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## Impacts of social distancing policy and vaccination during the COVID-19 pandemic in the Republic of Korea<sup>☆</sup>

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### ABSTRACT

This paper investigates the dynamic impact of social distancing policy on coronavirus disease (COVID-19) infection control, mobility of people, and consumption expenditures in the Republic of Korea. We employ structural and threshold vector autoregressive (VAR) models using big-data-driven mobility data, credit card expenditure, and a social distancing index. We find that the social distancing policy significantly reduces the spread of COVID-19, but there exists a significant, growing trade-off between infection control and economic activity over time. When the level of stringency in social distancing is already high, its marginal effect on mobility is estimated to be smaller than when social distancing stringency is low. The effect of social distancing also becomes secondary after vaccination. Increased vaccination is found to significantly reduce the critical cases while it increases visitors and consumption expenditures. The results also show that the effect of social distancing policy on mobility reduction is strongest among the population of age under 20 and the weakest among the population of age over 60.

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## 1. Introduction

The coronavirus disease (COVID-19) pandemic presented unprecedented challenges to public health and economic systems around the world. During the early stage of the pandemic,<sup>1</sup> and in the absence of vaccines, governments around the world combined physical distancing policies with stay-at-home orders, business and school closures, and restrictions on travel and mobility to reduce the virus transmission. Since then, social distancing policies have continued as an essential part of the overall strategy to contain the pandemic in many countries.

The Republic of Korea (ROK) was one of the first countries to be hit. The country witnessed a sharp rise of the confirmed cases and declared Daegu and Cheongdo—where the highly concentrated local transmissions were detected and announced—as special management zones in February 2020. While avoiding a nationwide lockdown, the ROK introduced strict social

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<sup>1</sup> The World Health Organization (WHO) declared COVID-19 as a pandemic on 11 March 2020.

distancing policies to control the virus spread. Following the successful control of this first outbreak, the government continued to manage the recurrent waves by strategically loosening and tightening social distancing measures, without forcing the whole economy to pause.

The ROK's outbreak control was considered broadly successful at least until the end of 2021. In December 2020, Bloomberg ranked the ROK as the fourth efficient health care systems based on its Health-Efficiency Index, next to Singapore; Hong Kong, China; the People's Republic of China (PRC); and Taipei, China, in the pandemic response (Miller and Lu, 2020). The ROK was one of the few countries that implemented strict border requirements instead of border closures. With these measures, international travel was still possible, although inbound travelers were subject to strict testing and quarantine rules for infection prevention and control (Ministry of Health and Welfare, 2020).

Central to the ROK's pandemic management was its social distancing policy, implemented through nationwide health campaigns which began in late February 2020. In early May 2020, the government introduced a more systematic program, wherein it classified social distancing approaches into three: Levels 1, 2, and 3. This was further specified into a 5-Level program (Levels 1, 1.5, 2, 2.5, and 3), implemented on 7 November 2020. After more than six months, the government simplified the program (to Levels 1, 2, 3, and 4) effective 9 July 2021.<sup>2</sup>

Before COVID-19 vaccines became available, social distancing was among the few options to effectively reduce the virus transmission. However, it also disrupted social and economic activities by restricting social gathering and people's mobility. This increased both the economic cost and resistance to the policy. Social distancing programs have evolved, reflecting the trade-off between infection control and economic activity. Yet, amid growing social distancing fatigue, their effectiveness has been increasingly questioned. COVID-19 is unlikely to be the last pandemic. Lessons learned today would be important in managing future health crises. In this regard, understanding the dynamic relationship between social distancing measures and their impacts on COVID-19 containment and economic activity is critical for effective policy preparedness and responses.

Literature lags due to lack of data on large scale pandemic cases and social distancing practices. This paper aims to analyze comprehensively the effectiveness and economic cost of social distancing policy during the pandemic's long duration. Existing studies tend to focus on one-sided effect of social distancing policy such as its containment effect or economic impact during a particular period, most often less than 1 year. We look at both how effectively social distancing contain the virus spread and how the effects of the measures on people's mobility and consumption spending change over recurrent pandemic waves.

Recent studies note that social distancing's effectiveness depends on various factors, particularly public behavior and economic cost. Public acceptance of the policy would wane if the economic cost of following social distancing rules were to increase and/or if restrictions were to be drawn out over a long time. More than two years into the pandemic, the effectiveness of the policy is naturally affected by social distancing fatigue and the economic cost. We contribute to the existing literature by empirically examining (i) dynamic responses of infection and economic activity (proxied by people's mobility and consumption expenditure) in recurrent pandemic waves over nearly two years, (ii) the effect of social distancing policy on infection control and mobility by different age groups, and (iii) vaccination effects on severe disease cases and economic activity.

We employ three novel data sets for the analysis of social distancing policy, people's mobility, and consumption expenditure. First, we create a daily social distancing index based on government-imposed social distancing programs. This new index measures the granularity of different social distancing measures, describing the restrictiveness of social distancing measures that the government's official programs have imposed over different levels or stringency. Second, we use daily mobility data for visitors to Seoul and Gyeonggi province (together called the Seoul Metropolitan Area) from January 2019 to October 2021, as compiled by Korea Telecom (KT). Third, we apply daily credit card usage data from the financial services company BC Card in the same area as a proxy for consumption expenditure.<sup>3</sup> We also compute weekly averages from daily data to utilize the mobility data measured by age group to capture any policy impact variation by age.

We investigate the effect of social distancing policy on both infection control and economic cost using a structural vector autoregressive (SVAR) model and a threshold vector autoregressive (TVAR) model. The estimated impulse response functions show the dynamic responses of health and economic variables to a change in social distancing policy within the vector autoregression (VAR) system, where the infection control and economic activity are two operating targets of the authority.

These empirical methods are useful and essential to capture dynamic relationships among social distancing policy, infections, and economic impacts. Indeed, several recent studies used VAR models to measure the health and economic impacts of mobility restrictions, including Arias et al. (2021). While we use VAR models to measure the impact of containment policy on health and economic outcomes, our paper are different from the earlier studies in terms of data and methodological approaches. First, we use high frequency and granular data such as daily social distancing index, daily mobility and daily credit card usage that specifically cover the geographically confined area, Seoul Metropolitan Area, to help us avoid major specification issues, while Arias et al. (2021) assessed the economic impacts of mobility policy using quarterly GDP for Belgium at the national level. Second, Arias et al. (2021) adopted a two-stage approach to address data and endogeneity issues in assessing causality. They estimated reproduction numbers, new cases, and death based on an epidemiological model and

<sup>2</sup> Each level specifies detailed guidelines with a set of rules and regulations for people, businesses, schools, and many public and commercial activities. Examples include guidelines on the number of people permitted for gatherings and protocols to be followed by establishments.

<sup>3</sup> BC Card holders comprise about 20% of market for credit cards in the ROK.

then applied a SVAR model using those estimates along with actual data for mobility, policy stringency, and economic sentiments to measure the impact of nonpharmaceutical policy interventions and trade-offs between virus containment and economic activities. While this methodology allows better generalization and application of their models where data are incomplete, the estimated variables from an epidemiological model will be subject to the accuracy of model specifications. Third, [Arias et al. \(2021\)](#) estimated a health policy equation from the SVAR model where the policy stringency level is contemporaneously affected by all of the other variables in the model assuming a positive relationship between them. Instead, we use a recursive SVAR assuming that a health policy authority mainly uses the number of confirmed cases in determining the level of social distancing policy. Fourth, we adopt a threshold vector autoregressive (TVar) model in addition to a SVAR model to capture asymmetric responses by regime.

Social distancing policy endogenously responds to the state of the pandemic in an economy, measured by the level of social infections. That is, when the social infection level, proxied by the number of confirmed people, increases, the government tightens social distancing policy. Then, people's mobility and economic activity (for example, consumption spending) decline. In such a case, the declines in mobility and economic activity can be in one part due to the increase in the infection level and in another due to the tightening of the social distancing policy. To precisely infer the effect of social distancing policy only, it is important to extract the exogenous changes in social distancing policy. SVAR models have been useful for identifying exogenous changes in policies such as monetary and fiscal policy. We also employ a SVAR model to identify exogenous shocks to social distancing policy and to infer its sole effects.

In general, social distancing policy, the social infection level, people's mobility, and economic activity interact each other dynamically. The Korean government in its public communication indicated that it considers both the social infection level and economic condition when making decisions on the level of stringency and detail measures in social distancing policy. Following its decision, the new level of social distancing stringency would influence mobility and hence infection levels. People's mobility and economic activity would be also influenced by social distancing stringency and social infection levels. Such interactions would occur recursively, while the intensity of such recursive interactions change over time. In this regard, the SVAR model can properly capture dynamic interactions among these variables under consideration.

We also employ a TVar model that allows non-linearity in responses. Effects of social distancing policy may not be uniform over time, subject to the status of the economy and varying initial conditions such as pandemic duration, existing social distancing stringency, and other factors affecting public behavior. Loosening and tightening actions may also have a different effect. The TVar is appropriate to account for such non-linear and asymmetric responses.

The results show that a tightening of social distancing policy significantly reduces the number of confirmed cases and reproduction rates ( $R_0$ ; the average number of people infected by one person). It also decreases mobility and consumption spending, and so increases economic cost. In the recurrent pandemic waves in the ROK, the responses in the number of confirmed cases have weakened while the responses in mobility and credit card spending have strengthened. This indicates that a significant and growing trade-off is experienced between infection control and economic activity. We also find that when social distancing policy is intensified, the marginal effect of a unit increase in social distancing on mobility is smaller than when measures are less restrictive. Using the weekly data with age group analysis, we find the mobility reduction is strongest among the young population of age under 20 and weakest among the old population of age over 60.

We also add analysis of the effect of vaccination programs on health and mobility during 10 March 2021 to 14 October 2021. We find that vaccination significantly contributes to a reduction in severe disease cases caused by COVID-19 while visitors and expenditure increase as vaccination rates improve. These new findings add especially to the literature on the COVID-19 vaccination, which has been limited to investigating the health effect of vaccinations rather than their economic impact.

The next section reviews the literature on non-pharmaceutical interventions and vaccinations during health crises, along with their effectiveness. Sections 3 and 4 discuss data on high-frequency visitor data and empirical modelling strategies. Section 5 then presents estimation results on the effects of social distancing policy and vaccination on COVID-19 infections, mobility, and economic activity. Section 6 concludes with policy implications derived from the estimation results.

## 2. Literature review

During the COVID-19 pandemic, a growing literature has developed on the effectiveness of policies to mitigate infections and deaths from the disease through lockdowns, canceled public events, school closures, including the wearing of masks in public. Such measures are collectively referred to as non-pharmaceutical interventions (NPIs).

Several studies find NPIs are effective for limiting mobility, which slows down the infection speed. However, some NPI measures take time to curb infections, and their effectiveness varies by country and specific measure ([Brzezinski et al., 2020](#); [Cacciapaglia and Sannino, 2020](#); [Engle et al., 2020](#); [Painter and Qiu, 2020](#); [Prem et al., 2020](#); [Thu et al., 2020](#); [Abou and Heydari, 2021](#)). For instance, [Deb et al. \(2020\)](#) find containment measures very effective in flattening the "pandemic curve," but some heterogeneity in effectiveness is observed across countries. The containment measures tend to be more effective in countries where they were implemented more quickly and in countries with lower temperatures and population density, a larger share of the elderly in total population, and stronger health systems.

