

# Estimation of the Impact of Comprehensive COVID-19 Testing in South Korea: A Cost-Benefit Analysis Using the Extended SEIR Model\*

Kilkon Ko\*\* and Minjun Hong\*\*\*

**Abstract:** Comprehensive COVID-19 diagnostic testing is regarded as a critical in preventing the spread of the virus, but only a few studies thus far have sought to assess the net benefits that sustained testing might offer, despite the importance accorded by researchers to evidence-based policy making. We performed a cost-benefit analysis using the extended SEIR model to assess whether maintaining the current level of COVID-19 testing is an economically rational choice compared with counterfactual scenarios. Our results suggest that the relationship between the net benefits and the level of testing assumes an inverted-U shape, which means that comprehensive diagnostic testing is effective in flattening the infection curve, but it is a financial burden to society. This study provides evidence that comprehensive diagnostic testing would not be a good strategy for countries with scant financial and medical resources, considering the costs. Furthermore, undertaking comprehensive diagnostic testing without implementing other strategies is a limited approach to preventing the spread of infectious diseases. Therefore, this study suggests that policy makers should find ways to improve the effectiveness of tests, not just increase the level of tests.

**Keywords:** COVID-19, cost-benefit analysis, comprehensive diagnostic testing, epidemiological model

---

\* This research is funded by the project, “Economic and Fiscal Impact after COVID-19 and Government Intervention” of the Center for Sustainable Public Accounting and Finance, Graduate School of Public Administration, Seoul National University.

\*\* Kilkon Ko is a professor in the Graduate School of Public Administration at Seoul National University, Korea Public Administration Research Center, and the director of Asia Regional Information Center at SNUAC. E-mail: [kilkon@snu.ac.kr](mailto:kilkon@snu.ac.kr).

\*\*\* Minjun Hong is a master’s student in the Graduate School of Public Administration at Seoul National University and a research assistant at the Asia Regional Information Center. E-mail: [hmj2815@snu.ac.kr](mailto:hmj2815@snu.ac.kr).

Manuscript received August 13, 2020; out for review August 15, 2020; review completed September 07, 2020; accepted October 13, 2020.

*Korean Journal of Policy Studies*, Vol. 35, No. 3 (2020), pp. 141-168.

© 2020 by the GSPA, Seoul National University

## INTRODUCTION

Few expected that COVID-19 would be a global-scale pandemic when the WHO office in China reported to the World Health Organization(WHO) viral pneumonia cases in Wuhan on December 31, 2019 (WHO, 2020a). However, it did not take long to realize the seriousness of COVID-19. The WHO declared a public health emergency of international concern on January 30, 2020. Almost six weeks later, on March 11, 2020, the WHO announced a global pandemic (WHO, 2020b). Subsequently, by early July 2020, more than 10 million had been infected, and the epidemic had claimed more than 500,000 lives. Even worse, the pandemic continued to spread, and there was deep concern about the possibility of a second wave (Leung, Wu, Liu, & Leung, 2020; Pedro, 2020).

Even though COVID-19 has caused a global pandemic, the infection level of the virus is quite different across countries. Korea, Vietnam, and New Zealand, among countries successfully controlled the infection very quickly, but other countries such as Brazil, India, and the United States did not. Among countries, the Korean management of the virus is impressive in many ways. Although Korea is geographically close to China and millions of people visit each other's country every year, the number of cases in Korea is significantly smaller than that of other countries. Korea's success is the result of transparency, testing, tracing, trust, and technologies (Comfort, Kapucu, Ko, Menoni, & Siciliano, 2020; Moon, 2020; Oh, Lee, Schwarz, Ratcliffe, Markuns, & Hirsch, 2020). Among them, rapid and comprehensive diagnostic testing is considered to be the most crucial factor in containing the spread of the virus.

However, comprehensive testing is very costly for many countries, causing governments to hesitate to adopt it. In Korea, if a medical doctor recommends the diagnostic test, the government pays the cost. In the United States, the Families First Coronavirus Response Act requires insurance companies to cover FDA-approved COVID-19 tests and associated costs. Similarly, the UK's NHS provides a free test if it is performed in a public facility. Although during a pandemic, people are likely to care less about this sort of economic cost than they do otherwise, policy makers still have to justify the use of taxpayer's dollars and show that their spending is economically and socially beneficial.

Although scholars emphasize the importance of evidence-based policy making (Banks, 2009; Black & Donald, 2002; Davies, 2012) and as well as that of an effective usage of resources in responding to catastrophes (Park & Cha, 2020), thus far there have been few studies on whether comprehensive testing for COVID-19 accrues net benefits to society or not. Instead, many take it for granted that such testing is an unquestionably beneficial. Furthermore, current research on COVID-19 has

focused on forecasting the prevalence of the disease and comparing government response between countries or with past experiences such as SARS or MERS rather than evaluating specific government strategies. However, if governments are to set realistic target goals and to achieve objectives, then they need to be able to objectively assess the relationship between the resources they have and the results they can expect from comprehensive testing (Kim & Kang, 2014). Given how long pandemics typically last, it is essential to evaluate the link between diagnostic tests and epidemic control effects. Such an evaluation can roughly identify a socially appropriate level of diagnostic testing. Thus, the purpose of this study is not to estimate the costs and benefits of the comprehensive diagnostic testing and thereby demonstrate policy is the correct one to adopt but to help policy and decision makers understand the strategy of comprehensive diagnostic tests by presenting rough estimate results.

We carried out a cost-benefit analysis of comprehensive diagnostic testing in Korea in order to gauge its long-term feasibility. First, we use the extended SEIR model to measure how changes in the rate of detection affects the number of infected patients and fatalities. Although effective control of COVID-19 produces many benefits, we focus on the value of saved lives, which allows for very conservative estimates of the benefits of comprehensive testing. Second, we estimate medical, travel, and work-loss costs as a means of measuring the costs of comprehensive testing using. Finally, we perform extensive sensitivity tests to gauge whether different assumptions produce a different net benefit of the comprehensive testing.

## **THE TREND OF COVID-19 AND COMPREHENSIVE TESTS IN SOUTH KOREA**

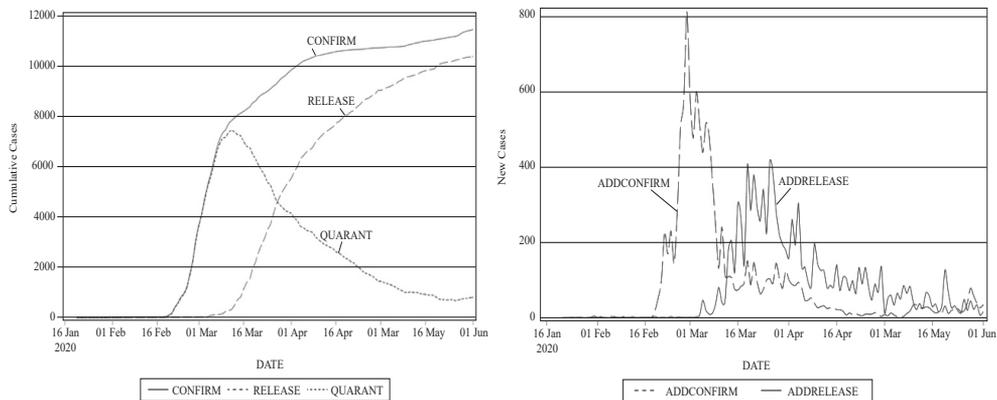
### **Evolution of COVID-19 in Korea**

About two weeks after the first case of COVID-19 in South Korea was announced on January 20, 2020, the KCDC issued the emergency use authorization of the first RT-PCR test kit within a week after applying for the approval of a company, Kogene Biotech. The development of the new test kits shortened the time it took to get results from two days to six hours (Jung & Lee, 2020). Between the day the first case was announced and February 17, only 31 Koreans had become infected and none had died. Many Koreans believed that they effectively controlled the spread of COVID-19.

