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Infectious disease control and its economic gains in a pandemic: the case of South Korea

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ABSTRACT
We investigate the role of the infectious disease control (IDC) system in curbing the spread of infectious disease and preventing economic damage during the COVID-19 pandemic. To this end, we propose incorporating a clustering analysis into the synthetic control method. This contributes to constructing a homogeneous donor pool, which is necessary for an unbiased treatment effect estimator. South Korea's effective IDC system, the so-called K-Quarantine, is estimated to have reduced the number of disease infections and to have prevented a 3.6% loss of GDP and a 0.3%p rise in the unemployment rate in South Korea in 2020. These results are robust in an alternative reduced-form regression analysis under various specifications.

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1. Introduction

Governments all over the world have been trying to flatten the curve of COVID-19 by implementing various quarantine measures. Among them, the role of infectious disease control (IDC) has been emphasised, including virus tests and contact tracing of confirmed and suspected infected people (Baldwin 2020; Baldwin and di Mauro 2020; Gourinchas 2020). It prevents secondary or higher-order infections during the disease's incubation period, curbing the spread of COVID-19. Besides, a successful IDC allows the government to adopt a low-intensity social distancing policy, eventually lowering economic sacrifices. This contrasts with the results of a high-intensity social distancing policy, such as a nationwide lockdown, which entails a substantial adverse economic impact (Figures 1, 2).

South Korea is an example of a country that efficiently controlled the epidemic in the early stages of the pandemic through an IDC system. We find that South Korea's IDC system, the so-called K-Quarantine, is still outstanding even when compared to other advanced economies in 2020 that have a similar institutional capacity concerning

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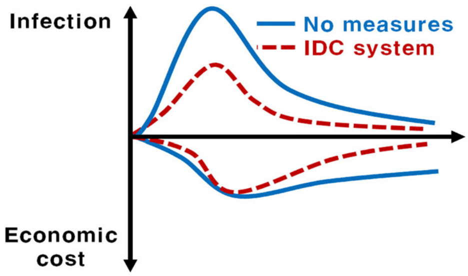

Figure 1. Infectious disease control.
Source: Authors' elaboration based on Gourinchas (2020) and Baldwin (2020).

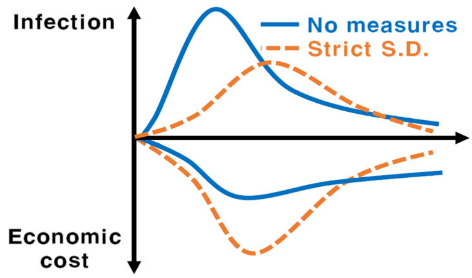

Figure 2. Strict social distancing.
Source: Authors' elaboration based on Gourinchas (2020) and Baldwin (2020).

public health and economic status. Figures 3 and 4 show that South Korea showed the highest IDC index and the lowest new infection rate per million people. This contrasts with other economies, for example, the U.S. and Sweden, where governments did not adopt an active IDC system in the early stages of the pandemic. Hence, the number of newly infected people in those countries surged by the end of 2020.

What made South Korea's fast and efficient IDC system possible? Related studies (Hur and Kim 2020) noted that a coincidental epidemic simulation was one reason, a simulation that was conducted by the Korea Centers for Disease Control and Prevention (KCDC) just before the outbreak of COVID-19. A KCDC research team tested a hypothetical scenario where a Korean family travelled to China and suffered from an unknown and highly contagious pneumonia. They simulated scenarios and discussed countermeasures to deal with infectious diseases, without specific information in advance regarding COVID-19. Shortly after the simulation, this unknown and highly contagious pneumonia spread in Wuhan, China. Thereafter, the KCDC quickly pushed for countermeasures based on its simulation and discussions[1].

A successful IDC system was, at least in part, due to luck, i.e., a simulation that the KCDC had conducted just before the real-world pandemic just about coinciding with the actual outbreak of COVID-19. Thus, we utilise this coincidental event to investigate the role of a well-functioned IDC system in curbing the spread of an infectious disease in the real world. First, we adopt a synthetic control method (SCM), as proposed by Abadie and Gardeazabal (2003) and by Abadie et al. (2010). Note that not only do we estimate the causal effects of the IDC system on the spread of the disease and the economic consequences, but we also contribute to the new methodology. We incorporate the clustering analysis method into the SCM to construct a synthetic control donor pool: candidate entities that make up the control group. After that, we conduct a reduced-form regression using high-frequency country panel data to check the consistency of the SCM results.

As a result, we found empirical evidence that an effective IDC system reduces the spread of COVID-19 and negative economic impacts in both the SCM combined with clustering analysis and in the reduced-form regression analysis. We estimate the economic gains in terms of GDP and the unemployment rate using the SCM combined with the clustering analysis. Finally, we discovered that a well-functioning IDC system prevented an additional 3.6% loss of GDP and a 0.3%p rise in the unemployment rate in South Korea in 2020.

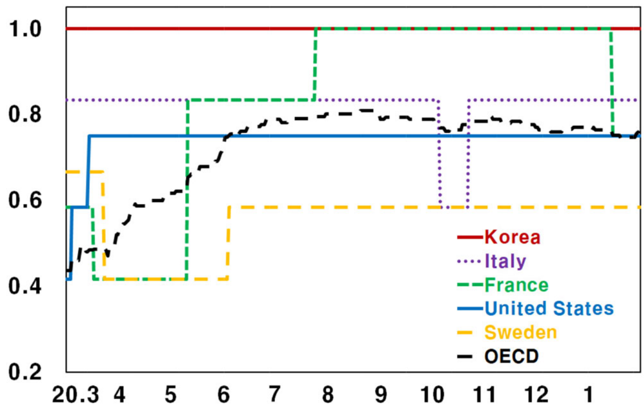

Figure 3. IDC index.
Source: Hale et al. (2020) & Author calculation.

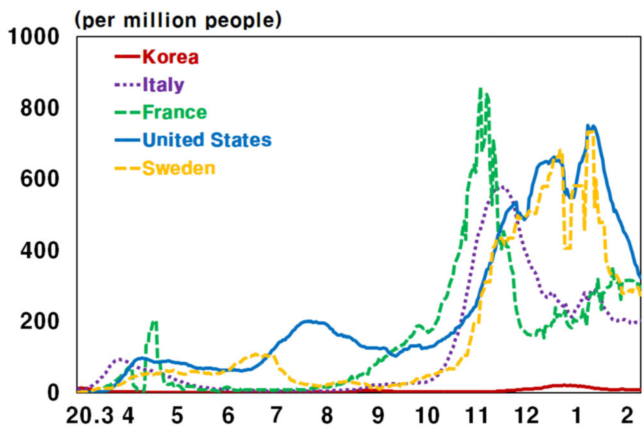

Figure 4. Daily confirmed cases.
Note: The Infectious Disease Control (IDC) Index in Figure 3 refers to the degree of testing and tracing policies calculated by the authors using data from the Oxford COVID-19 Government Response Tracker (OxCGRT). Its range is from 0 to 1, and the index number increases as IDC levels become stronger. Figure 4 shows the seven-day moving average of daily confirmed cases per million people in each country. Confirmed cases are from Our World In Data (OWID).
Source: Mathieu et al. (2020) & Our World In Data.