Although many studies find that lockdowns and NPIs can help control infection, many factors influence their effectiveness. Economic hardship during lockdowns may compromise compliance with mobility restrictions. As the pandemic persisted, social distancing fatigue weakened policy effectiveness. [Barro \(2020\)](#) investigates the effectiveness of NPIs in 45 cities

in the United States (US) during the 1918–1919 Great Influenza Pandemic. Based on the results, he argues that NPIs were not maintained long enough to have a significant effect on reducing overall deaths. Or the containment measures may flatten the curve by merely delaying the onset of the pandemic. Similarly, a simulation by [Forslid and Herzing \(2021\)](#) shows that during the COVID-19, an early quarantine only postpones virus transmission. However, when the length of quarantine is extended, economic cost increases. In addition, delayed quarantines increase the trade-off between infection control and economic cost by leading to higher peak levels of infection and fatalities against potential economic losses. [Goldstein et al. \(2021\)](#), using panel data for 152 countries, find that lockdowns tend to reduce the spread of the virus and the number of related deaths significantly. Yet, the effect also weakens significantly after 120 days of strict lockdown. Using data on 120 countries to analyze compliance to lockdown measures, [Yeyati and Sartorio \(2020\)](#) find that lockdown compliance declines over time and is lower in economies with stricter quarantines, lower incomes, and higher labor uncertainty.

Several studies focus on which specific NPIs are more effective. [Askitas et al. \(2020\)](#) find that cancellation of public events and restrictions on private gatherings have the most prominent effects on both mobility and COVID-19 cases, followed by school and workplace closures. [Chen and Qui \(2020\)](#) find that centralized quarantine is the most effective NPI measure, followed by lockdown, school closure, and wearing masks. Meanwhile, [Haug et al. \(2020\)](#) find that less disruptive NPIs can be as effective as more intrusive national lockdowns. They find that curfews, shop and restaurant closures, mandatory working from home, and closure of schools are the most effective. In contrast, enhancing testing capacity and case detection strategy, border health checks, and environmental cleaning have been least effective. [Abouk and Heydari \(2021\)](#) find that statewide stay-at-home orders had the biggest effect on reducing mobility in the US compared with other measures such as nonessential business closures and bans on large gatherings.

Studies also find that targeted quarantine measures rather than a shotgun approach can be more effective. [Acemoglu et al. \(2020\)](#) find that strict lockdowns for the most vulnerable group (elderly) reduce infections in the US. They argue that these combined with other actions that reduce interactions between the vulnerable elderly and other people and increase testing and isolation of the infected can prevent more deaths and limit economic losses. Other studies show that social distancing measures can have more effect when combined with other interventions selectively ([Ferguson et al., 2020](#); [Li et al., 2021](#)).

Some studies have examined the effect of COVID-19 vaccination by focusing on its role in mitigating public health risks. Many find that although vaccinations have had substantial impact in protecting against hospitalizations and deaths, inoculation programs need to be complemented with NPIs ([Moghadas et al., 2021](#); [Sah et al., 2021](#); [Vilches et al., 2021](#); [Yang et al., 2021](#); [Chen et al., 2022](#)). For instance, [Moghadas et al. \(2021\)](#) estimated that vaccination reduced non-intensive-care-unit hospitalizations by 63.5%, intensive-care hospitalizations by 65.6%, and deaths by 69.3%. Others found that NPIs can be relaxed after vaccination rates reach a certain threshold ([Marziano et al., 2021](#); [Yang et al., 2021](#); [Pan et al., 2022](#)). [Pan et al. \(2022\)](#) found that a vaccination coverage of about 50% was needed for the safe relaxation of NPIs where vaccine effectiveness was about 79%.<sup>4</sup>

A few studies use real-time, high-frequency data such as mobile data to measure mobility and its responses to the virus outbreaks and policy measures. For example, [Couture et al. \(2021\)](#) used smartphone data from 23 million devices visiting 37 million venues a day to develop indexes to quantify movements and social contacts in the US. [Barwick et al. \(2020\)](#), with mobile phone records for 71 million users, employ the difference-in-difference framework to study the COVID-19 labor market impacts in Guangdong, PRC. Unemployment measures using call records to the government hotline for unemployment benefits suggest that the unemployment rate rose about 30–60% from January to September 2020. [Chen and Pope \(2020\)](#) use smartphone data covering almost 2 million users in 2016 to document cross-sectional variation in geographic movement across cities and income groups. [Engle et al. \(2020\)](#), making use of the Google mobility data from smartphones, find that US counties with a higher share of older people, a larger share of jobs that are ‘teleworkable’, a higher median income, or lower use of public transportation are also more responsive to stay-at-home orders.

The dramatic rise and fall of COVID-19 cases in the early phase of the pandemic followed by the relatively low number of confirmed cases in the ROK have also drawn research attention. With intensive contact tracing and active quarantine policies, the virus seemed to have been under control until a case without travel history and epidemiological link was reported on 16 February 2020 ([Kim et al. 2020](#)). [Lee et al. \(2021\)](#) analyze the effects of school closure, social distancing, quarantine and isolation and find the absence of social distancing leads to an epidemic wave irrespective of the model assumption for the infection risk of the exposed. In the scenario that assumes non-infectivity of the exposed, early detection and isolation are significantly more effective than quarantine. In the scenario where the exposed also contribute to infection, quarantining them is as important as isolating the infectious. [Chen et al. \(2021\)](#) find that the combined interventions of non-lockdown social distancing and testing-contact tracing can reduce the reproduction rate to less than one and rapidly contain the epidemic. [Dighe et al. \(2020\)](#), examining the ROK’s “test, trace, isolate” strategy, argue that strong social distancing measures contributed to the country’s successful outbreak control, while early adoption of testing and contact tracing was important.

[Arias et al. \(2021\)](#) are one of a few studies using SVAR models with a focus on health and economic impacts and their tradeoffs of lockdown. They find that a positive stringency shock leads to a reduction in deaths at a small cost in terms of GDP. Among other studies using VAR models, [Raifu et al. \(2021\)](#) find that an increase in lockdown stringency has an

<sup>4</sup> The US Centers for Disease Control and Prevention describes vaccine effectiveness as a measure of how well vaccination protects people against outcomes such as infection, symptomatic illness, hospitalization, and death. It is typically measured through observational studies designed to estimate individual protection from vaccination under “real-world” conditions.

immediate negative effect on the stock market returns in Nigeria. [Klose and Tillman \(2022\)](#) find the same using a sample of 92 countries in a panel VAR model. [Mamatzakis et al. \(2022\)](#) assess the impact of lockdowns on household debt using a global neural networks panel VAR.

### 3. Data

We collected daily data for people's mobility, credit card spending, confirmed cases, and reproduction rates from 20 February 2020 to 14 October 2021; critical cases from 24 July 2020 to 14 October 2021; and vaccination rates from 10 March 2021 to 14 October 2021. For the weekly data, mobility measure by age group is added to analyze policy impact by age.

We used big-data driven mobility data from Korea Telecom (KT). The mobility is shown as the number of visitors to Seoul and Gyeonggi Province, together called the Seoul Metropolitan Area (SMA) which accounts for a majority share of confirmed cases in the ROK.<sup>5</sup> The number of visitors draw from the long-term evolution signal data that KT collects. The data serve as a reliable representative sample as the KT users account for 25% (17.4 million) of total mobile phone subscribers in the ROK.<sup>6</sup> Statistical methods are applied to estimate the entire visitor populations.

Data sets for analysis include the number of resident visitors and nonresident visitors at a district level at a daily frequency from 20 February 2020 to 14 October 2021 and at a weekly frequency from 7th week of 2020 to 41st week of 2021.<sup>7</sup> The weekly data additionally contain the number of visitors by age group. Resident visitors are defined by those who (i) live or work within a district, (ii) do not frequently or periodically visit tourism sites in the district (8 or fewer visits per month), and (iii) stay in the district for more than 10 minutes or stay in a tourism site for more than 30 minutes. Nonresident visitors are defined by those who (i) do not live or work within a district, (ii) do not frequently or periodically visit the district (3 or fewer visits per month), and (iii) stay in the district for more than 10 minutes or stay in a tourism site for more than 30 minutes.<sup>8</sup>

We also obtained daily credit card (BC card) expenditure data for Seoul and Gyeonggi province from the Data Lab of Korea Tourism Organization ([Korea Tourism Organization, 2021](#)). Credit card spending is a good proxy for private consumption as it is the top mode of payment in the ROK, accounting for more than 70% of payments for private consumption expenditure. The data include aggregate spending by BC credit card holders. It is worth noting that mobility data and credit card spending data are from separate sample groups. Daily confirmed COVID-19 cases and critical cases, reproduction rates were downloaded from Our World in Data ([Ritchie et al., 2020](#)). Vaccination rates were from the Open Government Data portal of the Ministry of Interior and Safety ([Ministry of Interior and Safety 2021](#)).

[Fig. 1](#) shows that the changes in the number of resident visitors and nonresident visitors to SMA generally move in the same direction but there are a few periods when they diverge. The changes in resident visitors tend to stay in positive territory except for several periods with caseload spikes in the first year of the pandemic whereas nonresident visitors continue to show negative growths throughout the periods. This implies that the pandemic hit hard long-distance leisure trips where short-distance leisure trips thrived even during the health crisis. Credit card spending tend to move together with the total number of visitors.

The ROK experienced three distinct outbreaks since February 2020 before its vaccination drive picks up speed in June 2021. The COVID-19 vaccination began on 26 February 2021, but due to vaccine shortages in the early stage, vaccination made slow progress until mid-2021. The last outbreak in the sample coincides with a rapid pick up in vaccination.

While the COVID-19 situation remained largely under control during the sample period, sporadic surges continued in often geographically or socially concentrated areas. The government combined efforts with government agencies and local government units to continually adapt to the changing situations.

The official social distancing programs in ROK have changed a few times during the pandemic, which makes it challenging to use the original data for an empirical analysis. To precisely measure the level of social distancing level in SMA, we first created a (new) normalized five-scale index by matching and linking different levels in each social distancing program so that it is comparable throughout the analysis period.<sup>9</sup> Then, a more refined social distancing policy index (SD) was constructed to adjust minor policy intensity changes within the same social distancing level. The adjustment was made using detailed public information such as press releases from the Central Disaster and Safety Countermeasures Headquarters. Most

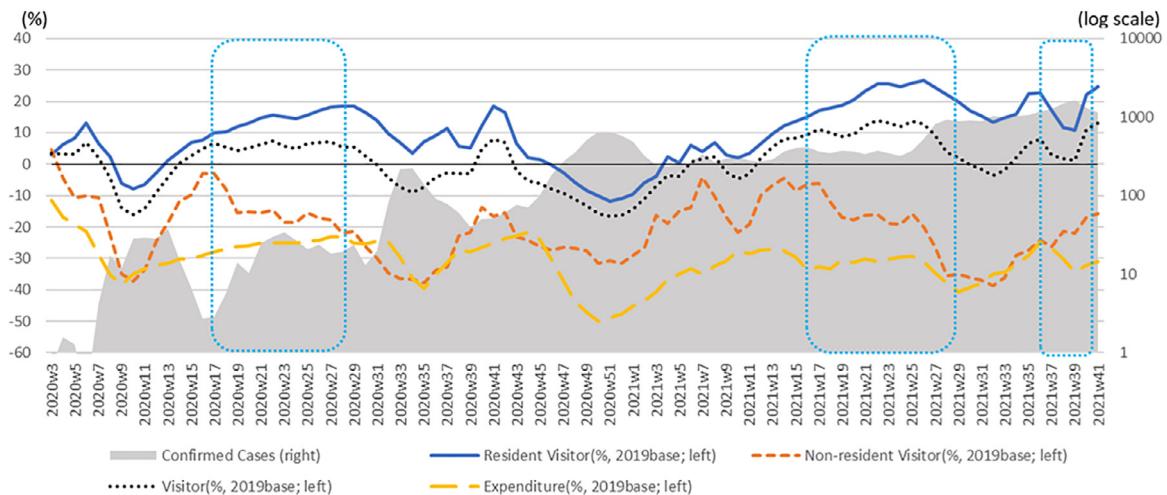
<sup>5</sup> As of 6 October 2021, Seoul had 104,723 confirmed cases, while Gyeonggi 94,107 cases. These accounted for 63% of the total confirmed cases in the ROK at the time.