However, owing to the gathering of members of Shincheonji, a religious cult group, there was an explosive outbreak in the city of Daegu and North Gyeongsang-

buk province, at which point the number of confirmed cases increased rapidly. On February 23, the government raised the country's infectious disease alert level to the highest one. The Central Disaster and Safety Countermeasure Headquarters, headed by the prime minister, which had been formed to strengthen the government-wide response to COVID-19 (H. Y. Kim, 2020), took immediate action and as a result, after the highest number of news cases in single day (813) was reached on February 29, the number of new cases began to decrease, as shown in Figure 1. Although it took a relatively long time for patients to recover, by March 13, the number of newly recovered patients was greater than the number of newly infected patients. Although the virus continued to spread via community transmission, there were no further explosive outbreaks in Korea until the end of July. Due to this successful containment of COVID-19, people regard Korea's responses as a successful exemplar.

**Figure 1.** The Trend of COVID-19 in South Korea



Data: Korea Centers for Disease Control

The factors that researchers suggest account for Korea's success include self-disciplined citizens, vigilant tracking systems, transparency, and comprehensive testing (Moon, 2020; Comfort et al., 2020; Oh et al., 2020; Her, 2020; Jeong et al., 2020; H. Kim, 2020). Among them, comprehensive diagnostic testing is considered to be the most crucial because it enabled the Korean government to track contacts and prevent unintended infection of family or others.

### **Comprehensive Diagnostic Testing in Korea**

Crises usually reveal the drawbacks of emergency response systems but they can

also offer an opportunity to adjust and develop them. Just as the SARS crisis uncovered problems in the Chinese public health system (Li, 2004), the 2015 MERS outbreak exposed deficiencies in the Korean public health and medical system. In the wake of 186 confirmed cases of MERS, from which 38 people died, and the quarantine of more than 16,000, many Koreans criticized the government for its delayed inefficient response, which motivated the government to reform infectious disease prevention protocols (Chang, 2017; see also Asia Regional Information Center website).

The Korean government usually publishes so-called white papers after a crisis that outlines problems in the process of responding to them and suggests improvements (although these white papers have been criticized on the grounds that they are simply a tool for placating the public rather than a serious investigation of issues [Lee, 2015]). Following the MERS crises, the Ministry of Health and Welfare published a white paper on the government's response to MERS, that emphasized the importance of testing in managing MERS (Ministry of Health and Welfare, 2016). The Korean government established a standard operating procedure in 2017 and then continued to revise basic operational frameworks in disaster management. Specifically, the Korean government has improved efficiency testing by coordinating test sites and laboratories. In addition, large private hospitals received approval to take part in the process of diagnostic testing (Yoon & Martin, 2020).

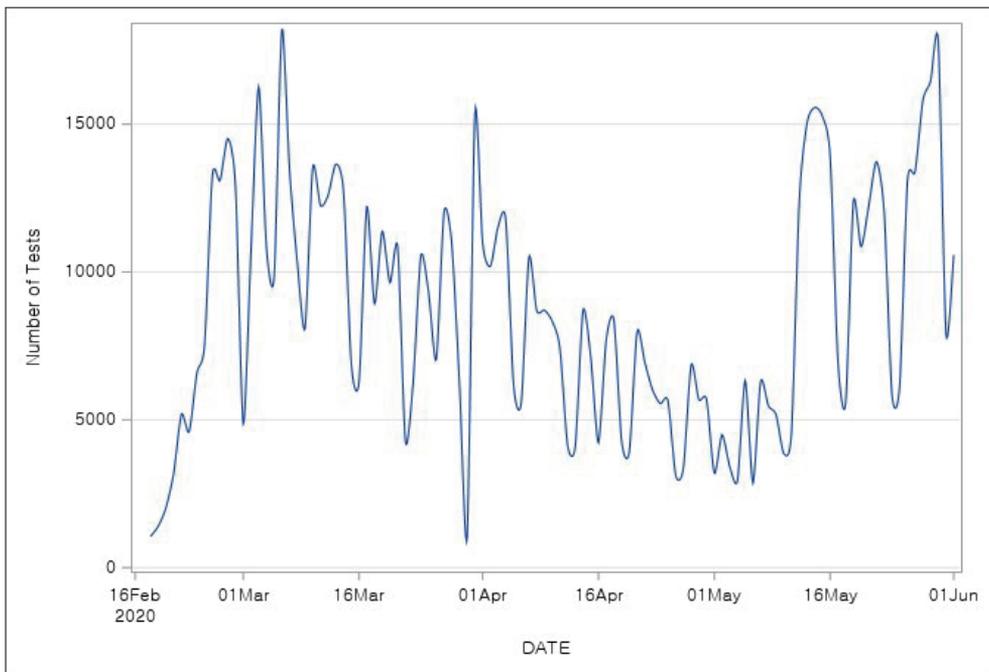
Although it is difficult to apply lessons from the SARS or MERS crisis because COVID-19 is spreading indiscriminately (Park & Cha, 2020), the Korean government has come to appreciate the importance of detecting infected people as a means of responding to epidemics (see Asia Regional Information Center website). With COVID-19, the Korean government has focused on early detection to minimize the potential spread of the virus instead of implementing partial or total lockdowns to prevent its spread. The national health insurance system in Korea guarantees that any citizen who meets the Korean Centers for Disease Control guidelines is eligible to receive the diagnostic test at no cost. However, in order to prevent an overrun of testing capacity, the Korean government also restricted testing to patients who had traveled overseas and had been in contact with confirmed patients, patients with clinical symptoms of the virus, patients whose doctor believed they could have the virus, and patients who had a connection with a domestic COVID-19 cluster.

In addition to the national guidelines, there are local ones as well. For instance, starting in early summer, as the number of confirmed cases kept increasing in Seoul, the city offered free COVID-19 testing to prevent infection clusters (Ock, 2020).

The government has established more than 600 screening clinics to improve patients' accessibility to diagnostic testing. The specimens collected via rapid on-site

tests are taken to testing facilities, and individuals are notified of the results by the hospital or public health center. Owing to the opening up of these testing centers, the maximum testing capacity quickly increased from 3,000 cases per day in February to almost 20,000 cases per day as of April (government of the Republic of Korea, 2020). As shown in Figure 2, the number of tests administered rose rapidly in late February as the risk of community infection among high-risk groups such as Shincheonji and residents in Daegu increased.

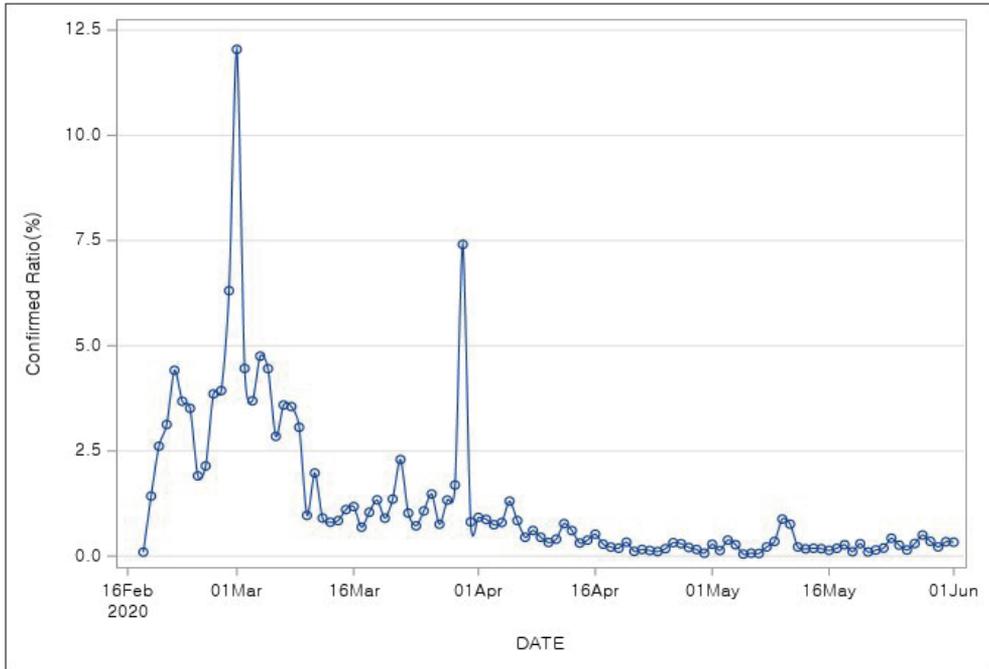
**Figure 2.** Testing Trends



Data: Korean Centers for Disease Control

Interestingly, the number of tests has not significantly decreased since then, although there are less than 100 positive cases confirmed per day. Such large-scale testing as conducted in Korea can reduce the risk of community infection but it at considerable cost. As shown in Figure 3, the number of detected cases per test has dropped to less than 1% since April 6. Since health resources should be allocated to generate the highest possible overall level of population health, the low detection rate raises the question “of whether comprehensive testing is cost effective.”