1.1. Literature

This article can be seen as part of a strand of literature studying factors affecting the prevention of COVID-19 and its impact on economies. For instance, Attar and Tekin-Koru (2022) studied the effects of governmental responses to COVID-19 on the spread of infection using country-panel data. Still, they did not distinguish between social distancing policies and IDC systems. Aum et al. (2021) and Baek et al. (2021) focus only on social distancing policy and found empirical evidence that it hurts the labour market. Chen et al. (2020) emphasised the importance of voluntary social distancing and IDC systems to curb the spread of disease. A series of studies have also shown that an IDC system is essential in curbing the spread of infection and reducing economic losses. Shaw et al. (2020) and Summers et al. (2020) argue that efficient testing and contact tracing, especially in East Asia, have contributed to successfully controlling infectious diseases. Also, Yalaman et al. (2021) find a significant negative association between any contact tracing policy and fatality rates from a cross-country panel data set. We perform a similar empirical analysis, but our contribution is to explicitly decompose the governmental response into both a social distancing policy and an IDC system, and to separately analyse the role of the IDC system in South Korea in 2020.

Various studies suggest that containment measures in response to the pandemic work differently depending on the characteristics of each country. For example, Gottlieb et al. (2020), who focus on the ability to work from home, say that economic sacrifices caused by lockdown measures depend on the demographic structure, education level, and income per capita. Moreover, Barrios et al. (2021) find that voluntary social distancing has been more effective in countries with higher institutional capital. Referring to these results, we estimate the causal effects of the IDC system under the control of national factors that may affect the effectiveness.

In terms of methodological aspects, Born et al. (2021) apply a synthetic control method to analyse the impact of a lockdown. They compare Sweden, which did not enforce a nationwide lockdown, with Western European countries using a synthetic control. The SCM is applied in various fields to analyse the effects of specific events. For example, Allegretto et al. (2017) applied a synthetic control to study minimum wage effects, and Bohn et al. (2014) document an effect of Arizona's immigration policy. In addition to economics, Heersink et al. (2017) and Pieters et al. (2017) apply this method in political study and in health sciences, respectively. Similarly, we use the synthetic control method to evaluate the IDC system's epidemical and economic gain. To do so, we propose an approach that incorporates the synthetic control method with the clustering analysis, a machine learning algorithm. Such incorporation improves the objectivity of the process of constructing a donor pool for the synthetic control analysis. Our approach contributes to making a homogeneous donor pool, which is necessary to get an unbiased treatment effect estimator. This application is in line with the view of Angrist and Frandesen (2022), who suggest that the machine learning method can be employed in variable selection for causal inference.

The rest of this article is organised as follows. Section 2 explains the synthetic control method incorporating the clustering analysis. We evaluate the epidemical and economic gains from a fast and efficient IDC system in Section 3. Section 4 presents the regression analysis result using high-frequency data. We conclude in Section 5.

2. Constructing a counterfactual South Korea economy

2.1. Synthetic control method: Theoretical background

Abadie and Gardeazabal (2003) and Abadie et al. (2010) propose a synthetic control method that estimates policy effects by building a counterfactual object in which the policy has not been implemented, comparing that with the actual object in which the policy intervention occurred.

Let Y_{it}^{I} be the outcome in which the policy would have been carried out, while Y_{it}^{N} is the outcome in which it wouldn't have been carried out. Suppose that the policy is implemented only to the first unit at a time $T_0 + 1$ and other units, $i = 2, \ldots, j + 1$, are not treated, as we define them as the donor pool. We can express the outcome of interest, Y_{it}, with the combination of Y_{it}^I and Y_{it}^N as below. Note that α_{1t} is a treatment effect of the policy intervention.

$$Y_{1t} = \begin{cases} Y_{1t}^N, & t \leq T_0 \\ Y_{1t}^I = Y_{1t}^N + \alpha_{1t}, & t > T_0 \end{cases}, \quad Y_{it} = Y_{it}^N, \ \forall t \ and \ i > 1 \tag{1}$$

In the synthetic control method, we usually assume that the outcome without policy implementation, Y_{it}^N, follows the linear factor model below:

$$Y_{it}^N = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \varepsilon_{it} \tag{2}$$

where δ_t is a time-fixed effect and Z_i is the individual characteristics that are invariant to policy intervention. θ_t is the vector of unknown parameters. μ_i is the unobservable factor loading. ε_{it} is an error term whose mean is 0. This linear factor model allows μ_i to vary according to time by including λ_t while conventional difference-in-difference and fixed effect panel regression models are not. Thus, we can estimate the consistent treatment effect even if unobservable and time-varying factors exist.

Let $W = (w_2, \ldots, w_{J+1})'$ be the weight vector, and then, we can express the linear factor model above as follows:

$$\sum_{j=2}^{J+1} w_j Y_{jt} = \delta_t + \theta_t \sum_{j=2}^{J+1} w_j Z_j + \lambda_t \sum_{j=2}^{J+1} w_j \mu_j + \sum_{j=2}^{J+1} w_j \varepsilon_{jt} \tag{3}$$

Abadie et al. (2010) showed that the estimated treatment effect, $\hat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}$ $(t > T_0)$, is asymptotically unbiased if the preintervention period, T_0, is large enough and there exists $w^* = (\mathrm{w}_2^*, \ \ldots, \ w_{J+1}^*)'$ satisfying below.

$$Y_{1t} = \sum_{j=2}^{J+1} w_j^* Y_{jt} \ \forall t \leq T_0, \ Z_1 = \sum_{j=2}^{J+1} w_j^* Z_j \tag{4}$$

They also showed that the synthetic control estimator could be unbiased even if we have a short preintervention period—even a single pre-treated data point—in an autoregressive setting. Suppose that the outcome variable's lagged value affects the outcome and observed predictors.

$$Y_{it+1}^N = \alpha_t Y_{it}^N + \beta_{t+1} \ Z_{it+1} + u_{it+1} \tag{5}$$

$$Z_{it+1} = \gamma_t Y_{it}^N + \Pi_t Z_{it} + v_{it+1} \tag{6}$$

where u_{it+1} and v_{it+1} are the mean zero error terms.

Similar to the previous example of a liner-factor model, they showed that the synthetic control estimator is unbiased if we have the weight satisfying below.

$$Y_{1T_0} = \sum_{j=2}^{J+1} w_j^* Y_{jT_0}, \quad Z_{1T_0} = \sum_{j=2}^{J+1} w_j^* Z_{jT_0} \tag{7}$$

In practice, however, it is hard to find exact weights that meet the above conditions in either the linear-factor model or autoregressive model. Instead, we use a weight vector that, in practice, minimises the sum of squared errors as follows.

$$W^* = \arg\min_W \sqrt{(Z_1 - Z_0 W)' V^* (Z_1 - Z_0 W)}\ , \tag{8}$$

such that $V^* = \arg\min_V \sqrt{(Y_1 - Y_0 W(V))'(Y_1 - Y_0 W(V))}$
where Z_1 and Z_0 are the predictors for the treated and control groups, respectively, and Y_1 and Y_0 are the outcomes in interest.

2.2. Construction of donor pool using clustering algorithm

Abadie et al. (2010) argue that constructing a homogeneous donor pool is essential to reduce the interpolation biases from synthetic control. The synthetic control method's basic concept is to estimate the policy effect by comparing the object under policy intervention with a counterfactual synthetic control where there are no policies enforced. Therefore, the donor pool for the synthetic control should be comprised of samples that would have homogeneous changes if the policy had not been implemented. Theoretically, the homogeneous donor pool contributes to making errors smaller from the predictor of the synthetic control, $Z_1 - \sum_{j=2}^{J+1} w_j^* Z_j$.