<sup>6</sup> Unlike the older call detail record (CDR) data, which is irregularly generated and has a large gap between data points, the long-term evolution signal data are generated every 5 minutes on average, even when a mobile phone is not being used. Thus, it is a more powerful tool in capturing accurate movement patterns as it generates 7,000% more data than CDR.

<sup>7</sup> There are 42 districts (called *Si* or *Gun*) in Gyeonggi Province, and 25 districts (*Gu*) in Seoul.

<sup>8</sup> Mobility measure for SMA is also available in Google's Community Mobility Reports. The measure is calculated based on the changes in the number of visits and length of stay using the 5-week period, Jan3-Feb 6, 2020, as a baseline. It is available for 6 places: retail & recreation; grocery & pharmacy; parks; transit stations; workplaces; and residential. However, the mobility measure developed by KT contains the number of unique visits by resident and non-resident visitors as well as by age group, therefore offering better demographic profile. Google data represent a sample of Google users who chose to participate in data collection while KT's mobility data represent visitor populations estimated from their service subscribers.

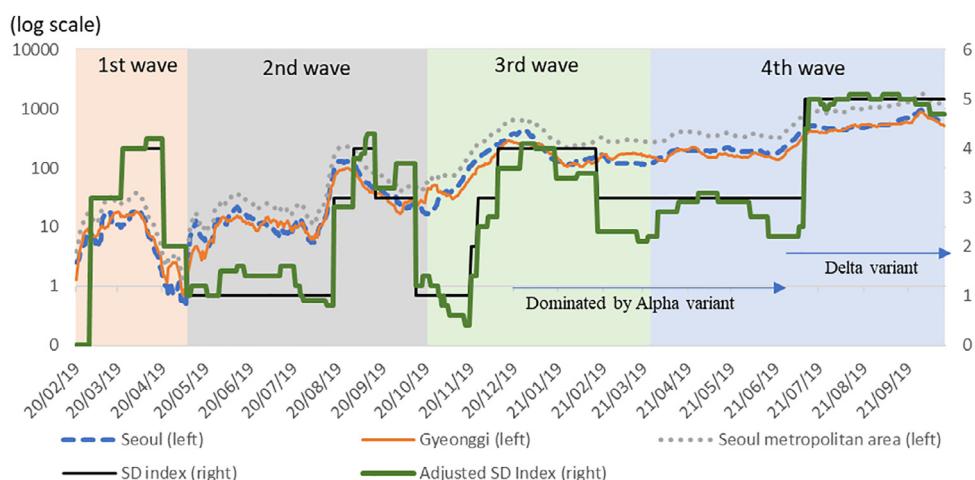
<sup>9</sup> Seoul Metropolitan Area is the metropolitan area of Seoul, Incheon, and Gyeonggi Province. It is one of the major target regions for the social distancing policy in Korea. This paper uses Seoul Metropolitan Area for analysis to term a geographical unit that covers both Seoul and Gyeonggi province.



**Fig. 1.** Weekly Trends of Average Daily Confirmed Cases, Visitors, and Credit Card Expenditure (Seoul Metropolitan Area)

Note: All variables, except for confirmed cases, exhibit growth rates compared to the same period in 2019.

Source: Authors' calculations using the data from Korea Telecom; and Korea Tourism Organization. Data Lab. <https://datalab.visitkorea.or.kr/datalab/portal/main/getMainForm.do> (accessed 27 October 2021).



**Fig. 2.** Confirmed Cases and Social Distancing Levels

SD = social distancing policy index.

Note: The COVID-19 phases are divided into the first to the fourth wave based on when the number of confirmed COVID-19 cases and the social distancing policy reached to local minimums after a local maximum of the number of confirmed cases: the first wave is from the beginning of the COIVD-19 pandemic to 5 May 2020, the second wave from 6 May 2020 to 19 October 2020, the third wave from 20 October 2020 to 23 March 2021, and the fourth wave from 24 March 2021, to the end of the analysis period. The periods by variant are based on information from public releases and news reports.

Source: Authors' calculations using the data from the Central Disaster and Safety Countermeasures Headquarters; and Korea Telecom.

adjustments led to  $\pm 0.1$  to  $0.5$  changes in SD. Minor policy changes include introducing quick response (QR) code-based entry logs (+0.1), banning gathering in entertainment spots such as discotheques, nightclubs and cabarets (+0.2), allowing high school seniors to return to school (-0.2), and easing restrictions on entry to concerts and sports stadiums (-0.4), to list a few.<sup>10</sup> Fig. 2 presents the new index and the refined index for social distancing policy in SMA.

For the purpose of analysis in this paper, we constructed a unique social distancing index for SMA. This has several advantages over Oxford's stringency index (Hale et al., 2021) which is more commonly used for cross-country analyses. First, our measure captures the level of social distancing in SMA while the Oxford stringency index is available only at the national level. In Korea, social distancing measures are defined and implemented at regional and local government levels. Second, Korea's social distancing policy underwent a few revisions in its structure during the sample period. This makes it difficult to conduct temporal comparison across different time periods during the full sample period. Therefore, there is a

<sup>10</sup> In the appendix, Table A1 describes how the normalized index was constructed by matching different social distancing schemes and Table A2 lists minor adjustments made to the normalized index following the government announcements.

strong case for devising a new standardized measure by accommodating different social distancing policy regimes during the sample period in a more consistent manner. Third, our social distancing index incorporated all minor policy adjustments that occurred daily or weekly even within the same social distancing regime. For example, in July 2021 (4th wave), the government implemented social distancing measures that had been the most stringent since the start of the COVID-19. Fig. A1 in the appendix, however, shows that the Oxford's stringency index remained at a relatively low level during the period. There is also an occasion in August–September 2020 when the stringency index and our social distancing index moved in the opposite direction.

#### 4. Empirical models

We assume a structural vector autoregressive (SVAR) model where the variables of interest are presented in a structural form equation:

$$A_0 y_t = c + A(L)y_{t-1} + \varepsilon_t \quad (1)$$

where  $y_t$  is an  $n \times 1$  vector of  $n$  endogenous variables,  $A_0$  denotes a matrix containing contemporaneous interactions among the variables,  $A(L)$  are a matrix polynomial in the lag operator  $L$ ,  $y_t$  is an  $n \times 1$  data vector, and  $\varepsilon_t$  is an  $n \times 1$  structural disturbance vector. By assuming that structural disturbances are mutually uncorrelated and  $\text{var}(\varepsilon_t) = \Lambda$ .  $\Lambda$  is a diagonal matrix where diagonal elements are the variances of structural disturbances.

To recover the structural form of the VAR, we begin with the reduced form as follows:

$$y_t = c + B(L)y_{t-1} + u_t \quad (2)$$

where  $B(L)$  are a matrix polynomial in the lag operator  $L$ ,  $u_t$  is a vector of the reduced-form residuals at time  $t$  and  $\text{var}(u_t) = \Sigma$ . In general, reduced-form residuals are linear combinations of the structural disturbances as follow:

$$\varepsilon_t = A_0 u_t \quad (3)$$

which implies:

$$\Sigma = A_0^{-1} \Lambda A_0^{-1} \quad (4)$$

Following Sims (1980), we impose recursive zero restrictions on contemporaneous structural parameters by applying Cholesky decomposition to the  $\Sigma$ . In this case,  $A_0$  becomes a lower triangular matrix.

In our empirical model,  $y_t$  includes four variables at either daily or weekly frequency: (i) the number of confirmed cases, (ii) the social distancing policy index (SD), (iii) the number of total, resident, or nonresident visitors to SMA, and (iv) the credit card expenditure. A logarithmic transformation is applied for the number of confirmed cases, mobility, and expenditure, and then multiplied by 100. Seven lags are included in the daily models, and 4 weeks are included in the weekly models. Seven dummy variables for each day of the week are also included in the daily models. For the last 7 months in the analysis when COVID-19 vaccination was administered, we use six variables to assess the impact of vaccination by adding critical cases and vaccination rates.

It is particularly interesting to assess the effects of SD shocks on the three variables: the severity of pandemic, mobility, and credit card expenditure. As we assume the number of confirmed cases is contemporaneously exogenous to SD, this model ordering implies that we exclude endogenous response of SD to the number of confirmed cases. In addition, SD is assumed to be contemporaneously exogenous to mobility and credit card expenditure. In other words, the number of confirmed cases would affect SD immediately while it would take a while before renewed SD affects the number of confirmed people. Changes in SD would first affect mobility, consumption expenditure, and then the number of confirmed cases. However, it requires some time for the infected to show symptoms and get tested before they count in the number of confirmed cases. SD may respond to economic activity (proxied by consumption expenditure), but it would again take some time before getting reflected in economic variables to influence the decision on SD as most economic data are announced with a lag of several weeks. Alternative identifying assumptions are tested for robustness in Section V.

In addition, a threshold vector autoregressive (TVAR) model is considered to capture any asymmetric responses depending on the regime. We assume the following structural threshold form equation:

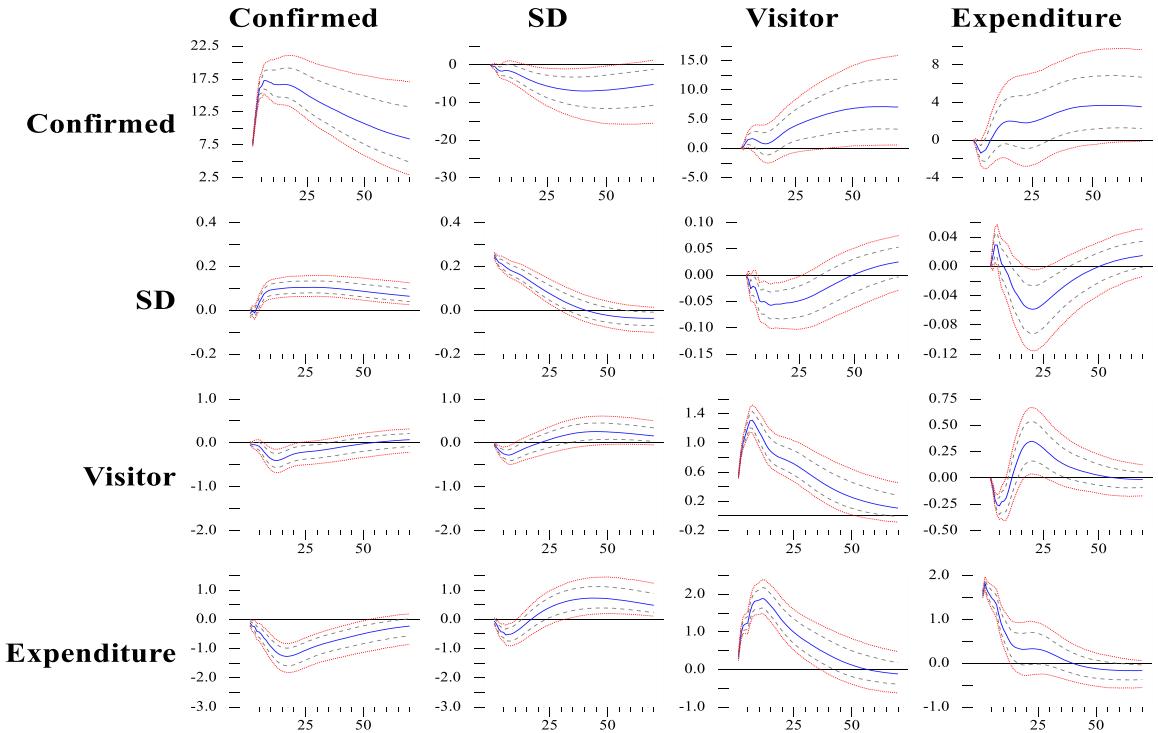
$$y_t = A^1 y_t + B^1(L)y_{t-1} + (A^2 y_t + B^2(L)y_{t-1})I(c_{t-d} > \gamma) + \varepsilon_t \quad (5)$$

where  $y_t$  is an  $n \times 1$  vector of  $n$  endogenous variables,  $B^1(L)$  and  $B^2(L)$  are a matrix polynomial in the lag operator  $L$ , and  $\varepsilon_t$  is an  $n \times 1$  vector of structural disturbances.  $c_{t-d}$  is the threshold variable that determines the regime, and  $I(c_{t-d} > \gamma)$  is an indicator function that equals 1 when  $c_{t-d} > \gamma$ , and 0 otherwise. We consider SD as the threshold variable,  $c_{t-d}$ .