**Figure 3.** The Ratio of the Number of New Positive Cases to the Number of New Tests



Data: Korean Centers for Disease Control

### Cost- Benefit Analysis of Medical Treatments

Many previous cost- benefit analyses of medical treatment have focused on methods of controlling the prevalence of malaria. H. S. Kim and colleagues (2018), for example, developed a mathematical model that they used to conduct a simulation that estimated the effect of control strategies on malaria incidence. Their cost-and-benefit analysis showed that early diagnosis without other measures would not be an effective strategy. They included averted medical expenses (inpatient and outpatient costs), nonmedical expenses (transportation costs), and costs due to productivity loss, and so forth. Benjamin Uzochukwu and colleagues (2009) used a decision tree model to compare the cost effectiveness of a rapid diagnostic test (RDT) for malaria to a syndromic approach and microscopy in Nigeria. Their results indicated that RDT is a more cost-effective approach for case management of malaria. In this research, deaths averted based on the use of the various diagnostic methods were considered as evidence of the effectiveness of strategies, while costs broadly included consumer costs (cost of registration, transportation to the health facility, etc.) and provider costs

(cost of staff time, RDT test kits, etc.).

Estelle Rolland and colleagues (2006) conducted a similar study for Tanzania with the difference that their cost-effectiveness analysis considered treatment during a malaria epidemic. They treated reduced overtreatment as a benefit. The costs included biomedical costs (RDT kits and drugs) and other costs such as wages of health workers and so on. They concluded that the best method would be determined by the level of prevalence of the disease. There have also been studies that have aimed to develop mathematical models to gauge disease transmission of and investigate the costs and benefits of approaches to the Ebola virus (Rosado et al., 2017; Kellerborg, Brouwer, & van Baal, 2020).

A number of researchers have also considered the accuracy and sensitivity of testing and what the cost of a false-negative result and a false-positive result is (Lubell et al., 2008; Mahony, 2009). Despite the differences among various studies as to the costs and benefits of medical treatments, there is wide agreement that the benefits usually consist of saving lives, reducing medical expenses, and securing economic gains. Diagnostic testing costs can be divided into three types: medical, nonmedical, and productivity (Severens & Wilt, 1999).

**Table 1.** Economic Costs and Benefits of Medical Treatments

	Goal	Benefits / Effectiveness	Costs
Diel & Nienhaus, 2019	implement a real-time influenza test in emergency rooms	revenue from administering a neuraminidase inhibitor, which reduced by one day the hospital stay of an influenza patient	rapid influenza test, external point of care, hospital opportunity cost (average daily reimbursement per bed, etc.), initial treatment with neuraminidase inhibitors, intrahospital transmission
Kim, Kang, Lee, Yoon, & Kim, 2018	evaluate costs and benefits of chemoprophylaxis and early diagnosis for malaria	medical costs, transportation costs, caregiver costs for inpatient treatment Costs of productivity loss, Malaria-related administrative costs	RDT kits (cost of RDT kits, logistical costs, cost of incidental material)
Suputtamongkol et al., 2010	compare the costs and benefits of diagnostic tests for leptospirosis	decreasing the length of time of the fever leads to less productivity loss	cost of the test, doxycycline side effects (which keeps the patient out of work longer), disease outcome (daily cost of not working, hospital costs)

Uzochukwu, Obikeze, Onwujekwe, Onoka, & Griffiths, 2009	compare the cost effectiveness of RDT to that of syndromic diagnosis and microscopy for malaria	deaths averted based on the use of the various diagnostic strategies	consumer costs (cost of registration, drugs, laboratory, admission, and transportation to health facility), provider costs (cost of staff time, training and supervision, unit cost of RDT test kit, cost of consumables sic as lancets), outpatient cost per visit, inpatient costs per day, costs of transportation, insurance, and waste, cost of using health centers and hospitals
Mahony, 2009	measure the cost testing strategies for the detection of respiratory viruses	-	costs of the laboratory tests (unit labor cost and hands-on time, actual reagent costs, mode labor cost, fringe benefits for medical laboratory technologists, hospital-associated costs), cost of hospitalization by infection status or diagnostic status (true positive, false positive, true negative, false negative)
Lubell et al., 2008	assess the impact of clinicians' response to RDT or microscopy results on the costs and benefits of testing for malaria	the averted cost of life years lost	RDT, microscopy, artemisinin combination therapy, antibiotics, false negative results, false positive results
Rolland Checchi, Pinoges, Balkan, Guthmann, & Guerin, 2006	compare the cost effectiveness of malaria treatment based on presumptive diagnosis to RDT-based treatment	reduced overtreatment (the number of false positives averted)	biomedical costs (RDT [paracheck kit], drugs), other costs (wages of community health workers, supervisors and drivers, vehicle rental and fuel)
Hueston & Benich, 2004	evaluate the comparative advantage of strategies such as rapid testing for influenza A	earlier recovery (additional work productivity)	diagnostic test (test kits), additional physician visits for drug reactions, hospitalization complications, medication costs (drugs)

## METHODOLOGY

### Extended SEIR Model

Since we already had data regarding the confirmed and fatality cases after implementing comprehensive diagnostic tests using Korean data, we needed to estimate the counterfactual benefits and costs in the absence of comprehensive testing. For the counterfactual analysis, we had to choose relevant models for simulating the trend of infection and fatality. In this paper we use the compartment model called the extended SEIR model that addresses weaknesses in the original SIR model (Daughton, Generous, Priedhorsky, & Deshpande, 2017; Fabricius & Maltz, 2020; Peiliang & Li, 2020; Wearing, Rohani, & Keeling, 2005).

The SIR model oversimplifies the transmission process. It assumes an instantaneous contact event, constant recovery rate, and population-wide homogeneous parameters (Chen, 2014). It also overlooks the latency period and assumes that all people get infected immediately, which can lead to significantly different predictions than those generated by models that take the latency period into account and to overestimations of the basic reproductive number (Brauer & Castillo-Chavez, 2012; Wearing et al., 2005).

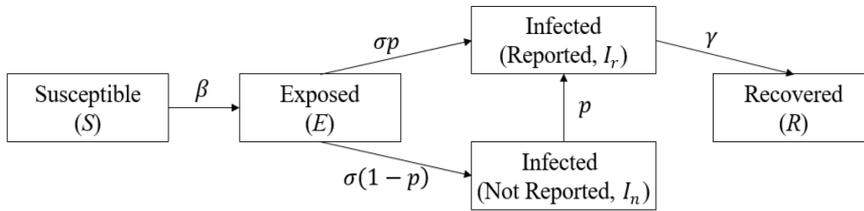
In the SEIR model, the latency period is considered: “Susceptible” denotes the fraction of the population that could be subjected to infection, “exposed” refers the number of individuals who have been exposed but do not yet show symptoms, “infected” represents the number of infected individuals after the latency period, and “removed” indicates the number of individuals who are no longer counted as infected either because they recovered or died (Li & Muldowney, 1994; Keeling & Rohani, 2011).

However, the SEIR model has weaknesses as well. First of all, additional parameters are required to fit empirical data, which is needed to do extra computational work. Such an estimation of more parameters leads to overfitting and reliability of prediction problems (Roda, Varughese, Han, & Li, 2020). For instance, the SEIR model requires data regarding the number of exposed cases, but it is not easy to identify initially latent cases or estimate the latency period.