On the other hand, restricting the homogenous donor pool also avoids the overfitting problem, which is a crucial concern for the SCM (Abadie 2021). When using the SCM, as the size of the donor pool increases, the likelihood of overfitting increases for fixed T_0, especially if T_0 is small.[2] Consider an extreme case where we have an infinite number of candidates in the donor pool. We can construct an arbitrary outcome variable of interest, Y_{1t} $(\forall t < T_0)$, or predictors, Z_1 with the combination of idiosyncratic variations of elements of the donor pool. Thus, the synthetic control unit constructed from a large donor pool may not represent the counterfactual effect correctly, even though the synthetic control closely regenerates Y_{1t} $(\forall t < T_0)$ and predictors, Z_1, due to the overfitting problem.

In consideration of the predictor's homogeneity, previous studies usually construct a donor pool based on geographical closeness. We call this the rule-of-thumb geographic criteria. They restrict a donor pool to either a state in the same country or to countries with similar origins and cultures, such as Europe[3]. Nevertheless, we cannot apply the rule-of-thumb geographic criteria when constructing a donor pool if the above assumption does not hold. For example, South Korea is surrounded by geographic neighbours like China, Japan, North Korea, Russia, and the Philippines. Even though some of them share some cultural origins, the so-called East Asian cultural sphere, their economic and political systems are quite heterogeneous since the East Asia region was a central stage for both World War II and the Cold War. Hence, it is difficult to group them in the same donor pool, as homogeneous predictors among

Table 1. Country-specific characteristics for clustering.

Category	Attribute	Indicator
Economy	GDP per capita	
	Services	Value-added, % of GDP
	Manufacturing	Value-added, % of GDP
	Participation rate	
Demography	Total population	
	Working-age population	Population aged 15–64
	Elderly population	Population aged 65+
Social and cultural	Democracy	EIU democracy index
	Education	UNDP Education index
	Institutional level of public health	Infant mortality rate
	Urbanisation	Urban population, % of total

Source: World Bank, EIU (2020), & UNDP (2020).

neighbouring countries cannot be guaranteed. In this respect, we suggest constructing a donor pool through clustering analysis. We can reduce the analyst's subjective sampling bias by building the donor pool based on data via a clustering analysis[4].

2.3. Constructing the donor pool and synthetic control

We first construct a homogeneous donor pool for South Korea by applying a clustering algorithm and then make the synthetic control. The SCM compares one outcome where the event happened and another outcome where it wouldn't have happened. Thus, we should consider control variables carefully that may affect the impact of the IDC system on the spread of infection and on the economic outcome, to construct a controlled donor pool and, eventually, a hypothetical South Korea. It looks similar to control covariates in the difference-in-difference regression analysis to reduce the endogeneity problem from the omitted variables. As criteria for the clustering analysis, we considered three categories: (i) industrial organisation structure, (ii) demographic structure, and (iii) social and cultural characteristics. Please see Table 1.

We include GDP per capita, the labour force participation rate, and the share of the service and manufacturing sectors to capture the industrial organisation structure. First, we consider the fact that industrial organisation structure is important because COVID-19 affected the service-oriented economy more than the manufacturing-oriented economy due to the higher risk of infection in the service industry, as it requires facing people directly. Secondly, we consider the demographic structure, such as the total population and the share of working-age and older people. We should consider demographic structure because that could affect the infection spread speed, the death rate due to COVID-19, as well as changes in participation in economic activities that depend heavily on the population structure. We also controlled for social and cultural characteristics. We consider a democracy and an education index to control for the similarity of a government's ability to impose social distancing policies and people's compliance with those. Finally, we also include the institutional level of public health and urbanisation rates, as they may affect an IDC system's effectiveness and the speed of disease spread.

As a result of the clustering analysis with 151 countries that have available data regarding the above categories, we can classify countries such as Austria, Czechia, Germany, Ireland, Italy, Japan, Singapore, Slovenia, Taiwan and South Korea into one

Table 2. Results of clustering.

Donor pool by clustering analysis
South Korea, Austria, Czechia, Germany, Ireland, Italy, Japan, Singapore, Slovenia, Taiwan

Source: Author Calculation.

group. Please see Table 2. Note that many countries neighbouring South Korea are not included in this cluster, but some countries in Western or Central Europe are. This indirectly shows that the rule-of-thumb criteria do not work properly in this case. To see the effects of an effective IDC system in South Korea concerning the spread of COVID-19 and the economic outcomes, we construct a donor pool with these countries. We exclude Japan, Taiwan, and Singapore because they also implemented successful IDC programs and avoided nationwide lockdowns during the sample periods.

We synthesise the donor pool countries and construct a hypothetical South Korea with similar characteristics as the real South Korea, but one that fails to have an effective IDC program in place during the early stages of the pandemic. As explained earlier, we build a virtual South Korea using the weighted average of countries in the donor pool. We include every economic and demographic structure, and the social and cultural characteristics variable used in clustering analysis for predictor variables Z in equation (8). Then we find the optimal weights vector following the computation algorithm suggested by Kaul et al. (2021). Note that the closer the covariates Z are to South Korea, the higher the weight value. This makes it acceptable enough to compare the actual South Korea and the counterfactual. As an outcome variable, we set the variables in interest, such as the ratio of the number of infected people to the total population before the first lockdown. For example, we construct a counterfactual for South Korea's daily infected-to-population ratio by the weighted-average of Czechia (0.36), Italy (0.24), Ireland (0.18), Germany (0.13), and Slovenia (0.09), as presented in Table 3.

We can compute the counterfactuals by averaging the interested outcome variables Y (for example, the daily number of new infections) of each country in the donor pool using the weights presented in Table 3, which are the results of Equation (8). To be specific, the counterfactual outcome $Y_t^* = \sum_{j=2}^{J+1} w_j^* Y_{jt}\ \forall\ t$ where j indicates each country in the donor pool and 1 represents South Korea, and Y_{jt} is the interested outcome of country j at time t. w_j^* represents the weights for country j, as suggested in Table 3.

3. Synthetic control analysis

3.1. Daily infections

Figures 5 and 6 illustrate the virtual and real daily infection rate per million people and its log transformation, respectively[5]. We use a seven-day moving average for daily infection data and map the first day of one infection occurring per million people of donor countries to Feb. 20, 2020, when South Korea exceeded that number for the first time.

In 2020, South Korea had three waves of COVID-19. In February and March, the first wave occurred in the Daegu area, located in the southeastern part of South Korea. Daily infections surged by around 12 per million.[6] After that, the number of

Table 3. Country weights for synthetic control.

Variable	Austria	Czechia	Germany	Ireland	Italy	Slovenia
Daily infection ratio	0.000	0.361	0.126	0.183	0.242	0.088
Retail & recreation (Google mobility data)	0.000	0.277	0.000	0.042	0.680	0.001
Workplace (Google mobility data)	0.000	0.339	0.001	0.254	0.272	0.134
GDP	0.000	0.433	0.019	0.169	0.266	0.114
Unemployment rate	0.000	0.249	0.120	0.265	0.270	0.096

Source: Author Calculation.

new infections was low and stable, below 1 per million, until August 2020. It then rebounded to around 7 per million in August and September. Then it increased by almost 20 per million in December as COVID-19 spread to the Seoul metropolitan area, where about half of the Korean population is concentrated.