In addition to the lag polynomials changing across regimes, contemporaneous relationships between variables may change as well.  $A^1$  and  $A^2$  reflect the “structural” contemporaneous relationships in each regime. We also impose recursive zero restrictions on contemporaneous structural parameters as in the baseline model.

The computation of impulse response functions of TVAR follows Koop et al. (1996). The nonlinear IRF structure of the model are defined as

$$NIRF_y(k, \Omega_{t-1}, \varepsilon_t) = E[y_{t+k} | \Omega_{t-1}, \varepsilon_t] - E[y_{t+k} | \Omega_{t-1}] \quad (6)$$



**Fig. 3.** Impulse-Response: Daily, Seoul Metropolitan Area, Total Visitors, SVAR

SD = social distancing policy index, SVAR = structural vector autoregression.

Note: The dashed and dotted lines are 68% and 90% probability bands, respectively. Each small chart represents the response of a variable in a given row to a one-standard-deviation shock in a variable in a given column.

Source: Authors' calculations.

where  $y_{t+k}$  is an  $n \times 1$  vector of  $n$  endogenous variables at horizon  $k$ ,  $\Omega_{t-1}$  is the information set before the time of shock  $t$ .

Eq. (6) implies that the impulse response depends on the initial conditions and that there is no restriction regarding the symmetry of the shocks. Moreover, in the less intense social distancing policy regime, the size of the policy shock matters since a small shock is less likely to induce a change in the regime. Therefore, the impulse responses function for TVAR model is conditional on the entire history of the variables and the size and direction of the shock.

We construct the nonlinear IRF using the bootstrap procedure like Balke (2000). We calculated the conditional expectations by simulating the model. We randomly draw vectors of shocks  $\varepsilon_{t+j}$ ,  $j = 1$  to  $k$  and then simulate the model conditional on an initial condition ( $\Omega_{t-1}$ ) and a given realization of  $\varepsilon_t$ . We repeat the simulation for  $-\varepsilon_{t+j}$  to eliminate any asymmetry that might arise from sampling variation in the draws of  $\varepsilon_{t+j}$ . This is repeated 500 times, and the resulting average is the estimated conditional expectation.

In addition to a 4-variable TVAR model, we also consider a 3-variable TVAR model only with the number of confirmed cases, SD, and mobility to save the degree of freedom in an analysis by age group using weekly data.

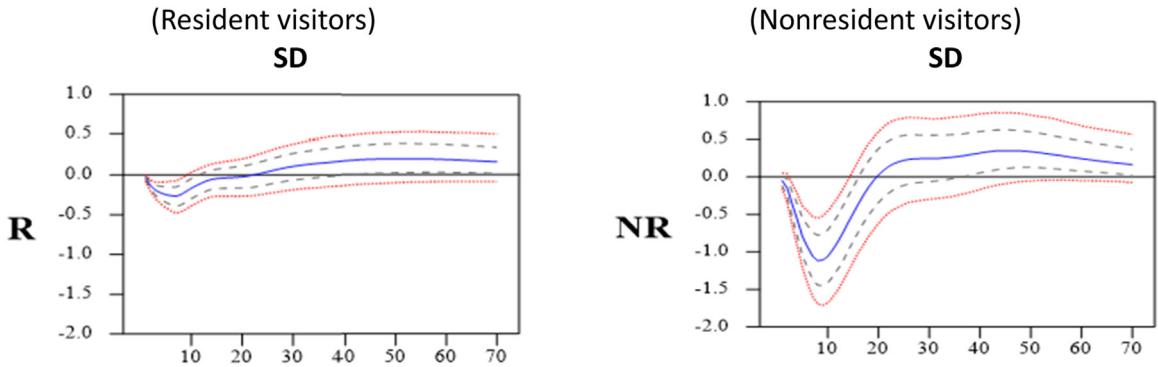
## 5. Results

### 5.1. Models with daily data

#### 5.1.1. Structural vector autoregression

Fig. 3 shows the impulse response from the four-variable SVAR model. The second column presents impulse responses to tightening social distancing policy shocks in SMA.

The impulse responses suggest that a tightening of social distancing policy by one standard deviation starts to decrease the number of daily confirmed cases in 18 days and its impact lasts for 56 days significantly at the 95% level. The maximum decrease of 7% is found in about 40 days. In addition, the number of visitors to SMA significantly decreases for the first 9 days, recovering to the original level at day 20 after the SD shock. Credit card expenditures show a significant decline



**Fig. 4.** Impulse-Response: Daily, Seoul Metropolitan Area, Resident/Nonresident Visitors, SVAR

NR = nonresident visitors, R = resident visitors, SD = social distancing policy index, SVAR = structural vector autoregression.

Note: The dashed and dotted lines are 68% and 90% probability bands, respectively.

Source: Authors' calculations.

from day 3 to 10, then quickly recovered to its initial level and increased thereafter.<sup>11</sup> The results suggest a trade-off exists between infection control and economic activity. Implementing the social distancing policy substantially reduces the number of confirmed cases and its impact lasts long. Its effect on credit card expenditures is also significant, but short-lived, which reflects the release of pent-up demand.

To assess the trade-off in a quantitative manner, we calculated the ratio of the gain and loss from social distancing where the gain is defined by declined confirmed cases and the loss by decreased mobility (or expenditure). The cumulative ratio is calculated, as shown below, using average percentage changes over the period of time since the tightening of social distancing measures:

$$\text{Cumulative Ratio}_{\text{mobility}} = \frac{\sum_{t=0}^T \Delta \text{Mobility}_t}{\sum_{t=0}^T \Delta \text{Confirmed}_t} / \frac{\overline{\text{Mobility}}}{\overline{\text{Confirmed}}} \approx \frac{\sum_{t=0}^T \Delta \log(\text{Mobility}_t)}{\sum_{t=0}^T \Delta \log(\text{Confirmed}_t)}$$

$$\text{Cumulative Ratio}_{\text{expenditure}} = \frac{\sum_{t=0}^T \Delta \text{Expenditure}_t}{\sum_{t=0}^T \Delta \text{Confirmed}_t} / \frac{\overline{\text{Expenditure}}}{\overline{\text{Confirmed}}} \approx \frac{\sum_{t=0}^T \Delta \log(\text{Expenditure}_t)}{\sum_{t=0}^T \Delta \log(\text{Confirmed}_t)}$$

This exercise shows, for example, that the cumulative ratio for mobility over a period of two weeks is 0.10 (0.18 for expenditure). It implies that given the gain of a 1% reduction in confirmed cases due to social distancing, mobility decreases 0.10% (0.18% for expenditure) on average during the period.

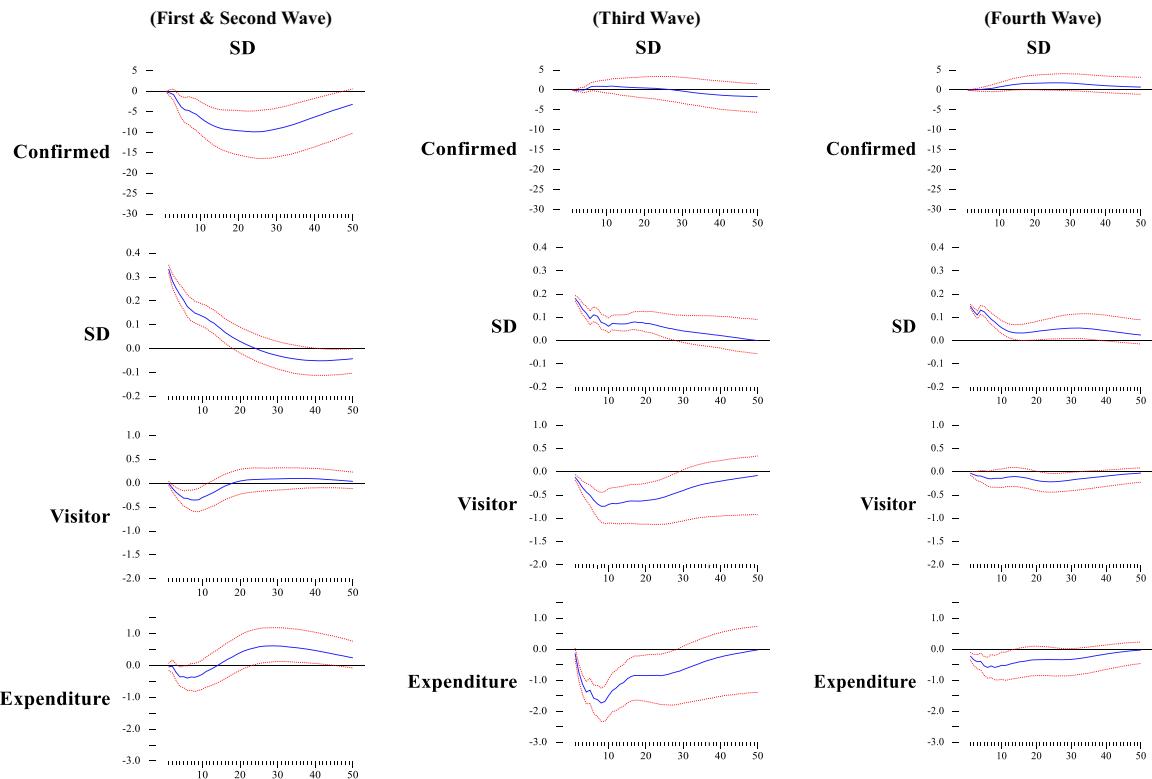
In response to a shock to the number of confirmed cases, the social distancing policy index increases in several days. This suggests that social distancing policy endogenously responds to the confirmed case shock with several days of delays. The mobility and credit card expenditure decline significantly. The declines in mobility and consumption expenditure are also significant under a shock to the number of confirmed cases. This implies the net effect of social distancing policy on economic activity may be smaller than observed following social distancing policy changes. With the confirmed cases rising, social distancing policy—which endogenously responds to confirmed cases—would be adjusted and the decline in economic activity may be due not only to tightened mobility restrictions but also to fear of infections.

Fig. 4 shows the impulse responses of resident and nonresident visitors to a tightening social distancing policy shock. Visits to SMA by residents significantly decrease up to 9 days (significant at 95% level) with the maximum fall, a 0.27% decline, happening 7 days after the shock. Nonresident visitors show a significant decline up to 14 days with a maximum decrease of 1.1% in about 8 to 9 days after the impact. Therefore, the effects of social distancing policy on nonresident visitors are stronger and more persistent than those on resident visitors, implying that mobility restrictions restrict long-distance travel much more than short trips.