We propose that the extended SEIR model offers a more realistic estimation of the number of positive cases and the number of deaths. We assumed that not all infected cases are directly reported (Kellerborg et al., 2020) because of the limited testing capacity, so we divide the infectious compartment into two compartments, one of which includes contagious people who have not been reported due to delay or no symptom and the other contagious people who have been reported. We assumed that

infected people could only recover if they are reported. The extended SEIR model is described in Figure 4.

**Figure 4.** Extended SEIR Model



The extended SEIR model can be estimated using differential equations. The parameters used for differential equations are explained in table 2.

$$\frac{dS}{dt} = -\beta SI_r - \beta SI_n$$

$$\frac{dE}{dt} = \beta SI_r + \beta SI_n - \sigma E$$

$$\frac{dI_n}{dt} = \sigma(1-p)E - pI_n$$

$$\frac{dI_r}{dt} = \sigma p E + pI_n - \gamma I_r$$

$$\frac{dR}{dt} = \gamma I_r$$

**Table 2.** Parameters of the Transmission Model in Korea

Parameters	Description	Value	Reference
$\beta$	transmission rate	estimated	data fitted
$\sigma$	progression rate	1/4.1 days	Korean Centers for Disease Control
$\rho$	detection rate (proportion reported)	estimated	data fitted
$\gamma$	removal rate	1/12.7 days	Korean Centers for Disease Control

The parameters of the extended SEIR model can be estimated using the actual trend of COVID-19. Among the parameters, the progression and removal rates can be directly measured using Korean Centers for Disease Control and Prevention(KCDC) data regarding the number of days a patient develops symptoms after infection and the number of days a patient stays in the hospital.

The estimated parameters allow us to calculate the basic reproductive number ( $R_0$ ). The  $R_0$  shows the average number of new infections produced by one infection and explains the early spread of disease. If  $R_0$  is less than 1, the virus will spread out, and the number of individuals infected increases.

$$R_0 = \frac{\beta}{\gamma} N$$

However, as we have noted, the original SEIR model is not sufficient to explain government interventions, so although the model can predict the number of cases expected in the early days, it cannot predict the number of cases expected in the long term. One way of addressing this problem is to model the transmission rate ( $\beta$ ) through a sigmoid function (Kellerborg et al., 2020). Sigmoid functions such as logistic function can describe the S-shaped curve for the cumulative number of infected cases (Yang, Zhang, Peng, Zhuge, & Hong, 2020). In the US and other European countries, the infection rate declined slowly, and the epidemic curves were skewed, so these curves did not reflect symmetric normal distribution (Ranjan, 2020). However, the infection rate declined more quickly in South Korea, and the epidemic curve followed the bell-shaped curve. We made adjustments to the transmission rate so that it would reflect the effect of efforts to mitigate the disease.  $\phi(x, \sigma^2)$  means the standard cumulative normal distribution function and  $R_i$  means achieved change in  $R_0$  (See Cleveland Clinic and SAS COVID-19 Development Team Github).

$$\beta = \beta(t) = (R_0 + R_i \phi(t - t_i, \sigma_t^2)) \frac{\gamma}{N}$$

### **Estimating Costs and Benefits of Medical Treatments**

We can measure the benefits and costs of the diagnostic test by comparing them with the test situation and without the test situation. Based on many previous pieces of research, we consider saving lives, saving medical expenses for treating infected patients, economic gains due to early recovery, and prevention to estimate the diagnostic test benefits.

## Costs

There are various types of costs associated with disease testing, such as travel time to visit hospitals, administrative costs to deal with patients, direct medical costs to treat patients, and so forth (WHO, 2003). In this research, costs of testing consist of two components: test costs and travel costs, the primary cost being the expense of the diagnostic test. While the amount of the costs can vary in Korea, if an individual gets a test that is not subsidized by the government, it costs around ₩160,000. Individuals also have to pay to travel to hospitals where tests are administered. According to the Korea Public Health Panel Study of 2017, the travel costs to procure a medical service at that time were around ₩23,583. If we adjusted that value using the price index, travel costs to get a COVID-19 diagnostic test would be about ₩24,022.

The total cost of diagnostic test is thus estimated to be ₩184,022. To estimate the cost of comprehensive diagnostic testing, we assume that the number of tests results reported ( $p$ ) is proportional to the number of diagnostic tests implemented if the test strategy does not change.

## Benefits

In this study, we consider three types of benefits. The first is averted treatment costs due to prevention. The National Health Insurance Service in South Korea has estimated that the total treatment cost for COVID-19 ranges from ₩90.4 billion to ₩98.5 billion under the assumption that the number of confirmed cases is 11,000 (the agency made this estimation in mid-May). The estimate also assumed that 50 percent of patients have mild cases, 49 percent have serious cases, and only 1 percent have critical cases (Seo, Lim, Kim, & Lee, 2020, B. G. Kim, 2020). In this paper, we assume that the ratio of patient severity of symptoms is constant in all counterfactual scenarios and calculate medical expenses per patient based on total treatment cost estimated by the National Health Insurance Service. Medical expenses per patient thus equal total treatment cost estimated by the National Health Insurance Service divided by 11,000, yielding a per patient cost of between ₩8,227,273 to ₩8,954,545.

The second is averted costs of productivity loss due to preventing infection. The averted cost of productivity loss per patient was computed by multiplying daily wages and number of work days lost due to hospitalization. We estimated each age group's daily wages by taking into account hours of work, hourly wages, and employment rates (available from Statistics Korea and the Ministry of Employment and Labor). The number of the work days lost, which was estimated to be the average

duration of hospitalization duration, information that was obtained from Korean Centers for Disease Control, is 12.7 days. The employment rate for individuals who are less than 15 is not estimated, so we assume that the employment rate for the population that is less than 20 to be zero.

**Table 3.** Productivity Statistics, 2019

Age Group	Employment Rate (%)	Number of Hours Worked	Hourly Wage (₩)	Productivity Loss per Patient (12.7 Days)
20-29	58.2	145.3/18.4	20,573	1,200,804
30-39	76.0	158.9/19.5	21,917	1,723,803
40-49	78.4	156.1/19.5	23,750	1,893,005
50-59	75.4	152.8/19.3	22,410	1,698,959
60 or above	41.5	140.9/18.5	16,760	672,767

Source: Korean Statistical Information Service, Statistics Korea, Economically Active Population Survey ([http://kosis.kr/statHtml/statHtml.do?orgId=101&tblId=DT\\_1DA7012S](http://kosis.kr/statHtml/statHtml.do?orgId=101&tblId=DT_1DA7012S)); Korean Statistical Information Service, Ministry of Employment and Labor, labor conditions by employment type ([http://kosis.kr/statHtml3/statHtml.do?orgId=118&tblId=DT\\_118N\\_LCE0004&vw\\_cd=MT\\_ZTITLE&list\\_id=101\\_ATITLE\\_10\\_A001\\_B001&seqNo=&lang\\_mode=ko&language=kor&obj\\_var\\_id=&itm\\_id=&conn\\_path=MT\\_ZTITLE](http://kosis.kr/statHtml3/statHtml.do?orgId=118&tblId=DT_118N_LCE0004&vw_cd=MT_ZTITLE&list_id=101_ATITLE_10_A001_B001&seqNo=&lang_mode=ko&language=kor&obj_var_id=&itm_id=&conn_path=MT_ZTITLE))

The third is averted costs of mortality due to prevention of infection. In 2012, the Korea Development Institute estimated the average wage loss and pain, grief, and suffering cost (PSG cost) due to emergency death (Lee, Kim, & Jung, 2012). The average wage loss was different in each age group, so we estimated the cost of mortality by age group while assuming that PSG cost is equal to all age groups, and we used the price index to adjust the costs of death. The cost of mortality per one deceased person equals the average wage loss plus PSG cost.

