in the RA's control variable A . This gives us two real roots and they are $A_1^* = 0.116$ and $A_2^* = -0.066$. Next, let us substitute these two candidate maximizers into equation (7). After performing the necessary computations using the method delineated in section 6.1, we infer that when $\beta = \zeta = \sigma^2 = 2$, $H_0 = 0.5$, and $H_M = 0.8$, $A_1^* = 0.116$ maximizes the RA's objective function.

¹⁹

See Walker *et al.* (2004) for additional details on this point.

As in section 6.1, to see the link between the RA's maximization problem and the notion of resilience, let us compute the *probability* that the RA's health intervention will improve the regional population's health status to at least $H_M=0.8$. This probability is given by the integral in the first part of the maximand in equation (7). Using $A_1^* = 0.116$ and the other parameter and indicator values mentioned in the preceding paragraph, we can evaluate the relevant integral and conclude that the probability we seek is 0.4617. In words, the probability that the RA's action will succeed in maintaining the health status of the population in our poor and sicker region above the threshold $H_M = 0.8$ is 46.17 percent. In accordance with the reasoning employed in section 6.1, we contend that the resilience of our sicker, economically disadvantaged region is also given by the probability 0.4617.

As an intuitive check on one of our key findings, note that when confronted with a healthier (sicker) population, it should be easier (harder) for the RA to improve the health status of the region's population to the desired threshold of $H_M = 0.8$. However, since we are analyzing a stochastic environment, this means that the probability of being successful when the RA uses action A should be higher (lower) when working with the healthier (sicker) population. This is indeed what happens in the two applications that we have presented here. Specifically, for the case of the healthier region analyzed in section 6.1, the RA's probability of being successful is 0.5214 which is clearly *larger* than the corresponding probability of 0.4617 which arises when the RA works with the sicker region.

Our analysis in this paper suggests a number of health-related policy measures that a RA ought to consider when seeking to promote the resilience of an economically disadvantaged region. First, a RA's decisions, including the kind or kinds of health interventions to undertake, need to be situated in a context that pays adequate attention to a poor region's existing *health infrastructure*

and the *financing* that will be necessary to intervene successfully. Second, irrespective of whether the region under consideration is relatively healthy or sick, adequate *engagement*²⁰ with the region's population is essential for a RA's health intervention(s) to be successful. Third, RAs need to pay attention to the health-related *heterogeneity* between different regions when determining which actions are most likely to be useful in a particular region. Fourth, by *collecting data* on the model parameters that we have discussed in this section, a RA can actually operationalize our model and, at the same time, shed light on which parameters to focus on when attempting to run the model in any given circumstance. Finally, since healthier regions are more likely to also be resilient, a RA seeking to enhance the resilience of sicker regions is likely to require more interventions and their success is likely to be more costly and hence require greater resources. These suggested health-related policy measures are broadly consistent with the practical work of Haldane *et al.* (2021) who have recently studied the experiences of 28 countries to learn how health systems can be made more resilient. This completes our discussion of health interventions in a poor region and resilience in the presence of a pandemic.

6. Conclusions

In this paper, we concentrated on a poor region and studied the connections between health interventions undertaken by a RA and this region's resilience in the presence of a pandemic such as Covid-19. First, we showed how a health intervention by the RA stochastically affected an appositely defined health indicator for this region. Second, we computed the probability that the health status of this region's population would fall below a minimum acceptable level in the presence of the health intervention. Third, we solved an optimization problem in which the RA

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Examples of such engagement include, but are not limited to, providing essential services, providing a way for the regional population to offer feedback on specific health interventions, and communicating all the known risks from a particular pandemic. See Haldane *et al.* (2021) for additional details.

maximized the likelihood that the health status of this region's population stayed above a minimum acceptable level at a given economic cost. Finally, we discussed the nexuses between our region's health status and its resilience by presenting two applications of our theoretical framework.

The analysis conducted in this paper can be extended in a number of different directions. In what follows, we suggest three possible extensions. First, it would be useful to study a scenario in which the minimum acceptable health threshold H_M is not exogenously specified but determined endogenously in an appropriately specified model. Second, it would also be instructive to study a scenario in which it is not possible---or possible only at great cost---for a RA to reverse the deleterious impacts of one or more respiratory ailments suffered by the people living in the region under study. Finally, one could examine an extended model in which the competence of the RA is explicitly modeled with the objective of shedding light on the ways in which the quality of governance affects the likelihood of the success of alternate health interventions. Studies of health interventions that incorporate these aspects of the problem into the analysis will provide additional insights into the nexuses between optimal health interventions and the resilience of economically disadvantaged regions.

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