Even though the last wave of infections in 2020 almost doubled compared to the first wave, there was still successful prevention of the disease compared to the counterfactual results. If there had been no effective IDC process, our SCM (black line) shows that the number of new infections in the first wave would have exceeded 60 per million people, which is four times larger than the actual data. The differences between these two economies become more considerable in the second and third waves. According to our SCM analysis, the number of new infections would have surged by 570 per million in the second wave had there been no IDC system, and by 830 per million people in the third wave, which is 41 times larger than the actual data.

Additionally, the grey lines indicate outcomes based on the restricted donor pool, repeatedly excluding one or two countries from the donor pool to check for the robustness of counterfactual South Korea. Each counterfactual Korea (grey line) is re-estimated using the SCM from the various restricted donor pools. Note that if the grey lines appear along similar paths, our counterfactual is robust concerning the composition of the donor pool.

3.2. Mobility

We compare economic activity between actual and counterfactual economies by applying the SCM to Google mobility data. We focus on the categories, retail & recreation[7] and the workplace, as they are closely related to the two key economic variables, i.e., consumption and labour supply.

Figure 7 shows the time-series variation of mobility in retail & recreation activities. In the actual data, in the first wave, the mobility regarding retail & recreational activities decreased by 35% compared with the pre-COVID-19 period. It recovered to pre-COVID-19 levels until the second wave, but then it was reduced again in the second and third waves, as much as in the first wave. Workplace mobility showed a similar pattern, as above, as shown in Figure 8. It was down by around 15% at the wave's peak compared to the pre-COVID-19 level and recovered after each wave.

Now, we turn to the counterfactual results. Mobility in terms of retail & recreation activities plunged 80% in the first wave and was reduced by around 40%-50% compared to the pre-COVID-19 level in each of the second and third waves. Workplace

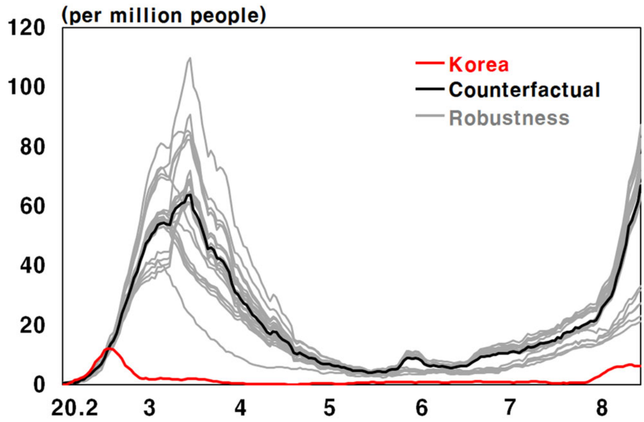

Figure 5. Daily infections (up to Aug. 2020).
Source: Mathieu et al. (2020), OWID, & Author Calculation.

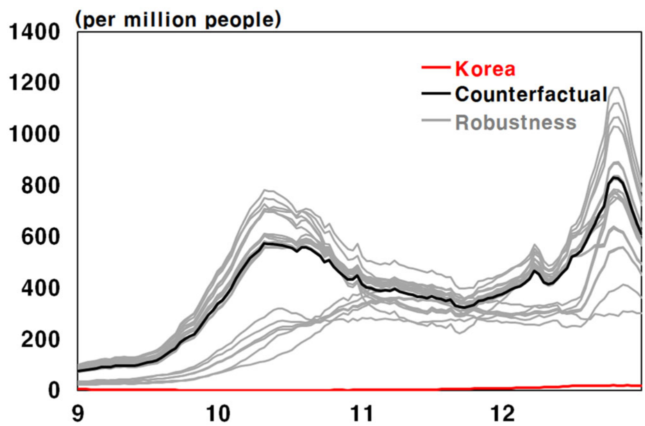

Figure 6. Daily infections (Sep. 2020 and after).
Note: Figures 5 and 6 illustrate the daily infections per million people. The red lines are the actual values of South Korea. The black lines are counterfactual outcomes. The grey lines indicate each outcome based on the restricted donor pool, repeatedly excluding one or two countries to check the robustness of the counterfactual South Korea (Born et al. 2021). The date on the X axis shows a virtual calendar tailored to the rate of infected people in South Korea. The start date is when each country hit 1 confirmed case per million people.
Source: Mathieu et al. (2020), OWID, & Author Calculation.

mobility in this virtual South Korea also decreased dramatically compared to the actual data. It was reduced to half of its pre-COVID-19 level after the first wave. It recovered a bit, but still stayed at a level of 70%-80% of the mobility seen before COVID-19. These results show a sharp contrast with South Korea's actual values, as they recovered to pre-COVID-19 levels between each wave. We notice that they were reduced at most by around 20%, even at the wave peaks.

These variations in mobility are closely related to the government's social distancing policies. Depending on the spread of the disease, the government endogenously determines the level of social distancing. During the first wave, the Korean government announced the first version of its social distancing policy, which was comparable to the third level of the current version of the five-level policy. After that, the Korean government eased social distancing to the lowest level, but they tightened it

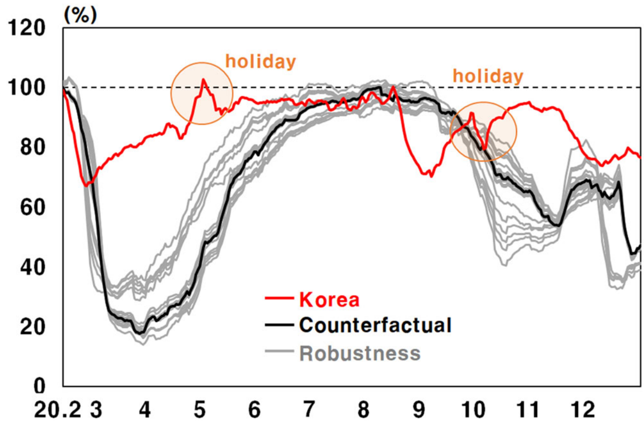

Figure 7. Mobility in retail & recreation.
Source: Google & Author Calculation.

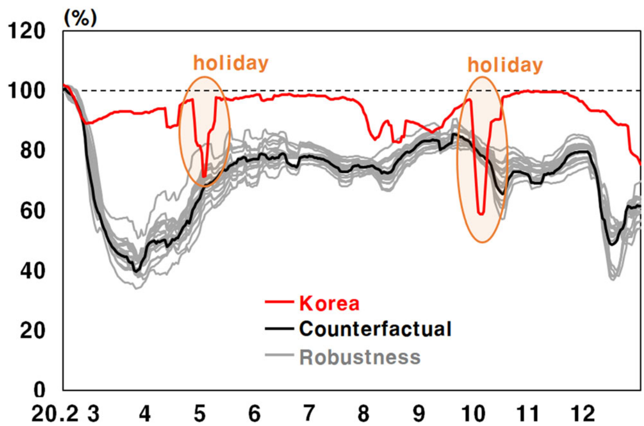

Figure 8. Workplace mobility.
Note: Figure 7 shows the mobility in retail & recreation of the actual and virtual South Koreas, respectively. Figure 8 illustrates workplace mobility. The red lines are the actual values of South Korea. The black lines are counterfactual outcomes. The grey lines indicate each outcome based on the restricted donor pool, repeatedly excluding one or two countries to check the robustness of the counterfactual South Korea (Born et al. 2021). The date on the X axis shows a virtual calendar tailored to the rate of infected people in South Korea. The start date is when each country hit 1 confirmed case per million people.
Source: Google & Author Calculation.

again to the fourth level because of the third wave, as the disease spread across the Seoul metropolitan area. However, the government has not once declared a full-on nationwide lockdown, as the IDC system has worked as planned against each wave of the virus.