To calculate the total productivity loss and the total costs of mortality, we relied on the KCDC's reported distribution of confirmed cases and deceased age groups, as productivity is different from each group of people. In South Korea, more than 50 percent of those confirmed to have COVID were between 20 to 49. In contrast, 77.6 percent of those who died from COVID-19 were over 70. If we did not take the distribution into account, we would end up underestimating the total cost. Total productivity loss equals the cumulative number of confirmed cases by age group multiplied by the employment rate and daily wage by age group and the average length of hospital stay, while total productivity equals the cumulative number of cases by age group multiplied by the costs of mortality per deceased by age group.

**Table 4.** Estimation of the Cost of Mortality due to Emergency Death (in ₩)

Age Group	Average Wage Loss	PSG cost	Cost of Mortality per Deceased
1-9	257.31	97.65	354.96
10-19	365.01		462.66
20-29	457.40		555.05
30-39	473.20		570.85
40-49	389.17		486.82
50-59	247.54		345.19
60-69	118.66		216.31
70-79	41.52		139.17
80 or above	5.60		103.25

Source: Lee, Kim, & Jung (2012)

**Table 5.** Distribution of confirmed cases and deceased by age groups as of May 31, 2020

Age Group	Confirmed Cases (%)	Total Deaths (%)	Case Fatality Rate (%)
1-9	157 (1.37)	0 (0.00)	0.00
10-19	655 (5.71)	0 (0.00)	0.00
20-29	3,176 (27.69)	0 (0.00)	0.00
30-39	1,292 (11.27)	2 (0.74)	0.15
40-49	1,521 (13.26)	3 (1.11)	0.20
50-59	2,039 (17.78)	15 (5.56)	0.74
60-69	1,405 (12.25)	39 (14.44)	2.78
70-79	725 (6.32)	80 (29.63)	11.03
80 or above	498 (4.34)	131 (48.52)	26.31
Total	11,468 (100)	270 (100)	2.35

Source: Korean Centers for Disease Control and Prevention press release

Table 6 shows the summary of variables to evaluate costs and benefits for an additional diagnostic test with values adjusted according to the price index.

**Table 6.** Estimated Costs and Benefits for a Patient

	Value (₩)	Note
<b>Costs</b>		
diagnostic test	184,022	test kits plus travel costs
<b>Benefits</b>		
averted treatment cost per patient	8,227,273-8,954,545	(total treatment cost estimated by National Health Insurance Service) ÷ 11,000
averted productivity loss per patient	672,767-1,893,005	employment rates × daily wage × average hospital stay length
averted cost of mortality per deceased	103.26 million-570.58 million	average wage loss + PSG cost

## RESULTS

### Estimates Parameters of the Baseline Scenario

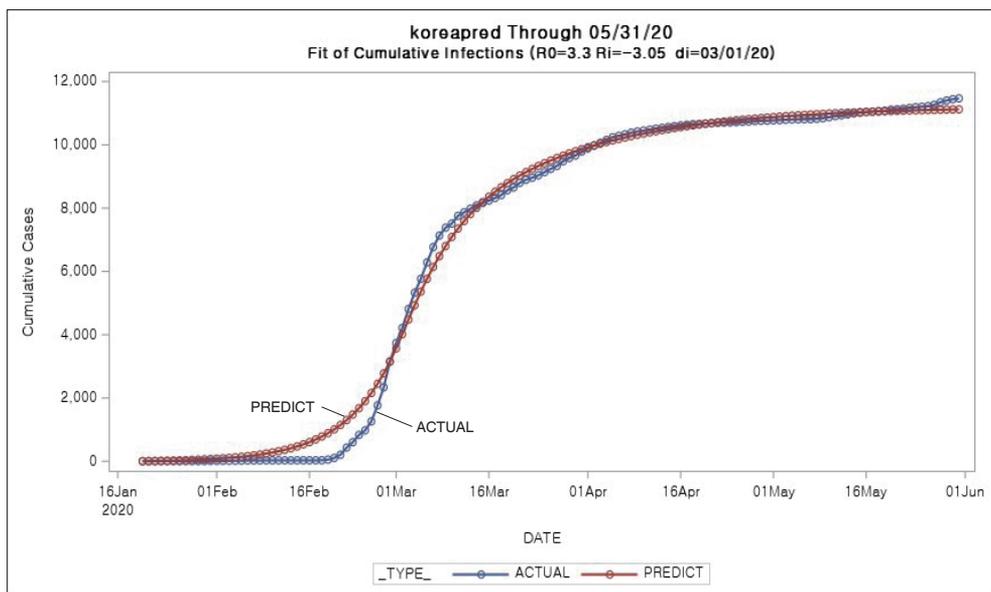
To evaluate the effect of comprehensive diagnostic testing for preventing the spread of infection, we created counterfactual scenarios in which different numbers of COVID-19 tests were administered. We compared the baseline scenario—the current number of COVID-19 tests being administered—to counterfactual scenarios. The proportion of reported cases thus also changes due to our assumption that the number of reported cases is proportional to the number of diagnostic tests administered.

**Table 7.** Estimated Parameters as of May 31, 2020

		Estimate	Standard Error	Pr> t	Wald 95% Confidence Interval
<b>Parameters</b>	basic reproductive number ( $R_0$ )	3.296	0.024	<.0001	3.248 : 3.345
	achieved change in $R_0$ ( $R_i$ )	-3.048	0.051	<.0001	-3.149 : -2.946
	mean time for the intervention to take effect	March 1	1.217	<.0001	February 27: March 03
	proportion reported ( $p$ )	0.202	0.065	0.002	0.074 : 0.331
<b>Appropriacy of Model</b>	R-square	0.9953			

Table 7 shows the estimation of the parameters of the extended SEIR model. The basic reproductive rate ( $R_0$ ) was estimated as 3.296 (95% confidence interval, 3.248 to 3.345), and the average proportion reported was 20.2%. The mean date that the intervention takes effect was assumed to be March 1, 2020. That is because the effect of interventions is not immediate due to the latency period of COVID-19.

**Figure 5.** Estimated Parameters by Daily Number of Cumulative Confirmed Cases



### Estimated Costs and Benefits

Figure 6 shows the number of confirmed cases depending on the number of COVID-19 tests administered, which varied from 80% to 120% from the baseline. The implication is that the more tests administered, the smaller the proportion of cases that go unreported. Such information could help to prevent secondary infection. In the case of testing 20% less than the baseline, the number of confirmed cases can be estimated to be 13,066, and the difference with baseline is 1,691. In contrast, the number of confirmed cases can be estimated to be 9,834 when the number of diagnostic tests increases by 20% from the baseline.

**Figure 6.** Prediction of the Number of Confirmed Cases by the Number of COVID-19 Tests Administered as of May 31, 2020

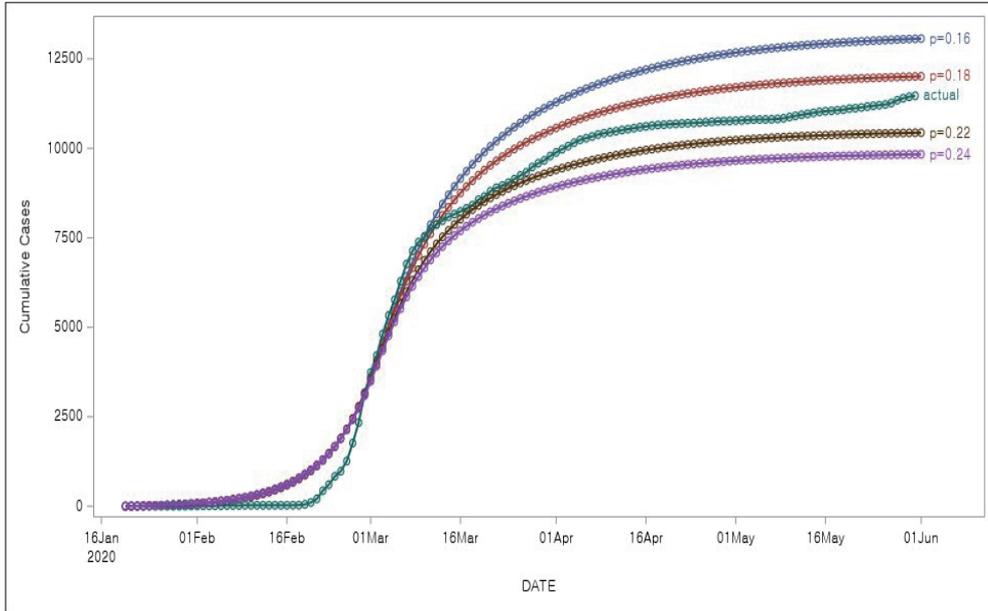


Table 8 shows the result of the cost-benefit analysis for diagnostic tests. The baseline cost of test kits was estimated to be ₩145.73 billion. The National Assembly Budget Office (2020) estimated that by June 26, 417,961 tests had been administered at a cost of approximately ₩47.3 billion. This estimation was based on health insurance claims filed by medical institutions, so the number of diagnostic tests administered and the cost is less than what we estimate in our study. Given this difference, our estimated cost is reasonable.