Fig. 5 presents the impulse responses during each wave of the COVID-19 pandemic.<sup>12</sup> The decline in confirmed cases is significant during the first and second waves, but not in the third and the fourth waves. Mobility and consumption expenditure significantly decrease in all subperiods, with varying degrees. The declines are larger later, particularly in the third wave, than in the first and second waves. This suggests that while the health benefit of social distancing declines with

<sup>11</sup> When Seoul and Gyeonggi are considered separately, overall results are similar but the extent to which expenditure declines and the duration of the impact is stronger in Seoul than Gyeonggi.

<sup>12</sup> The data in the first wave are lumped together with the ones in the second waves due to the limited number of samples.



**Fig. 5.** Impulse-Response: Daily, Seoul Metropolitan Area, Total Visitors, SVAR

SD = social distancing policy index, SVAR = structural vector autoregression.

Note: The dotted lines are 68% probability bands. The first wave is from 20 February 2020 to 5 May 5 2020; the second wave from 6 May 2020 to 19 October 2020; the third wave from 20 October 2020 to 23 March 2021, and the fourth wave from 24 March 2021 to 14 October 2021.

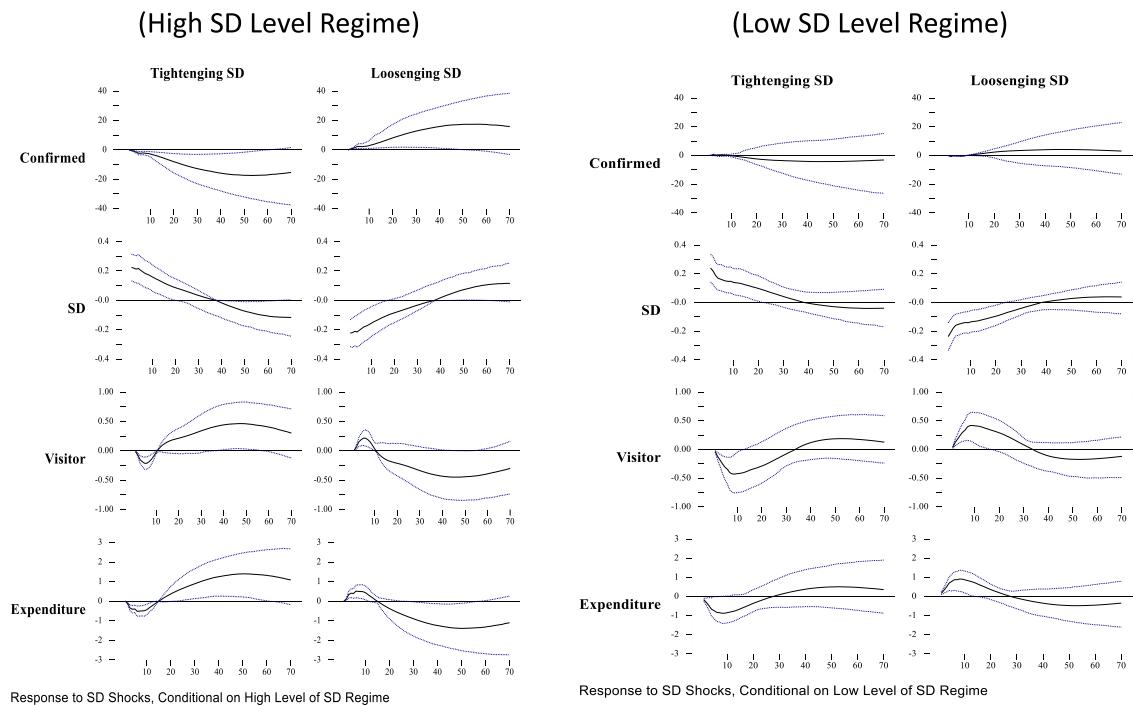
Source: Authors' calculations.

recurrent outbreaks, the economic costs continue to be significant. That is, the trade-off in social distancing policy between infection control and economic activity may have increased over time. Net gains from tighter mobility restrictions appear to diminish with repeated outbreaks as economic activity declines significantly while the number of confirmed cases does not.<sup>13</sup>

To assess the effectiveness of social distancing policy on flattening the curve, we use the reproduction rate instead of the number of confirmed cases. Fig. A3 in the appendix shows the reproduction rate decreases in response to the tightening social distancing policy shock, although with a slight delay. The reproduction rate significantly declines in 13 days with the peak of impact at -0.0158% at day 19. Then, reproduction rate slowly recovers to original level in the long term. Responses of other variables are similar to those of confirmed cases in the model. In the first column of graphs, SD increases over time in response to the shocks to the reproduction rate. Reproduction rate shocks decrease mobility and consumption expenditure significantly. Fig. A4 shows the impulse response to tightening social distancing policy shocks in the models with resident and nonresident visitors. Resident visitors significantly decrease up to 7 days at the 95% significance level with the maximum effect of -0.22% in 6 days after the shock. On the other hand, nonresident visitors show a significant decrease up to 14 days, with a maximum decrease of about 1% in about 8 days after impact. As in the model with the confirmed cases, the effects on nonresident visitors are larger and more persistent than those on resident visitors.

For robustness check, we first experiment with alternative assumptions on lag lengths. In the earlier daily VAR models, we used seven lags. When we consider alternative lag lengths, the results are similar. Fig. A5 in the appendix shows the impulse response to tightening shocks to social distancing policy when four and ten lags are assumed. We also consider alternative identifying assumptions. We initially assumed that the number of confirmed cases is contemporaneously exogenous to visitors and expenditures, but not to social distancing policy. Alternatively, we assume that (i) social distancing policy is contemporaneously exogenous to the number of confirmed cases, visitors, and expenditure, and (ii) these three variables are contemporaneously exogenous to social distancing policy. Fig. A6 suggests that the results are not qualitatively different.

<sup>13</sup> Fig. A2 in the appendix shows an adjusted version of Fig. 5 where the shock is in the same size in each wave.



**Fig. 6.** Impulse-Response: Daily, Seoul Metropolitan Area, Total Visitors, TVAR

SD = social distancing policy index, TVAR = threshold vector autoregression.

Note: The dotted lines are 90% probability bands.

Source: Authors' calculations.

### 5.1.2. Threshold vector autoregression

This section uses the threshold VAR models to investigate if the effectiveness of social distancing measures varies by the initial level, size, and direction of a policy shock. The effects of tightening or loosening social distancing measures may depend on its level at the time of implementation. Beginning from a more relaxed level, a tightening of social distancing measures may control the spread of infection with less economic damage. But when social distancing policy is already strict, additional tightening may no longer exert expected effects.<sup>14</sup> The size of shocks may also matter. The policy effects may not be proportional to the size of tightening (or loosening) actions. Moreover, the effects may be asymmetric, depending on whether the social distancing policy is being made more stringent or relaxed.

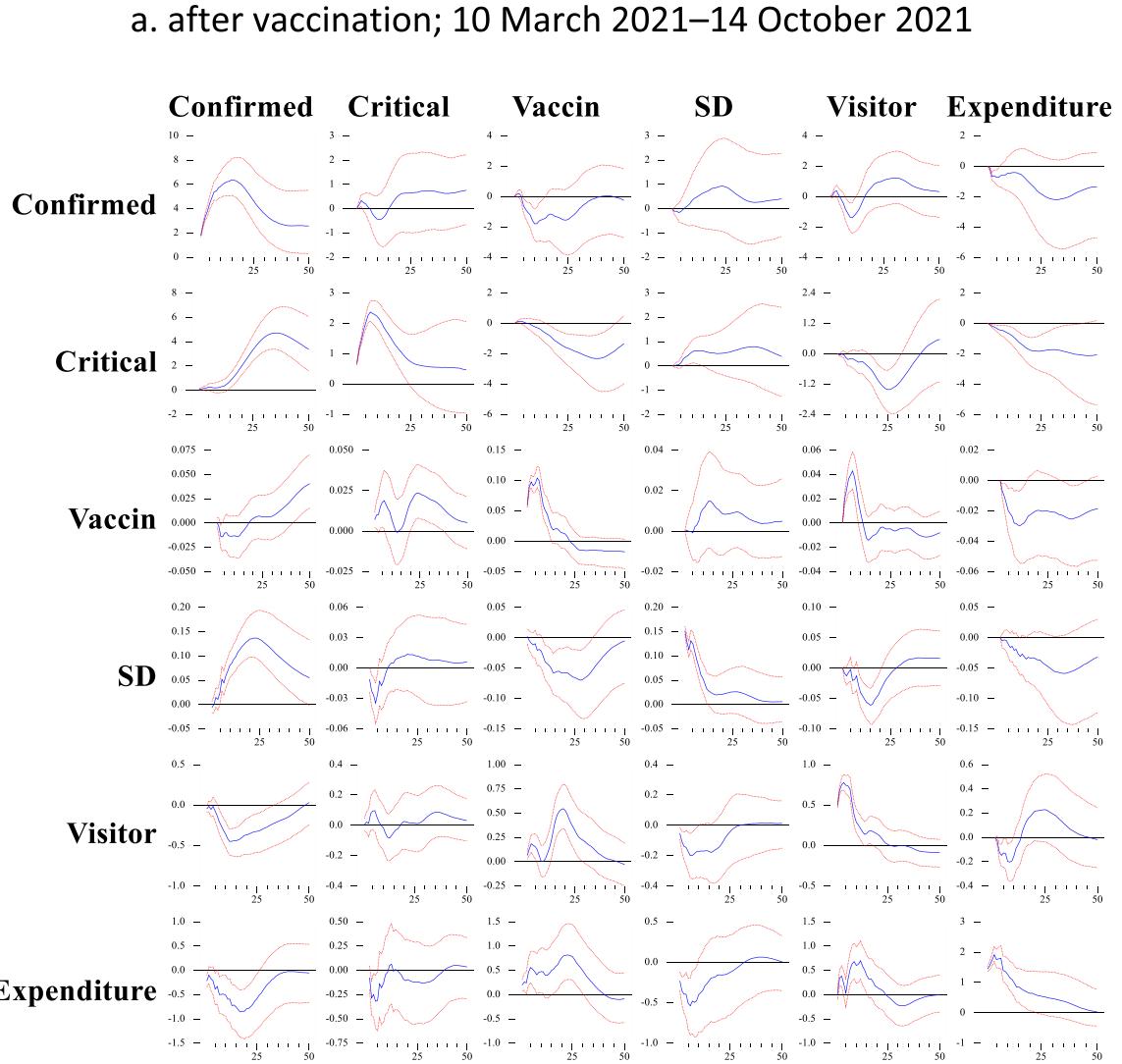
Fig. 6 presents the impulse responses to tightening and loosening social distancing policy shocks, when the level of social distancing regime is either stringent or relaxed. Results show that under the restrictive regime (a high SD level), SD shocks have a stronger effect on the number of confirmed cases by up to -17.2% in responds to a positive one standard deviation SD shock, compared to -4.5% when the policy regime is more relaxed (a low SD regime). The high SD level regime has a weaker effect on visitors (up to -0.21% vs. -0.43%) and expenditure (up to -0.51% vs. -0.88%) than under the low SD level regime.