3.3. Macroeconomic outcomes

We compare quarterly GDP and unemployment rates between the actual and virtual South Koreas. We find an additional 3.6% sacrifice of GDP would have occurred in 2020 if South Korea had failed to have an effective IDC system in place (Figure 9).

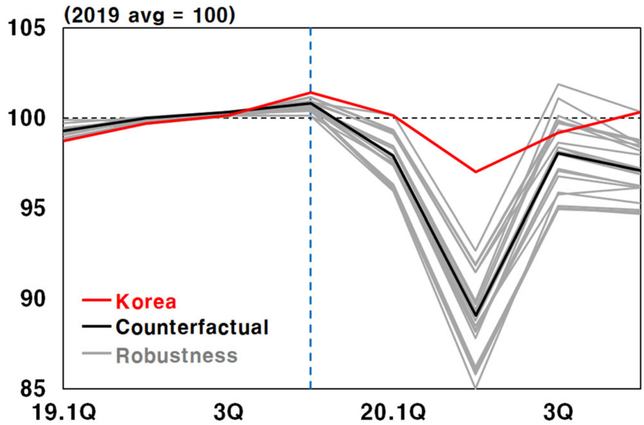

Figure 9. GDP level.
Source: OECD & Author Calculation.

The counterfactual analysis showed sizable inverse growth, minus 4.6%, which is 5.4 times larger than the actual GDP growth rate in South Korea. On the other hand, South Korea's unemployment rate was 0.3%p higher on average than in the real data in the counterfactual economy (Figure 10). These results include the effects of a more assertive social distancing policy and the voluntary restraint shown by people due to the spread of the disease, as mentioned in the previous mobility results.

Figures 11 and 12 show economic gain defined by the difference between the actual and the counterfactual economy of Korea. The grey lines indicate each outcome based on the restricted donor pool. The blue area represents a 86% confidence interval of gain in Korea, as calculated using the permutation method suggested by Firpo and Possebom (2018).[8]

4. High-frequency regression analysis

We reconfirm that the effectiveness of the IDC system shown in the previous results is captured in daily-frequency regression analysis.

4.1. Data

(1) Model-inferred DIStancing measure

As a dependent variable, the measure of preventing infection, we consider the Model-Inferred DIStancing (MIDIS) index suggested by Attar and Tekin-Koru (2022). They define and derive the MIDIS index, marked as d, from an extended SEIRD model, as in equation (10).[9] The index d_t^j measures how effectively country j prevents any further spread of an epidemic at a given level of infection at time t.

A basic SEIRD model accounts for the transition from the susceptible (S) to the exposed (E) by contact between susceptible and infected individuals with the pure probability of transmission (β). Therefore, this basic model can be interpreted as explaining the infection dynamics in a natural state without any measures to suppress the infection or restraint from contact with people. However, in reality, countries

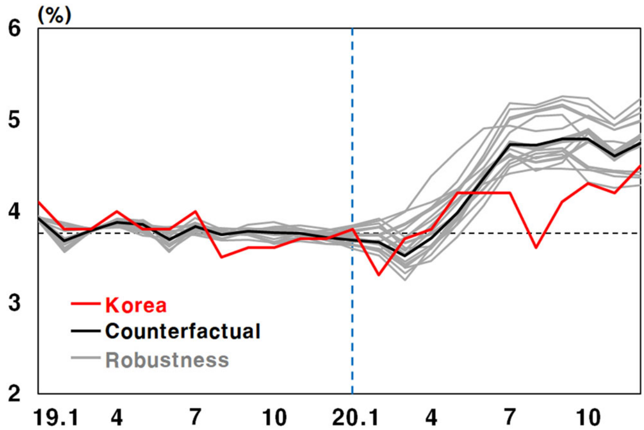

Figure 10. Unemployment rate.
Note: Figure 9 shows the GDP level of both the actual and virtual South Koreas. Figure 10 shows the unemployment rate. The red lines are the actual values of South Korea. The black lines are counterfactual outcomes. The grey lines indicate each outcome based on the restricted donor pool, repeatedly excluding one or two countries to check the robustness of the counterfactual South Korea (Born et al. 2021).
Source: OECD & Author Calculation.

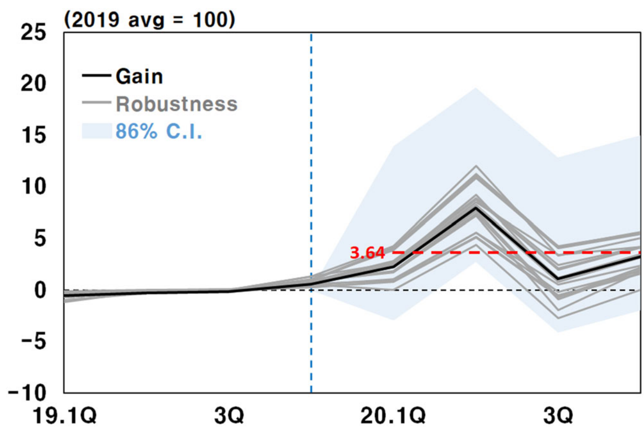

Figure 11. GDP gain.
Source: OECD & Author Calculation.

have made various efforts to slow down the infection and people have refrained from meeting, not allowing it to spread. To represent this as a model, the transmission rate is adjusted in the extended version (SEIRD). By introducing the MIDIS index, d_t^j, the prevention of the spread of infection, which is a mixture of the government's distancing policies, timely quarantine of confirmed patients, and people's refraining from going out, is expressed in the model. Using this adjustment, we can identify differences in the rate of additional spread between countries and by date at the same degree of spread.

$$(Basic\ SEIRD)\ transmission\ rate \ = \ \beta S_t^j I_t^j \tag{9}$$

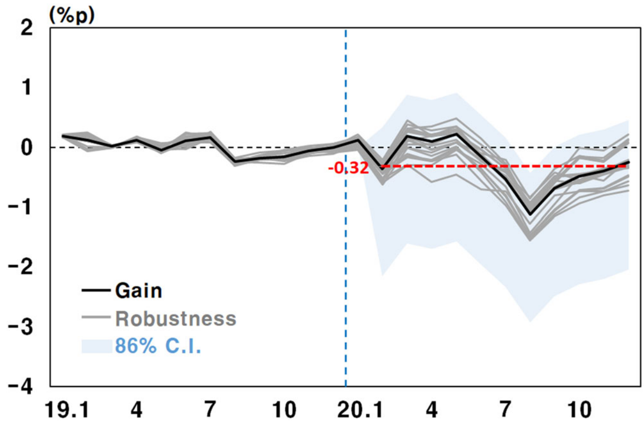

Figure 12. Unemployment rate gain.
Note: Figures 11–12 show economic gain defined by the difference between actual and counterfactual economy of Korea. The grey lines indicate each outcome based on the restricted donor pool, repeatedly excluding one or two countries to check the robustness of the counterfactual South Korea (Born et al. 2021). The blue area represents a 86% confidence interval calculated by the method suggested by Firpo and Possebom(2018)
Source: OECD & Author Calculation.

$$(Extended\ \ SEIRD)\ \ transmission\ \ rate = \zeta^j(1 - d_t^j)S_t^j(1 - d_t^j)I_t^j \tag{10}$$

where ζ^j is the country-specific transmission parameter and $d_t^j \in [0, 1]$

Note that we calculate daily MIDIS by country and utilise it as a proxy variable for curbing the spread of COVID-19.