In scenario 1, the cumulative incidence of infection increases as the number of diagnostic tests administered decreases, resulting in negative benefits and positive costs. The total benefit is ₩-30.34 billion to ₩-12.26 billion, the total cost is ₩-36.52 billion, and the net benefit is estimated to be ₩6.18 billion to ₩24.26. In scenario 3, the increase in the number of diagnostic tests administered seems to have a positive effect in preventing the spread of the virus. The total benefit of more tests is estimated to be ₩5.79 billion to ₩21.93 billion. The net benefit is ₩-7.97 billion to ₩8.17 billion, which indicates that an increase in the number of diagnostic tests administered can be efficient, although it may also not be. However, administering too many diagnostic tests would be uneconomical even if it could mitigate the spread of the virus. In scenario 4, the net benefit was ₩-16.43 billion

to ₩-0.74 billion despite the decrease in the spread of infection. The result of the analysis implies that merely increasing the number of diagnostic tests without implementing an effective testing strategy is not economically effective when the number of infected cases continues to grow.

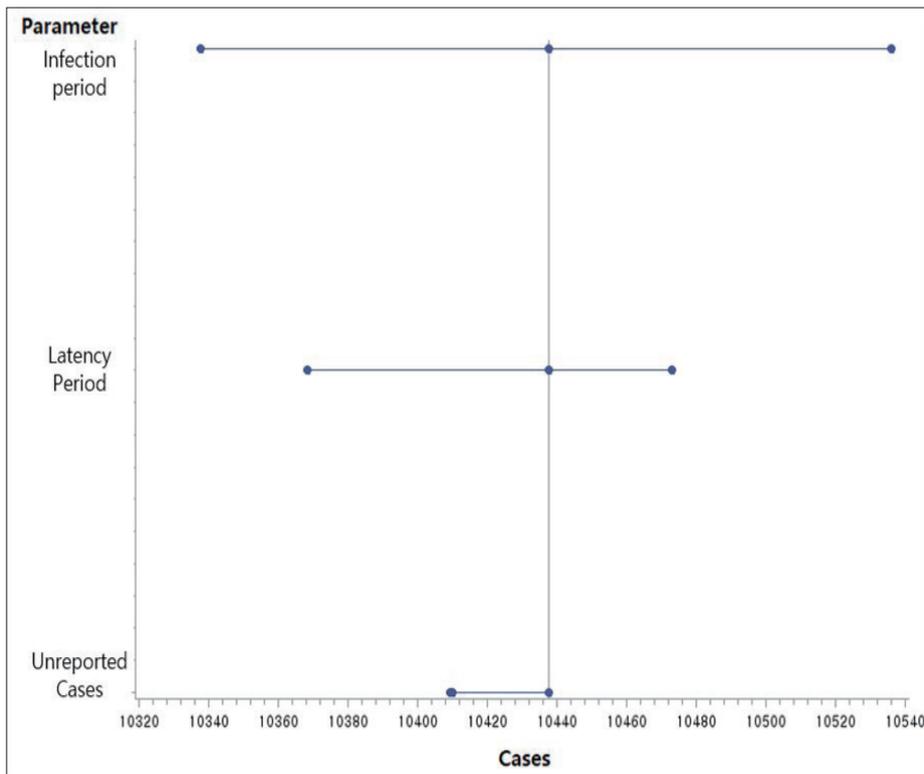
**Table 8.** Cost-Benefit Analysis for Diagnostic testing by Number of COVID-19 Tests Administered as of May 31, 2020 in Billion ₩ (\$US1 =₩1228.00 on June 1, 2020)

	Scenario 1 (80%)	Scenario 2 (90%)	Baseline (100%)	Scenario 3 (110%)	Scenario 4 (120%)
<b>Predictions</b>					
cumulative incidence	13,066.07	12,012.72	11,468	10,437.70	9,834.92
deceased estimate	307.05	282.29	270	245.28	231.12
total number of tests	728,657.6	819,739.8	910,822	1,001,904	1,092,986
proportion reported	0.161	0.181	0.202	0.222	0.242
medical expenses	107.37-117.00	98.72-107.56	94.24-102.69	85.77-93.46	80.82-88.06
valuation of human life	46.48	42.73	40.87	37.13	34.98
productivity loss	16.12	14.82	14.15	12.88	12.13
test kits	116.58	131.15	145.73	160.30	174.87
travel costs	17.50	19.69	21.87	24.06	26.25
<b>Benefits</b>					
averted medical expenses	-22.76--4.68	-13.32-3.97	-	0.78-16.92	6.18-21.87
averted Valuation of Human Life	-5.61	-1.86	-	3.74	5.89
averted productivity loss	-1.97	-0.67	-	1.27	2.02
total benefits	-30.34--12.26	-15.85- 1.44	-	5.79-21.93	14.09-29.78
<b>Costs</b>					
Test Kits	-32.15	-17.58	-	11.57	26.14
Travel Costs	-4.37	-2.18	-	2.19	4.38
total costs	-36.52	-19.76	-	13.76	30.52
<b>Benefit to Cost Ratio</b>					
net benefits (total benefits - total costs)	6.18-24.26	3.91-21.20	-	-7.97-8.17	-16.43--0.74

### Sensitivity Analysis

The number of infections prevented due to additional testing changes if we alter the parameters of the extended SEIR model. Figure 10 shows the result of the sensitivity analysis in which we increased the testing level to 110% of the baseline. The Y-axis shows the parameters of interest and the X-axis reflects the differences in the number of infected cases compared to the baseline scenario. Estimates on the left-hand side vary with one day more for the infection period, and one day less for the latency period. The difference in the number of infected cases for a given parameter value is on the right-hand side. We also consider the cases in which the initial number of unreported cases is 2 and 5 because for the baseline, we assume that the initial number of unreported cases was 0.

**Figure 7.** Results of Sensitivity Analysis



The results show that the parameter that has the most significant impact is the length of the infection period. Reducing the infection period by one day would prevent around 99 cases and increasing the infection period by one day would increase the number of confirmed cases to 98. The number of confirmed cases decreases when the infection period is shorter because that the reproductive number estimated decreases. Reducing or increasing the latency period by 1 day results in only a relatively small number of cases being prevented. When the latency period was 3.1 days, the difference between confirmed cases in this scenario and those in the baseline was 69.26. When the number of unreported cases is 2 and 5, the estimated cumulative confirmed cases as of May 31 are 10,410 and 10,409, respectively, which is slightly fewer than the baseline.