The trade-off between infection control and economic activity is small in the high SD level regime, but large in the low SD level regime. At the high SD level, economic activities have been already reduced and the number of confirmed cases tends to be high. Therefore, a marginal effect of more stringent measures on economic activities may be small but its impact on reducing the number of infected cases can be higher, compared with the low SD level. Regarding the impacts of the different size in a policy shock, we find that two standard deviation shock tend to have almost twice as large effect as one standard deviation shock, except in a few cases. On the impacts by the direction of a shock, we find that in each (high or low) SD regime, the impact of tightening and loosening SD policy shocks is mostly similar in absolute terms.

### 5.1.3. Structural vector autoregression for the vaccination effects

COVID-19 vaccinations in the ROK started on 26 February 2021. But the vaccination rate increased rapidly only after June 2021. By 14 October 2021 (the last day in our analysis), 78% of total population received at least one dose of COVID-19 vaccine and 62.3% were fully vaccinated.

<sup>14</sup> This study uses the average of social distancing in the analysis period as the threshold level to determine being low or high.



**Fig. 7.** Impulse-Response: Daily, Seoul Metropolitan Area, Total Visitors, SVAR

SD = social distancing policy index, SVAR = structural vector autoregression, Vaccin = vaccination rate.

Note: The dotted lines are 68% probability bands.

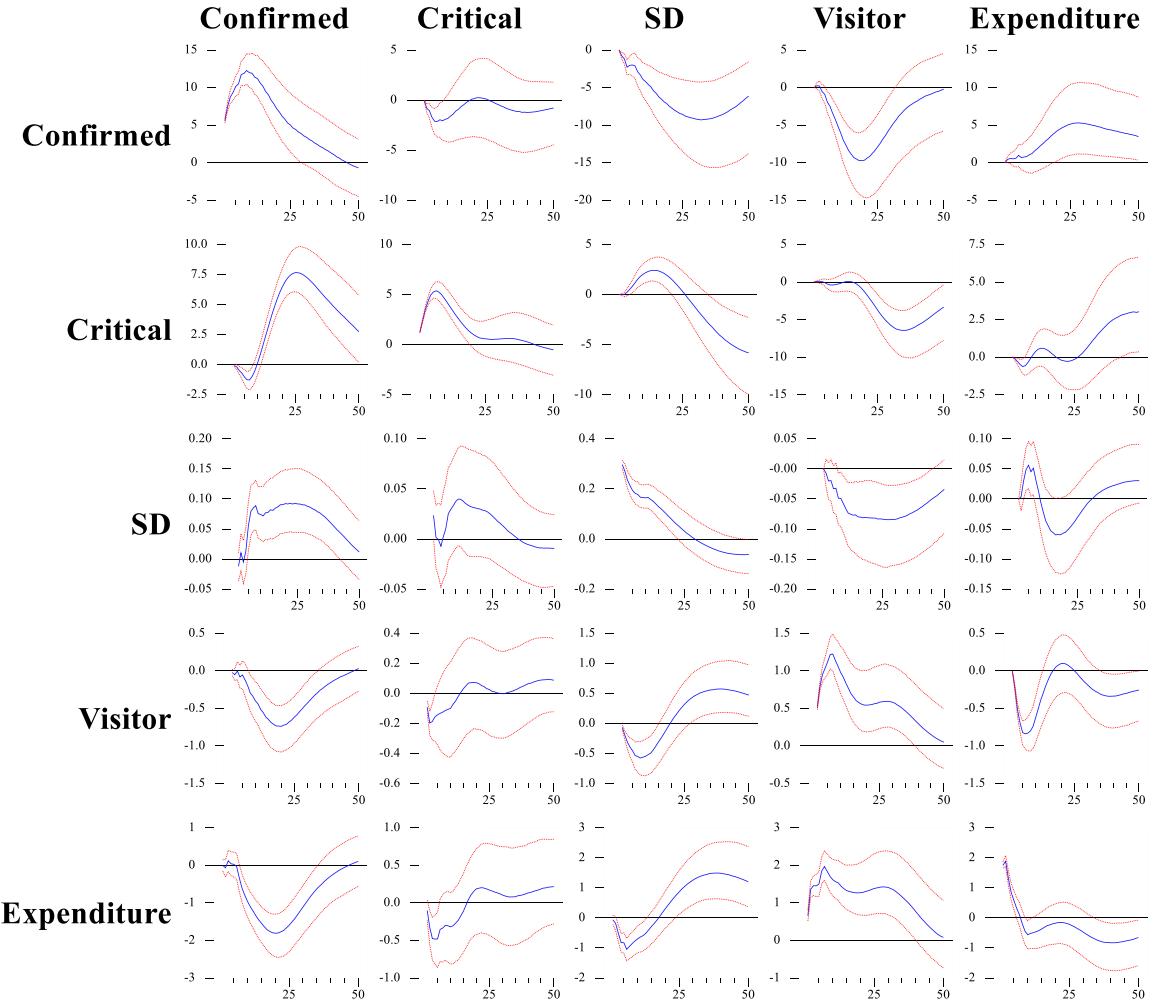
Source: Authors' calculations.

To assess the vaccination impact on health (critical cases, particularly) and economic outcomes, daily SVAR models were employed for 10 March 2021 to 14 October 2021 when the vaccination data are available. They cover six variables: (i) confirmed cases, (ii) critical cases, (iii) vaccination rates, (iv) the social distancing policy index (SD), (v) the number of visitors in SMA, and (vi) credit card expenditures. This is compared with the period of no-vaccination using the same variables without the vaccination rates in the SVAR model.

The impulse responses in Fig. 7a suggest that under the presence of the vaccination variable in the model, the negative SD impacts on the number of visitors and expenditure remain valid. Vaccination shows an immediate effect in reducing the number of confirmed cases. Vaccination also leads to a significant decline of the critical cases in about two weeks. The number of visitor and consumption expenditures significantly rose in response to an increase in the vaccination rate. The results suggest that social distancing measures could be adjusted to avoid unnecessary trade-offs when vaccines are available. Vaccination helps reduce the critical cases and therefore mitigate economic damage of COVID-19.

Fig. 7a and b show that the effect of social distancing measures on daily critical cases is subject to vaccination. Arias et al. (2021), which do not include vaccination periods, find that mobility restriction in Belgium significantly reduced deaths while incurring only a small cost of GDP reduction. We use daily critical cases instead of deaths to assess the effect of social distancing. This is because the COVID-19-related mortality rate in Korea remained very low during the analysis pe-

## b. Before vaccination; 24 July 2020–25 February 2021



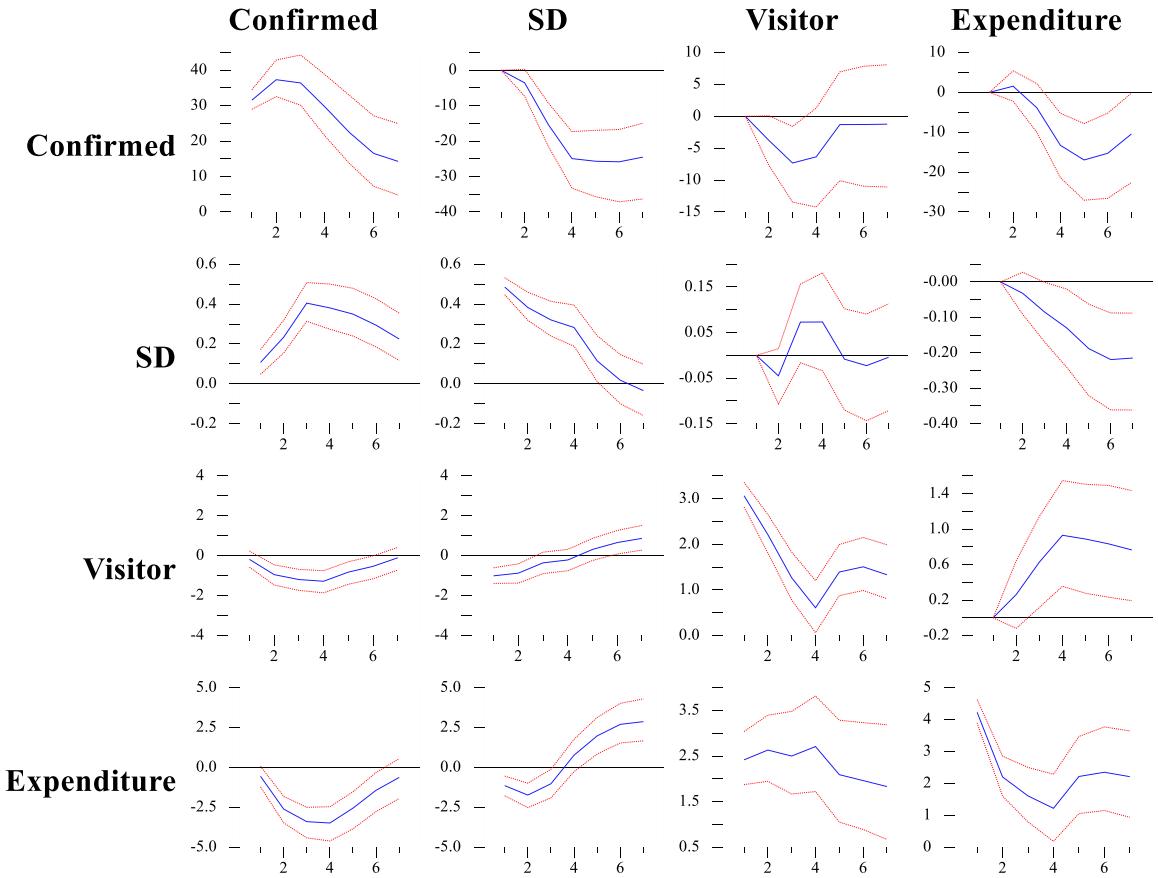
**Fig. 7. Continued**

riod with the average number of daily deaths per million people being less than 0.1, compared to 5.5 in Belgium. Therefore, the marginal effect of social distancing on daily deaths would not be very significant. Fig. 7b shows that before vaccination, social distancing measures significantly reduced the number of critical cases albeit with a time lag of about a month after implementation. But Fig. 7a shows that the effect of social distancing measures on critical cases became insignificant after vaccination.<sup>15</sup> In both cases, their impact on expenditure was negative.

### 5.2. Models with weekly data

Fig. 8 shows impulse responses from the four-variable weekly VAR model. In response to a tightening of social distancing policy, the confirmed cases decrease with over time, registering the largest decline of 25% at the fourth and fifth weeks. Significant declines of visitors and expenditures are found in the first two weeks. These are similar to the findings in the models with daily data. In response to an increase in the number of confirmed cases, SD increases sharply and persistently. The number of visitors and expenditures decline substantially and significantly. This is consistent with what the models with the daily data presents.

<sup>15</sup> When the critical rate, which is the ratio of deaths and critical cases to new cases, is used instead of critical cases and confirmed cases, the SVAR results show that social distancing measures also had a limited impact in reducing the critical rate. The results are available upon request.



**Fig. 8.** Impulse-Response: Weekly, Seoul Metropolitan Area, Total Visitors, SVAR

SD = social distancing policy index, SVAR = structural vector autoregression.

Note: The dotted lines are 68% probability bands, respectively. Each column shows the impulse responses of the corresponding variable to each shock in a given row.