(2) Measure of social distancing and IDC systems

Measures for the stringency of a social distancing policy and the IDC system are from the Oxford COVID-19 Government Response Tracker (OxCGRT). We use the stringency index, calculated by Hale et al. (2020), as a proxy variable for the intensity level of social distancing policy, i.e., administrative quarantine. The indicator shows compulsory containment and closure policies, such as school and workplace closures, restrictions on gatherings, and travel regulations. The higher the stringency index, the stronger the intensity of the social distancing policy.

On the other hand, we construct the IDC index using policy information about testing and tracking confirmed patients. This index is calculated by compiling the variables shown in Table 4. A high IDC index implies that a country aggressively carried out its medical quarantine.

$$\text{IDC} = \frac{1}{2}\left(\frac{\text{Testing Policy}}{3} + \frac{\text{Contact Tracing}}{2}\right) \tag{11}$$

4.2. Empirical specification and results

To see if the IDC system is effective in mitigating the spread of the virus and adverse economic outcomes, we use the following specification with a logit transformed dependent variable, such as

Table 4. Infectious disease control policies.

Name	Coding	Description
Testing Policy	0	No testing policy
	1	Only those who (i) have symptoms and (ii) meet specific criteria, e.g., core workers, those admitted to hospital, those who came into contact with a known case, and those who returned from overseas.
	2	Anyone showing COVID-19 symptoms
	3	Open public testing
Contact Tracing	0	No contact tracing
	1	Not done in any cases
	2	Done in all identified cases

Source: Oxford COVID-19 Government Response Tracker (OxCGRT).

$$y_{jt}^{Logit} = \log \frac{y_{jt}}{1 - y_{jt}} = \beta_0 + \beta_1 \overline{SocDist_{jt}} + \beta_2 \overline{IDC_{jt}} + \beta_3 \overline{VoSocDist_{jt}} \times \overline{IDC_{jt}} + X_j' \gamma + \varepsilon_{jt}$$

.

On the left-hand side, the term y_{jt} is the dependent variable. For example, MIDIS and the economic activity measure of Google's Community Mobility range between zero and one. Since an ordinary least squares model can generate predictions outside the unit interval that is the domain of the dependent variables, we adopt a logit transformed generalised least squares (GLS) model to handle the bounded nature of the dependent variable (Papke and Wooldridge 1996; Baum 2008). On the right-hand side, $SocDist_{jt}$ and IDC_{jt} are the intensity level of the social distancing policy and the IDC measures for country j, at day t, which have a unit interval, too. We take the past seven-day moving average, including the current period t represented with an upper bar in the regression equation. It reflects the uncertain time lag that the policy variation has an effect because of the four- to six-day incubation period of the virus, and also a delay in receiving the test results from the COVID-19 PCR test (Lauer et al. 2020). We also employ a seven-day moving average of deceased or confirmed cases per 1,000 people to control the level of virus spread, and also those can be proxies for voluntary social restraint, reflecting the fact that people are reluctant to engage in outdoor activities based on the number of deaths or infections. The country-specific characteristics, X_j, are time-invariant during the sample period. We controlled the continent on which the country is located, and GDP per capita, and the service sector share of GDP, for the economic status. In addition, we controlled average education levels, infant mortality, urbanisation rate, the Social Progress Index, the ratio of the population above 65 to the total population, and ethnic fractionalisation for the social and demographic statuses. Table 5 shows the basic statistics and data sources. As in Attar and Tekin-Koru (2022), we use 30 days of data after the 500th confirmed case in each country where more than 500 confirmed cases have occurred.

We estimate the above regression equation with MIDIS, the percentage change of mobility in retail and recreation from the normal time,[10] and the percentage change of mobility in the workplace from the normal time as dependent variables. In Table 6, columns (1) to (12) are the results obtained by a logit-transformed GLS estimation with a binomial distribution, as in Papke and Wooldridge (1996) and Baum (2008). We controlled IDC and Social Distance measures separately or together to

Table 5. Variable exploration.

Variable	#Obs	Min	Max	Mean	S.D	Explanation and data source
MIDIS	1,770	0.35	0.88	0.72	0.08	Provided by Attar and Tekin-Koru (2022)
Retail	1,650	0.03	1.00	0.37	0.19	Percentage of Mobility in retail and recreation compared to the normal time(=1), Google mobility.
Workplace	1,650	0.08	1.00	0.51	0.20	Percentage of Mobility in the workplace, Google mobility We normalise the normal time mobility to 1
SocDist	1,770	0.11	1.00	0.77	0.20	Stringency Index (Oxford COVID-19 Government Response Tracker, hale et al., 2020)
IDC	1,770	0.00	1.00	0.58	0.25	Infectious Diseases Control Index (Oxford COVID-19 Government Response Tracker)
Deceased per thousand	1,770	0.00	11.74	0.34	1.09	The deceased per thousand, OWID
Infected per thousand	1,770	0.30	263.29	6.47	16.32	The infected per thousand, OWID
Continent	1,770	–	–	–	–	Africa, Asia, Europe, North America, South America
Log GDP per capita	1,680	7.68	11.47	10.06	0.88	The logarithm of GDP per capita, World Bank
Service value-added/GDP	1,770	0.42	0.77	0.57	0.08	Service Value-added to GDP share, IMF
Social Progress Index	1,680	0.39	0.90	0.74	0.12	Social Progress Imperative
Human capital index	1,620	0.34	0.88	0.65	0.14	World Bank
Infant Mortality	1,770	1.90	104.30	13.77	16.69	Infant Mortality per 1,000 live births, World Bank
Urbanisation rate	1,770	0.26	1.00	0.72	0.18	Share to population, World Bank

check their effects on curbing disease and economic activity. Notice that we also controlled national attributes, X_{it}, in all specifications from (1) to (12).

Models (1) to (4) show that IDC and SocDist increase the logit transformed MIDIS. In model (4), the interaction term between IDC and SocDist has a negative coefficient, which means a diminishing marginal effect of IDC on the logit transformed MIDIS when SocDist increases. We apply the same interpretation to the marginal effect of the SocDist variable. Even though the regression results are estimated to be significant, it is still hard to interpret them directly. The dependent variables are logit transformed, and our interest is MIDIS, not logit-transformed MIDIS. Thus, we need to translate the result into an understandable form. One concern is that the marginal effects, $\frac{\partial y_{jt}}{\partial IDC_{it}}$ and $\frac{\partial y_{jt}}{\partial SocDist_{it}}$, depend not only on the estimated coefficients of IDC, SocDist, and their interaction, but also on other covariates' values (Ai and Norton 2003; Uberti 2022). For these reasons, we report the marginal effects of IDC (or SocDist) on the unit range of SocDist (or IDC), fixing the location to Asia and the other covariates at their mean values for illustration purposes.