**Table 9.** Result of Sensitivity Analysis in Increasing the Test Level to 110% of the Baseline in Billion ₩ (\$US1 =₩1228.00 on June 1, 2020)

	Infection Period = 11.7	Infection Period = 13.7	Latency Period = 3.1	Latency Period = 5.1	Unreported Cases = 2	Unreported Cases = 5
<b>Estimated Parameters</b>						
R <sub>0</sub>	3.084	3.507	2.908	3.710	3.240	3.165
R <sub>i</sub>	-2.837	-3.259	-2.693	-3.448	-3.003	-2.944
D <sub>i</sub>	March 1	March 1	March 1	March 1	March 1	March 1
P	0.200	0.202	0.153	0.261	0.190	0.173
R-square	0.995	0.995	0.995	0.995	0.995	0.994
<b>Prediction</b>						
cumulative incidence	10,337.78	10,536.14	10,368.44	10,473.04	10,410.08	10,409.42
deceased estimate	242.93	247.59	243.65	246.11	244.63	244.621
<b>Cost-Benefit Analysis</b>						
net benefits (total benefits - total costs)	-6.61-9.46	-9.33-6.88	-7.03- 9.06	-8.46-7.76	-7.60-8.52	-7.59-8.53

## CONCLUSION

Although the benefit of comprehensive diagnostic testing in the response to COVID-19 is the prevention of the exponential spread of the virus, governments need to ensure that taxpayer money is being used effectively in light of resource constraints. A cost-benefit analysis of comprehensive diagnostic testing of COVID-19 helps us understand its effectiveness. Despite the importance of such a cost-benefit analysis in responding to COVID-19, the Korean government has focused on mathematical models that predict the spread of disease and has relied on the lessons learned from mismanagement of previous infectious diseases such as SARS and MERS, and on data derived from comparing the responses of different government to these epidemics. A cost-benefit analysis that evaluates the efficiency and effectiveness of the government's response in the early stages of the crisis is critical, since the COVID-19 crisis is expected to be prolonged and the government's approach early on could prove to be a burden to the national economy.

In this paper, we have considered whether the current level of COVID-19 testing is economically justifiable. According to our analysis results, if the test level were 80% of our current level (May 31, 2020), there would be net benefits of ₩6 to ₩24 billion. But if we increased the test level to 120% of the baseline, net costs would be ₩1 to ₩16 billion. Such results suggest that comprehensive diagnostic testing is effective in preventing infections but is also costly to society.

Our findings should be carefully interpreted. First, the net benefits accrued by reducing the number of tests would be smaller if we take psychological stress and the contraction of economic activities due to the growing number of infections into account. Second, the medical costs per test would be smaller owing to economies of scale and technological innovations. In such a case, the marginal gains secured by reducing the number of tests would be far smaller than we have estimated. Third, if there is a large outbreak and  $R_0$  is high, the net benefits of tests would be higher than we estimated.

Nevertheless, our paper has important implications for policy makers. First, if a country does not have enough resources to bear the net costs of comprehensive diagnostic testing, the Korean model would not be a good solution. Second, the government should not overestimate the effectiveness of the comprehensive diagnostic testing. In Korea, although the number of newly infected patients has significantly decreased below 100 per day since mid-April, the Korean government did not reduce the number of tests administered. As a result, the detection of cases per 1,000 tests dropped to below 10 in July 2020. The overreliance on the diagnostic test may discourage the search for more cost-effective policy alternatives.

**Funding:** This research was supported by ‘Economic and Fiscal Impact after COVID-19 and Government Intervention’ project funded by Center for Sustainable Public Accounting and Finance, Graduate School of Public Administration, Seoul National University.

**Conflicts of Interest:** The authors declare no conflict of interest.

## REFERENCES

- Banks, G. 2009. Evidence-based policy making: What is it? How do we get it? In K. Anderson (ed.), *World Scientific Reference on Asia-Pacific Trade Policies* (pp. 247-263). Canberra: Productivity Commission.
- Black, N., & Donald, A. 2001. Evidence based policy: Proceed with care. *BMJ*, 323(7307): 275-279.
- Brauer, F., & Castillo-Chavez, C. 2012. *Mathematical models in population biology and epidemiology*. New York: Springer.
- Chang, J. 2017. Public health disasters and the evolution of pandemic response structures: A case study of MERS in Korea. *Korean Journal of Policy Studies*, 32(1): 27-52.
- Chen, D. 2014. Modeling the spread of infectious diseases: A review. In D. Chen, B. Moulin, & J. Wu (eds.), *Analyzing and modeling spatial and temporal dynamics of infectious diseases* (pp. 19-42). New York: Wiley.
- Cleveland Clinic and SAS COVID-19 Development Team. Developer Documentation [Internet]. 2020. From <https://github.com/sassoftware/covid-19-sas>
- Comfort, L., Kapucu, N., Ko, K., Menoni, S., & Siciliano, M. 2020. Crisis decision making on a global scale: Transition from cognition to collective action under threat of COVID-19. *Public Administration Review*, 80(4): 616-622.
- Daughton, A. R., Generous, N., Priedhorsky, R., & Deshpande, A. 2017. An approach to and web-based tool for infectious disease outbreak intervention analysis. *Scientific Reports*, 7(46076): 1-10.
- Davies, P. 2012. The state of evidence-based policy evaluation and its role in policy formation. *National Institute Economic Review*, 219(1): R41-R52.
- Diel, R., & Nienhaus, A. 2019. Cost-benefit analysis of real-time influenza testing for patients in German emergency rooms. *International Journal of Environmental Research and Public Health*, 16(13): 1-16.
- Fabricius, G., & Maltz, A. 2020. Exploring the threshold of epidemic spreading for a stochastic SIR model with local and global contacts. *Physica A: Statistical*

- Mechanics and Its Applications*, 540(123208): 1-12.
- Government of the Republic of Korea. 2020. Tackling COVID-19: Health, quarantine, and economic measures, Korean Experience, March 31. Retrieved on August 9, 2020, from <https://ecck.eu/wp-content/uploads/2020/03/Tackling-COVID-19-Health-Quarantine-and-Economic-Measures-of-South-Korea.pdf>.
- Her, M. 2020. How is COVID-19 affecting South Korea? What is our current strategy? *Disaster Medicine and Public Health Preparedness*, April 3, 1-3.
- Hueston, W. J., & Benich, J. J. 2004. A cost-benefit analysis of testing for influenza A in high-risk adults. *Annals of Family Medicine*, 2(1): 33-40.
- Hyun, J. H., Lee, J. H., Park, Y. J., Jung, E. K. 2020. Interim epidemiological and clinical characteristics of COVID-19 28 cases in South Korea. *Public Health Weekly Report*, 13(9): 464-474.
- Jeong, G. H., Lee, H. J., Lee, K. H., Han, Y. J., Yoon, S., Lee, J., ... & Yang, J. W. 2020. Epidemiology and important lessons from the coronavirus disease 2019 (COVID-19) outbreak in South Korea. Preprint, retrieved on August 10, 2020, from <https://ssrn.com/abstract=3559575>
- Jung, J. R. & Lee, J. H. 2020. Superior medical tech expedites response to COVID-19 outbreak. Ministry of Culture, Sports, and Tourism, March 5. Retrieved on August 8, 2020, from <http://www.korea.net/Government/Current-Affairs/National-Affairs/view?affairId=2034&subId=5&articleId=182932>.
- Keeling, M. J., & Rohani, P. 2011. *Modeling infectious diseases in humans and animals*. Princeton, NJ: Princeton University Press.
- Kellerborg, K., Brouwer, W., & van Baal, P. 2020. Costs and benefits of early response in the Ebola virus disease outbreak in Sierra Leone. *Cost Effectiveness and Resource Allocation*, 18(1): 1-9.
- Kim, B. G. 2020. How much is virus treatment costing the government? Korea Herald, May 7. Retrieved on August 8, 2020, from <http://www.koreaherald.com/view.php?ud=20200507000738>.
- Kim, H. 2020. The impact of COVID-19 on long-term care in South Korea and measures to address it. International Long Term Care Policy Network, May 7. Retrieved on December 12, 2020, from <https://ltccovid.org/wp-content/uploads/2020/05/The-Long-Term-Care-COVID19-situation-in-South-Korea-7-May-2020.pdf>.
- Kim, H. Y. 2020. Alert for COVID-19 outbreak raised to highest level. Ministry of Culture, Sports, and Tourism, March 5. Retrieved on August 8, 2020, from <http://www.korea.net/NewsFocus/policies/view?articleId=182589>
- Kim, H. S., Kang, G., Lee, S., Yoon, C. G., & Kim, M. 2018. Cost-benefit analysis of malaria chemoprophylaxis and early diagnosis for Korean soldiers in