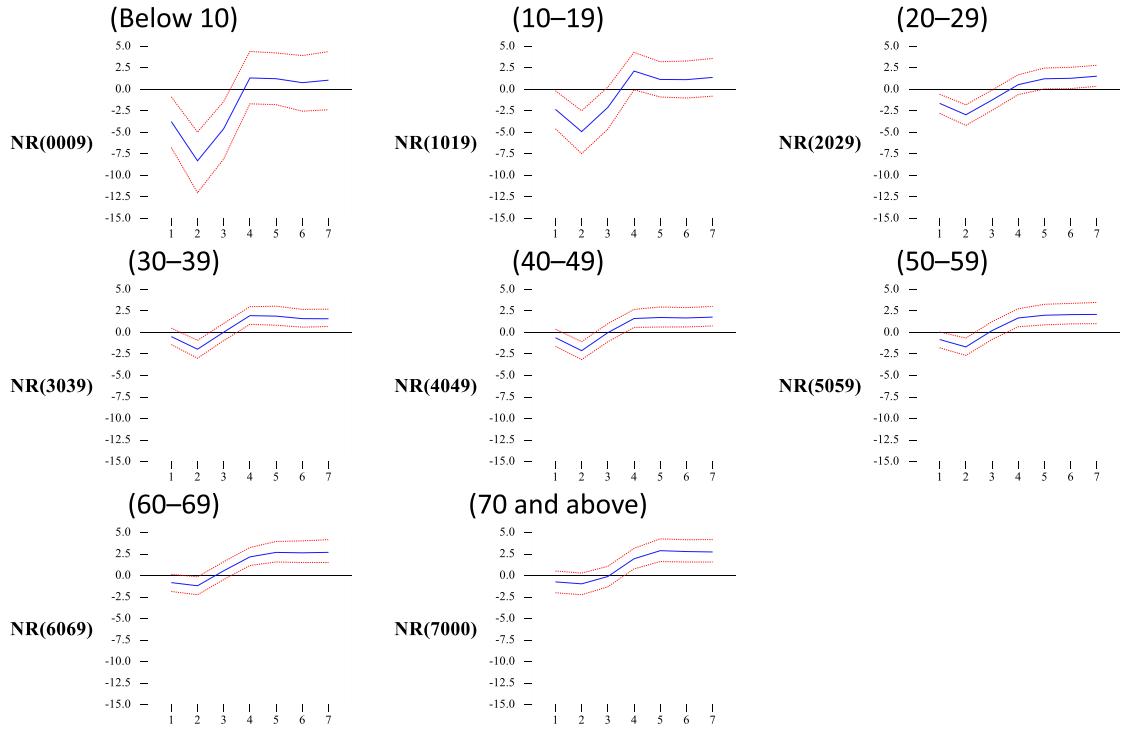
Source: Authors' calculations.

For resident and nonresident visitor models using weekly data, the SD effect on nonresident visitors is larger than that on resident visitors, consistent with the daily data results. In the weekly models where the number of confirmed cases is replaced with the reproduction rate, the results are qualitatively similar to those drawn from the daily data. When the samples are analyzed for Seoul and Gyeonggi province separately, the SD effects on visitors and expenditure are larger in Seoul than in Gyeonggi province, which is similar to the results in the models with daily data.<sup>16</sup>

We conduct an analysis by age group for nonresident visitors who are heavily affected by social distancing policy shocks. The three-variable VAR is conducted without expenditure. This is to improve the degree of freedom in the weekly models and the expenditure variable is not available by age group. Fig. 9 show the nonresident visitor responses to a tightening of social distancing policy by age group in the SMA.

We observe varying degrees of SD impact by age group. For the age groups below 20, mobility of nonresident visitors initially decreased significantly and then recovered to its original level in the fourth week. The decrease is the largest for the age group below 10. School closures and restrictions to face-to-face learning activities may have contributed to the huge decrease in the youth group's mobility. In the case of those in their 20s to 50s, the mobility significantly decreases in the early stages and increases above the original level from the fourth week. However, the mobility of age groups above 60 does not decline significantly right after a SD shock and it even exceeds the initial level in 3–4 weeks. This may be because the old age group includes retirees and is less affected by business closures and work-from-home arrangements. While older people are far more vulnerable to serious complications of COVID-19 infection than the young, they are less likely to follow social distancing rules. This suggests that additional measures are needed to protect the older population during severe outbreaks.

<sup>16</sup> The results are available upon request.



**Fig. 9.** Impulse-Response: Weekly, Seoul Metropolitan Area, Nonresident Visitors, SVAR by Age Group  
 SVAR = structural vector autoregression, NR = nonresident visitors.

Note: The dotted lines are 68% probability bands.

Source: Authors.

## 6. Conclusion

This paper investigates the effects of COVID-19 social distancing policy on infection control, mobility of people, and consumption expenditures in Korea. Unlike the early literature on social distancing policy, its focus is on the effects on both infection control and economic activities (mobility and consumption expenditure) to assess the policy trade-offs. We employed a big-data driven mobility dataset from telecommunications company to precisely measure mobility of people at a high frequency. We also used daily credit card expenditure data to measure private consumption. To measure intensity of social distancing policy, we constructed a social distancing policy index based on public announcements to measure the modification of social distancing policy restrictions over time. The number of confirmed cases and the reproduction rate ( $R$  values) are used to show time-varying evolution of COVID-19 impacts. We employed the structural and threshold VAR models to consider dynamic interactions among these variables such as endogeneity of social distancing policy actions and analyze the policy effects.

The main results can be summarized as follows:

- First, the VAR results show a tightening of social distancing policy significantly reduces the number of confirmed cases and the virus reproduction rates. But it also decreases mobility and consumption expenditure significantly, generating a trade-off between infection control and economics activity. In addition, the effects of social distancing policy differ under various conditions. For example, as time passes, the effect on the number of confirmed cases decreases but the effects on mobility and consumption expenditure increase. This implies that the policy trade-offs between infection control and economic activity increase over time.
- Second, using the threshold VAR model, the results show that the effects of social distancing measures depend on the initial level, size, and direction of a policy shock. When the social distancing level is high, economic activity has been already severely constrained and therefore responds less to a marginal increase in social distancing. That is, the trade-off is weaker in the high social distancing policy level than in the low level.
- Third, when we introduced the vaccination variable in the model, the effects of social distancing on the number of visitors and expenditures remain negative. The results also show that an increase in vaccination rates leads to a significant decline of the critical cases in about two weeks and an increase in the number of visitors and consumption expenditures. This suggests that vaccination could mitigate COVID-19 impacts on economic activities if social distancing measures are adjusted to avoid unnecessary trade-offs.

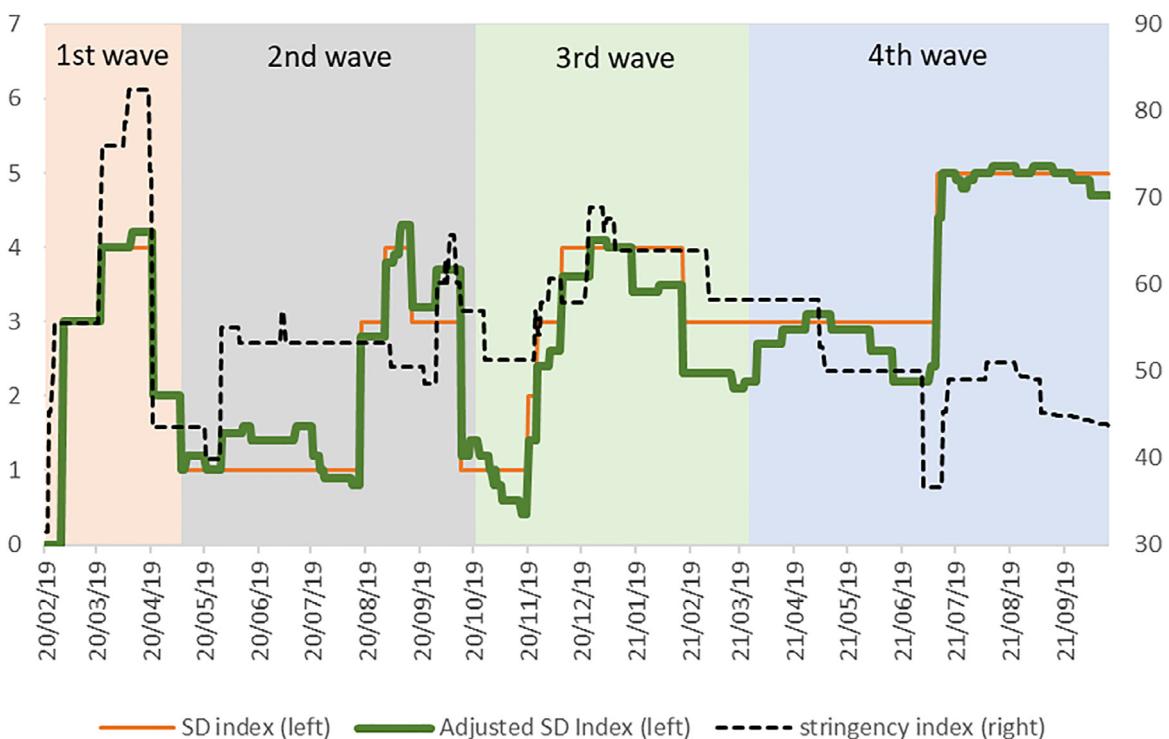
- Fourth, using the weekly data with different age group analysis, the results show the social distancing effect on mobility is strongest among young population of age under 20 and weakest among old population of age over 60. This suggests that additional measures and incentives may be needed to raise adherence of the older population to social distancing.

The findings suggest that social distancing policy implemented by the Korean government has exerted significant effects on the mobility of people and consumer spending, while its effectiveness on infection control has weakened over time. However, these effects are not uniform, subject to various conditions such as pandemic duration, initial social distancing levels, other factors affecting public behavior, and different age groups.

Our paper provides some early lessons from the policy responses to the unprecedented challenges posed by the pandemic. In the absence of COVID-19 vaccines, social distancing measures were among the very few options to curb the virus spreads. But the results clearly show the policy trade-offs between infection control and economic activity. Our results present a starting point for policy makers in understanding the dynamic effects of NPIs on economic activity and how these effects change under various conditions to create policy trade-offs. And this paper provides empirical evidence on various related issues for effective public policy responses.

## Appendix

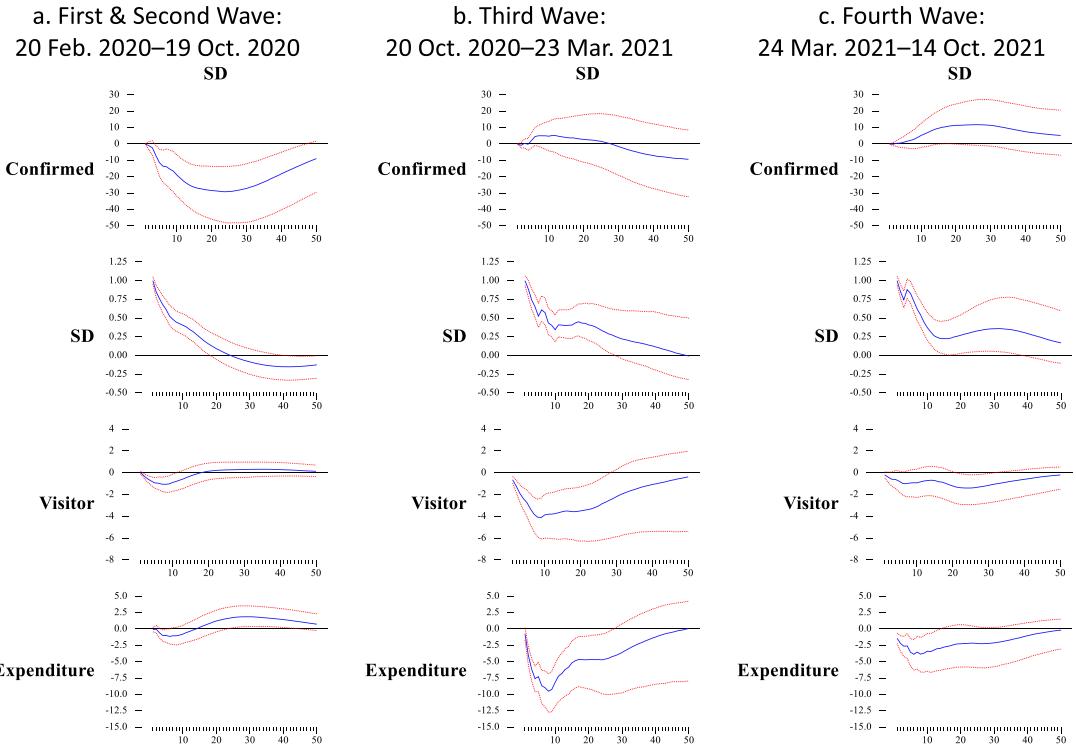
Figs. A1, A2, A3, A4, A5, A6 and Tables A1 and A2



**Fig. A1.** Social Distancing Index vs. Government Stringency Index  
SD = social distancing policy index.

Note: The COVID-19 phases are divided into the first to the fourth wave based on when the number of confirmed COVID-19 cases and the social distancing policy reached to local minimums after a local maximum of the number of confirmed cases: the first wave is from the beginning of the COIVD-19 pandemic to 5 May 2020, the second wave from 6 May 2020 to 19 October 2020, the third wave from 20 October 2020 to 23 March 2021, and the fourth wave from 24 March 2021, to the end of the analysis period. The periods by variant are based on information from public releases and news reports.