Figure 13 shows the marginal effects of an IDC system on MIDIS computed from model (4) with an interaction term by the SocDist level. The solid line illustrates the estimated marginal effect of an IDC system, and the shaded area is the 95% confidence interval. The marginal effect of an IDC system on MIDIS is statistically different from zero and positive if the SocDist level does not exceed 0.9. Specifically, the overall marginal effect of an IDC system on MIDIS is around 0.05 to 0.20, and it gradually decreases and finally disappears as the social distancing level increases.

Table 6. Regression results.

	Logit transformed MIDIS				Logit transformed mobility (Retail)				Logit transformed mobility (Workplace)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IDC(MA)	0.36		0.25	0.77	−0.61		0.17	0.83	−0.61		0.15	1.09
	[0.27,0.44]		[0.16,0.33]	[0.43,1.11]	[-0.83,-0.39]		[-0.03,0.37]	[0.22,1.45]	[-0.81,-0.41]		[-0.04,0.33]	[0.43,1.75]
	(0.00)		(0.00)	(0.00)	(0.00)		(0.09)	(0.01)	(0.00)		(0.12)	(0.00)
SocDist(MA)		0.87	0.80	1.16		−2.99	−3.05	−2.58		−2.99	−3.05	−2.41
		[0.73,1.00]	[0.66,0.94]	[0.93,1.39]		[-3.20,-2.77]	[-3.27,-2.83]	[-3.05,-2.10]		[-3.23,-2.75]	[-3.31,-2.79]	[-2.91,-1.91]
		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
SocDist(MA) × IDC(MA)				−0.70				−0.92				−1.25
				[-1.14,-0.26]				[-1.71,-0.12]				[-2.09,-0.41]
				(0.00)				(0.02)				(0.00)
Observations	1380	1380	1380	1380	1320	1320	1320	1320	1320	1320	1320	1320

Note: The dependent variable is the logit transformed MIDIS, mobility in retail and recreation, and workplace. For independent variables, SocDist($\in [0, 1]$) indicates the intensity level of the social distancing policy. IDC($\in [0, 1]$) is the level of infectious disease control. Deceased and Confirmed are the number of dead and confirmed cases per a thousand people. We commonly control for continent and countries' characteristics regarding the social and cultural status, economic status, and population structure. See Table 5 for details about the variables. The 95% confidence intervals are in brackets and the P-values are in parentheses. See Table A2 in online appendix for the full results with all the covariates.
Source: Author Calculation.

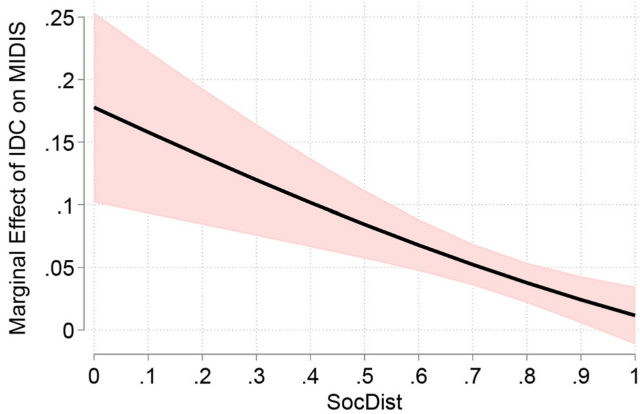

Figure 13. Marginal effects of an IDC system on MIDIS, conditional on SocDist.
Source: Author Calculation.

Figure 14 shows the marginal effects of the social distancing policy in model (4) by the level of IDC. It has a significant positive marginal effect on MIDIS, decreasing as the IDC indicator rises, but its effect does not disappear even at the maximum value of the IDC indicator.

Next, we investigate how each type of quarantine affects economic activity. We use Google's Community Mobility data as proxy variables for economic activity. Specifically, the mobility of retail & recreation is compatible with the variation in consumption, and the mobility of workplaces is a proxy for labour supply. Models (6) to (8) and (10) to (12) show that social distancing policies negatively impact logit-transformed economic activities. These results are natural and consistent with our expectations.

Meanwhile, the IDC system's intensity negatively affects logit-transformed economic activity in models (5) and (9) that only include an IDC system without any social distancing policy variable. This occurs because the omitted social distancing policy variable biases the estimated coefficients of the IDC system. However, once we include the social distancing policy variable in the regression model, the regression results show a positive coefficient of the IDC system on logit-transformed economic activity, as in models (7) to (8) and (11) to (12).

We also transform the results of models (8) and (12) with interaction terms into interpretable forms, as shown in Figures 15 to 18, respectively. Figures 15 and 17 show the marginal effect of an IDC system on mobility in retail and recreation and in the workplace. It has a significant positive marginal effect until around 0.7 of the social distancing policy level. Both IDC system marginal effects have hump-shaped curves maximised at around 0.3 for the mobility in retail and recreation and at around 0.4 for the workplace. This means that we can relieve any adverse economic impacts of a social distancing policy through a combination of an IDC system and other measures, without weakening the marginal effect of the IDC system until the degree of 0.3 to 0.4 on the social distancing policy index.

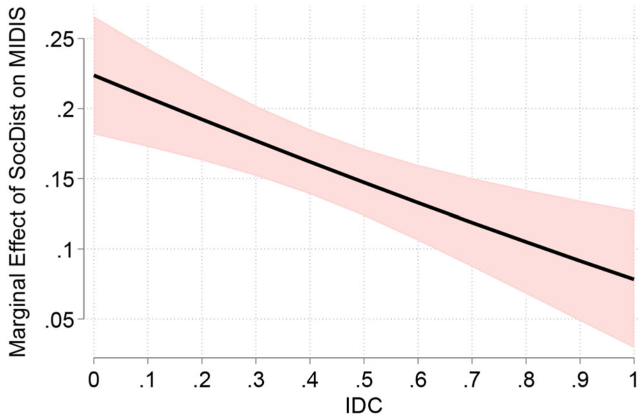

Figure 14. Marginal effects of SocDist on MIDIS, conditional on SocDist.
Source: Author Calculation.

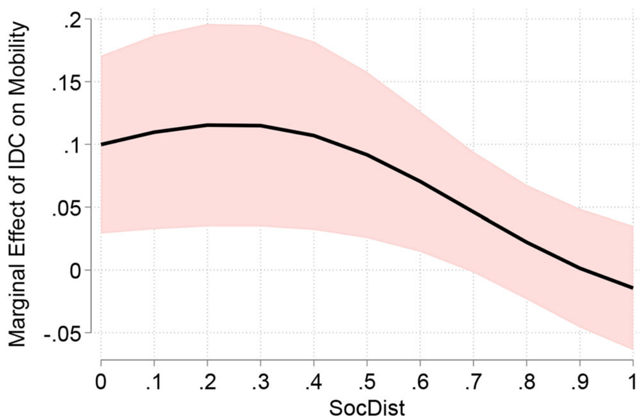

Figure 15. Marginal effect of IDC measures on mobility in retail and recreation conditional on SocDist.
Source: Author Calculation.