- malaria risk regions. *Journal of Korean Medical Science*, 33(10): 1-15.
- Kim, Y., & Kang, M. 2014. The measurement of health care system efficiency: Cross-country comparison by geographical region. *Korean Journal of Policy Studies*, 29(1): 21-44.
- Lee, D. 2015. Government administrative control tower in crisis management system: Definition, issues, and policy implications. *Korean Journal of Policy Studies*, 30(3): 125-145.
- Lee, H. J., Kim, H. Y., Jung, D. H., 2012. Prefeasibility guidelines for medical facility projects. Korea Development Institute.
- Leung, K., Wu, J. T., Liu, D., & Leung, G. M. 2020. First-wave COVID-19 transmissibility and severity in China outside Hubei after control measures, and second-wave scenario planning: A modelling impact assessment. *Lancet*, 39(395): 1382-1393.
- Li, M. Y., & Muldowney, J. S. 1995. Global stability for the SEIR model in epidemiology. *Mathematical Biosciences*, 125(2): 155-164.
- Li, X. 2004. The SARS crisis and the prospect of Chinese government reform. *Korean Journal of Policy Studies*, 18(1): 41-54.
- Lubell, Y., Reyburn, H., Mbakilwa, H., Mwangi, R., Chonya, S., Whitty, C. J., & Mills, A. 2008. The impact of response to the results of diagnostic tests for malaria: cost-benefit analysis. *BMJ*, 336(7637): 202-205.
- Mahony, J. B., Blackhouse, G., Babwah, J., Smieja, M., Buracond, S., Chong, S., ... & Goeree, R. 2009. Cost analysis of multiplex PCR testing for diagnosing respiratory virus infections. *Journal of Clinical Microbiology*, 47(9): 2812-2817.
- Ministry of Health and Welfare. 2016. The 2015 MERS outbreak in the Republic of Korea: Learning from MERS.
- Moon, M. J. 2020. Fighting against COVID-19 with agility, transparency, and participation: Wicked policy problems and new governance challenges. *Public Administration Review*, 80(4): 651-656.
- National Assembly Budget Office. 2020. NABO fiscal trends and issues 2(13).
- Ock H. J. 2020. COVID-19 testing free for all Seoul residents. *Korea Herald*, June 8. Retrieved on August 9, 2020, from <http://www.koreaherald.com/view.php?ud=20200608000784>.
- Oh, J., Lee, J. K., Schwarz, D., Ratcliffe, H. L., Markuns, J. F., & Hirschhorn, L. R. 2020. National response to COVID-19 in the Republic of Korea and lessons learned for other countries. *Health Systems and Reform*, 6(1), e1753464.
- Park, S., & Cha, Y. 2020. The moderating effect of demographic and environmental factors in the spread and mortality rate of COVID-19 during peak and stag-

- nant Periods. *Korean Journal of Policy Studies*, 35(2): 77-105.
- Pedro, S. A., Ndjomatchoua, F. T., Jentsch, P., Tcheunche, J. M., Anand, M., & Bauch, C. T. 2020. Conditions for a second wave of COVID-19 due to interactions between disease dynamics and social processes. *medRxiv*. Retrieved on August 10, 2020, from <https://doi.org/10.1101/2020.05.22.20110502>.
- Peiliang, S. U. N., & Li, K. 2020. A SEIR model for assessment of current COVID-19 pandemic situation in the UK. *medRxiv*. Retrieved on August 10, 2020, from <https://doi.org/10.1101/2020.04.12.20062588>.
- Ranjan, R. 2020. Estimating the final epidemic size for Covid-19 outbreak using improved epidemiological models. *medRxiv*. Retrieved on August 10, 2020, from <https://doi.org/10.1101/2020.04.12.20061002>.
- Roda, W. C., Varughese, M. B., Han, D., & Li, M. Y. 2020. Why is it difficult to accurately predict the COVID-19 epidemic? *Infectious Disease Modelling* 5:271-281.
- Rolland, E., Checchi, F., Pinoges, L., Balkan, S., Guthmann, J. P., & Guerin, P. J. 2006. Operational response to malaria epidemics: Are rapid diagnostic tests cost-effective? *Tropical Medicine and International Health*, 11(4), 398-408.
- Rosado, R. M., Charles-Smith, L., & Daniel, B. 2017. Control and Cost-benefit Analysis of Fast Spreading Diseases: The case of Ebola. *Online Journal of Public Health Informatics*, 9(1)
- Seo, J. W., Lim S. H., Kim, Y. J., & Lee, E. J. 2020. COVID-19 treatment in Korea cost \$57,562 per critically ill, bill charged on state. *Pulse*, May 8. Retrieved on August 9, 2020, from <https://pulsenews.co.kr/view.php?year=2020&no=471089>.
- Severens, J. L., & van der Wilt, G. J. 1999. Economic evaluation of diagnostic tests. *International Journal of Technology Assessment in Health Care*, 15(3): 480-496.
- Suputtamongkol, Y., Pongtavornpinyo, W., Lubell, Y., Suttinont, C., Hoontrakul, S., Phimda, K., ... & Day, N. 2010. Strategies for diagnosis and treatment of suspected leptospirosis: a cost-benefit analysis. *PLoS Neglected Tropical Diseases*, 4(2), e610: 1-6.
- Tan-Torres Edejer, T., Baltussen, R., Adam, T., Hutubessy, R., Acharya, A., Evans, D. B., & Murray, C. J. L. 2003. *Making choices in health: WHO guide to cost-effectiveness analysis*. Geneva: World Health Organization.
- Uzochukwu, B. S., Obikeze, E. N., Onwujekwe, O. E., Onoka, C. A., & Griffiths, U. K. 2009. Cost-effectiveness analysis of rapid diagnostic test, microscopy and syndromic approach in the diagnosis of malaria in Nigeria: Implications for scaling-up deployment of ACT. *Malaria Journal*, 8(1): 1-15.

- Wearing, H. J., Rohani, P., & Keeling, M. J. 2005. Appropriate models for the management of infectious diseases. *PLoS Medicine*, 2(7): 621-627.
- World Health Organization. 2020a. Novel coronavirus (2019-nCoV). Situation Report 1, January 21. Retrieved on December 12, 2020 from [https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200121-sitrep-1-2019-ncov.pdf?sfvrsn=20a99c10\\_4](https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200121-sitrep-1-2019-ncov.pdf?sfvrsn=20a99c10_4).
- World Health Organization. 2020b. WHO Director-General's opening remarks at the media briefing on COVID-19, March 11. Retrieved on August 9, 2020 from <https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020>.
- Yang, W., Zhang, D., Peng, L., Zhuge, C., & Hong, L. 2020. Rational evaluation of various epidemic models based on the COVID-19 data of China. *arXiv:2003.05666*. Preprint, retrieved on August, 10, 2020 from <https://doi.org/10.1101/2020.03.12.20034595>.

### APPENDIX

#### A. Change in Net Benefit by the Number of COVID-19 Tests Administered in Billion ₩ (\$US1 = ₩1228.00 on June 1, 2020)

Testing (%)	Cumulative Incidence	Deceased Estimate	Total Benefits	Total Costs	Median Net Benefits
10	35,555.87	835.56	-339.49--304.86	-153.84	-168.34
20	31,711.96	745.23	-286.65--254.85	-137.08	-133.68
30	25,760.42	605.37	-204.84--177.42	-120.32	-70.82
40	21,365.48	502.08	-144.43--120.25	-103.56	-28.79
50	18,272.09	429.39	-101.91--80.00	-86.79	-4.16
60	16,016.58	376.39	-71.08--50.83	-70.03	9.07
70	14,341.25	337.01	-47.78--28.86	-53.27	14.90
80	13,066.07	307.05	-30.34--12.26	-36.52	15.22
90	12,012.72	282.29	-15.85 ~ 1.44	-19.76	12.56
100	11,468.00	270.00	-	-	-
110	10,437.70	245.28	5.79 ~ 21.93	13.76	0.10
120	9,834.92	231.12	14.09 -29.78	30.52	-8.59
130	9,320.36	219.02	21.14-36.45	47.29	-18.50
140	8,876.42	208.59	27.24-42.22	64.06	-29.32
150	8,489.88	199.51	32.55-47.25	80.82	-40.91