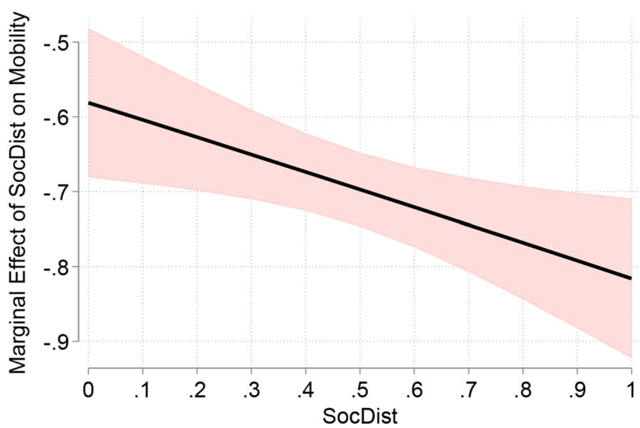

Figure 16. Marginal effect of SocDist on mobility in retail and recreation conditional on IDC measures.
Source: Author Calculation.

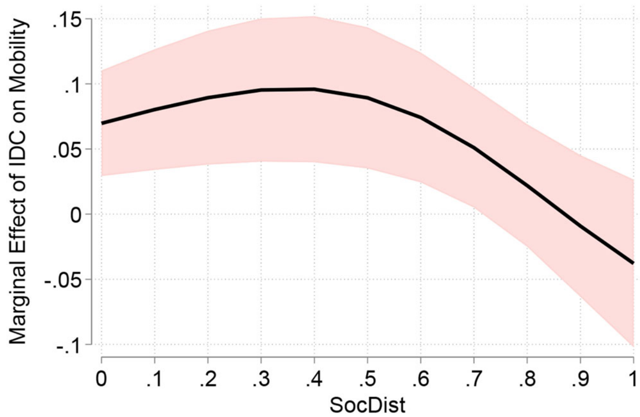

Figure 17. Marginal effect of IDC on mobility in workplace conditional on SocDist.
Source: Author Calculation.

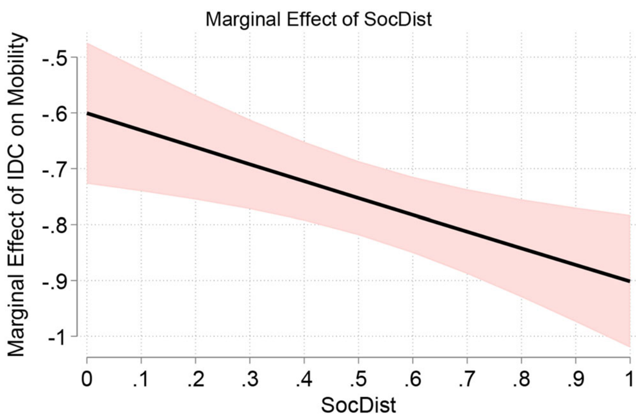

Figure 18. Marginal effect of SocDist on mobility in workplace conditional on IDC.
Source: Author Calculation.

On the other hand, the marginal effects of the social distancing policy index have negative effects on mobility, and their effects become stronger as the IDC measures increase, as in Figures 16 and 18.

We interpret these results as saying that an aggressive IDC system can complement a strong social distancing policy restricting economic activities as both measures increase MIDIS. Besides, the effect of the IDC measures on economic activity can be more substantial if we consider the second-round effect that the IDC measures curb the spread of infection and then decrease the intensity of social distancing. These results imply that both types of measures, separately, have some association with reduced coronavirus transmission. Based on these empirical results, we argue that the infection can be controlled through aggressive IDC measures with a relatively low level of administrative containment, such as a social distancing policy without any nationwide lockdown.

5. Discussion

We found that South Korea's effective IDC system in the early stages of the pandemic helped to reduce the number of COVID-19 infections and to lessen the negative economic impacts throughout 2020. If there had been no effective IDC system, the number of new cases in the first and second waves would have been four times and 75 times larger than the actual data, respectively. The IDC system also prevented a 3.6% loss of GDP and a 0.3%p rise in the unemployment rate in South Korea in 2020.

At first glance, these results seem to contradict some previous studies, such as Aum et al. (2021) and Baek et al. (2021), insisting that the social distancing policy hurts the labour market. However, our work is differentiated in that the IDC concepts here are explicitly disentangled from the government's social distancing policy. As suggested in Section 4, the strength of a social distancing policy reduces the number of new infections, but also negatively affects economic activity. On the other hand, the IDC system, which excludes any social distancing policy, reduces the number of new infections and has a positive effect on economic activity. Thus, our results support the previous studies, which argue that efficient testing and contact tracing have contributed to successfully controlling infectious disease and to reducing the economic shock from the pandemic (Chen et al. 2020; Barrios et al. 2021; Shaw et al. 2020; Summers et al. 2020; Gottlieb et al. 2020; Yalaman et al. 2021).

However, our study has limitations, as we only focus on an effective IDC system's role in the early stages of a pandemic and its short-run effects in 2020. Regarding the longer-term results, our approach cannot identify the effect of the IDC system on the rate of long-term COVID-19 infections, or subsequent economic consequences, as many other factors must now be accounted for as the pandemic continues. For example, the successful vaccine development and the increased vaccination rate dramatically decreased the number of new infections. Thus, governments all over the world relieved the stringency of their social distancing policies in 2021. However, newly-occurring variants of COVID-19, such as delta and omicron, have raised the number of new COVID-19 infections in many countries under a 'Living with Coronavirus' policy. Thus, further studies are needed in the future to analyse the longer-term effects of COVID-19.

6. Conclusion

We found that an effective IDC system contributed to curbing the spread of the disease and relieving a pandemic's economic injuries. In addition, a low-intensity social distancing policy due to an effective IDC system significantly mitigated any economic losses caused by the occurrence of COVID-19.

Based on these results, we can derive some policy implications. First, we can minimise economic costs by combining a high-intensity IDC system and a low-intensity social distancing policy, while maintaining voluntary quarantine by the people before any vaccine is developed. In line with the IDC system, we can also emphasise that voluntary social distancing is essential for successful disease control. The IDC system can be overloaded due to the failure of voluntary social distancing. In that case, economic losses would become more extreme due to the strengthening of administrative quarantines, such as nationwide lockdowns. Thus, voluntary social distancing is a necessary condition for a successful IDC system. In addition, the ‘economy’ and ‘disease control’ are not matters of choice, and quarantine policies need to be implemented keeping the following points in mind, in order to ensure economic activity: it is necessary to recognise that spending to improve an IDC system is an investment in social infrastructure, a substructure to all economic activities, and a country must maintain the highest level of medical quarantine systems.

Disclosure statement

No conflict of interest has been reported by the authors.

Notes

1. Even before the World Health Organization mentioned that the new pneumonia was due to COVID-19, the KCDC began to develop a ‘pancorona test method’ to analyse all coronavirus types, which played a crucial role in identifying patients in the early stages of COVID-19 in Korea.
2. Kaul et al. (2021) showed that if we blindly use long-period pre-intervention (large T_0) data, the bias can increase, because the covariates’ weights in the estimation decrease and the bias from the covariates does not vanish in optimization.
3. See Abadie et al. (2010) and Born et al. (2021)
4. For a detailed explanation, see A1 in Online Appendix.
5. See A3 in Online Appendix for the placebo test for the significance of the results.
6. This value is based on the seven-day moving average daily infection data.
7. The retail & recreation category includes restaurants, cafes, shopping centres, theme parks, museums, libraries, and movie theatres.
8. A 86% confidence interval is the widest range in our setting
9. See Online Appendix A2 for details about the SEIRD model.
10. We normalised the mobility in normal time to one.

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