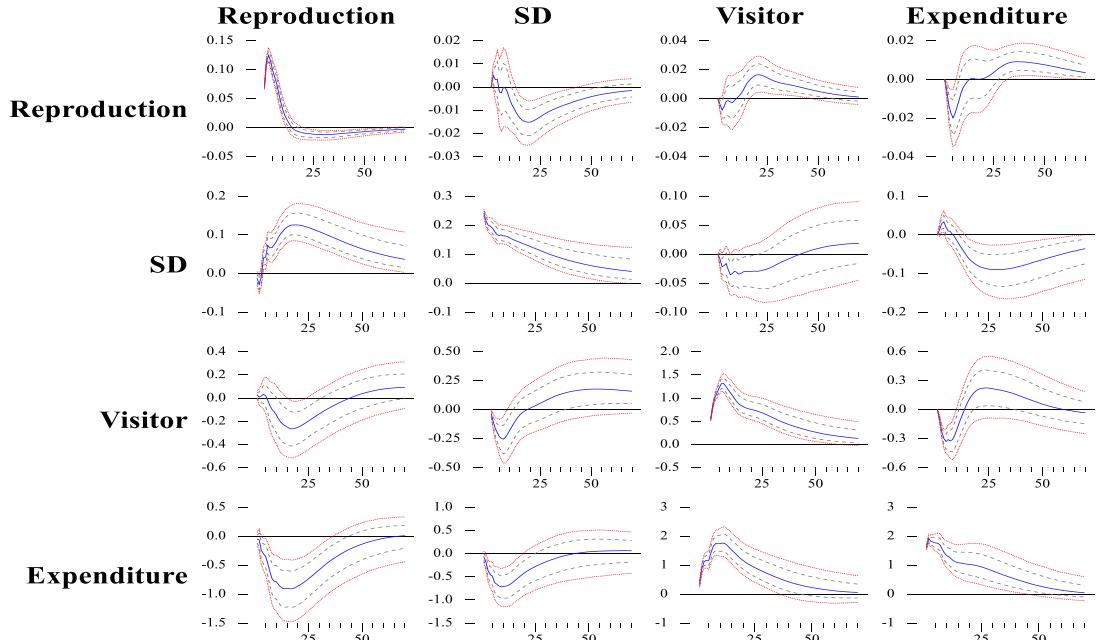
Source: Authors' calculations using the data from the Central Disaster and Safety Countermeasures Headquarters; Hannah Ritchie, Edouard Mathieu, Lucas Rodés-Guirao, Cameron Appel, Charlie Giattino, Esteban Ortiz-Ospina, Joe Hasell, Bobbie Macdonald, Diana Beltekian, and Max Roser. 2020. Coronavirus Pandemic (COVID-19). <https://ourworldindata.org/coronavirus> (accessed 27 October 2021).

**Fig. A2.** Impulse-Response with normalized shocks: Daily, Seoul Metropolitan Area, Total Visitors, SVAR

SD = social distancing policy index, SVAR = structural vector autoregression.

Note: The dotted lines are 68% probability bands. The first wave is from 20 February 2020 to 5 May 5 2020; the second wave from 6 May 2020 to 19 October 2020; the third wave from 20 October 2020 to 23 March 2021, and the fourth wave from 24 March 2021 to 14 October 2021; The shock in each wave has been normalized so that it is in the same magnitude

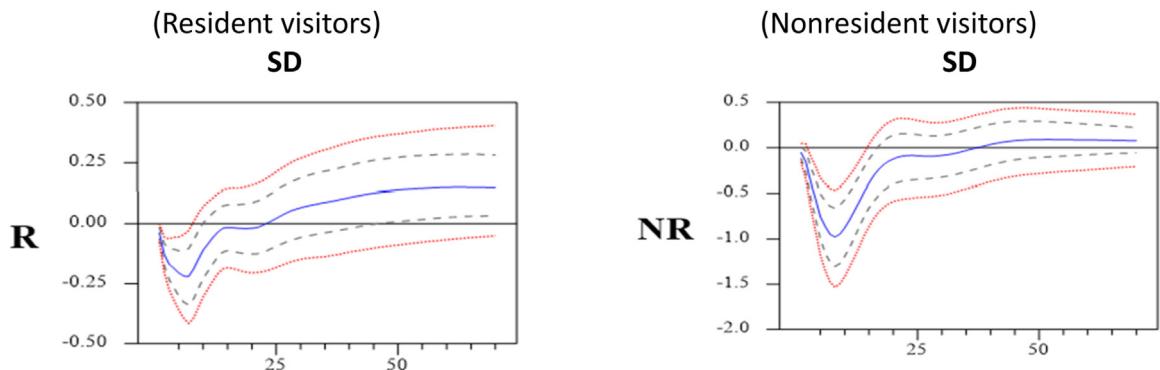
Source: Authors' calculations.

**Fig. A3.** Impulse-Response: Daily, Seoul Metropolitan Area, Total Visitors, SVAR – Reproduction Rates

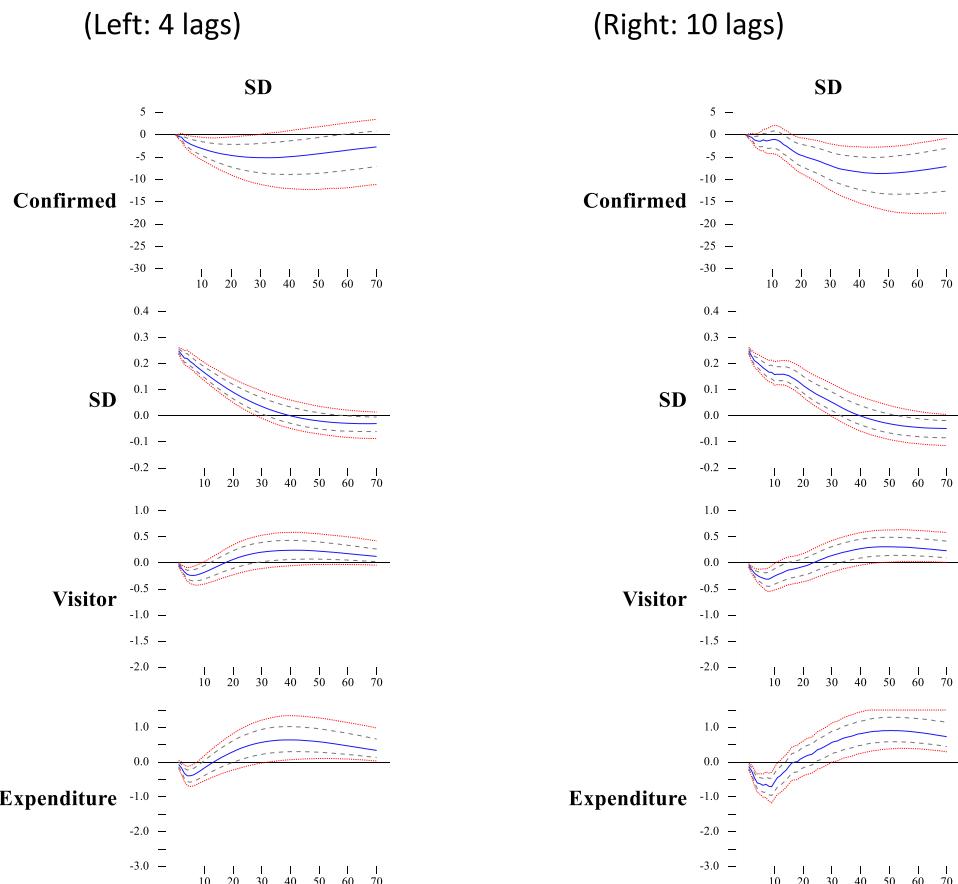
SD = social distancing policy index, SVAR = structural vector autoregression

Note: The dashed and dotted lines are 68% and 90% probability bands, respectively. Each column shows the impulse responses of the corresponding variable to each shock in a given row.

Source: Authors' calculations.



**Fig. A4.** Impulse-Response: Daily, Seoul Metropolitan Area, Resident/Nonresident Visitors, SVAR—Reproduction Rates  
 NR = nonresident visitors, R = resident visitors, SD = social distancing policy index, SVAR = structural vector autoregression.  
 Note: The dashed and dotted lines are 68% and 90% probability bands, respectively.  
 Source: Authors' calculations.



**Fig. A5.** Impulse-Response: Daily, Seoul Metropolitan Area, Total Visitors, SVAR  
 SD = social distancing policy index, SVAR = structural vector autoregression.  
 Note: The dashed and dotted lines are 68% and 90% probability bands, respectively.  
 Source: Authors' calculations.

**Table A1**

Normalized social distancing index: matching different social distancing schemes.

Entire analysis period	Feb 29, 2020-June 27, 2020	June 28, 2020-Nov 6, 2020		Nov 7, 2020-June 30, 2021		July 1, 2021 onwards	
Normalized index	Prior to the 3-level scheme	3-Level Social Distancing		5-Level Social Distancing		4-Level Social Distancing	
Level	Concept	Level	Concept	Level	Concept	Level	Concept
1	Distancing in daily life	1	Distancing in daily life (< 50)	1	Distancing in daily life (100 or less SMA)	1	Continuous containment (less than 250 SMA)
2	Relaxed social distancing			1.5	Onset of epidemic at community level (more than 100 SMA)	2	Community-level epidemic (250 or more SMA)
3	Social distancing	2	Social distancing (50-100)	2	Rapid spread of local transmission (300 or more nationwide)	3	Regional epidemic (500 or more SMA)
4	Enhanced social distancing	Enhanced level 2	Enhanced social distancing (50-100)	2.5	Onset of nationwide epidemic (400-500 or more nationwide)		
5		3	Highly-enhanced distancing (100 or more and doubling twice within a week)	3	Nationwide epidemic (800-1000 or more nationwide)	4	Nationwide epidemic (1000 or more SMA)

Notes: The Korean health authority officially considered the number of confirmed cases as one of the major risk assessment factors in determining a social distancing level. The numbers and descriptions in parentheses refer to the indicators related to confirmed cases during each social distancing scheme: 3-level: the number of daily confirmed cases (2-week average); 5- and 4- levels: the number of daily confirmed cases (1-week average); SMA = Seoul Metropolitan Area

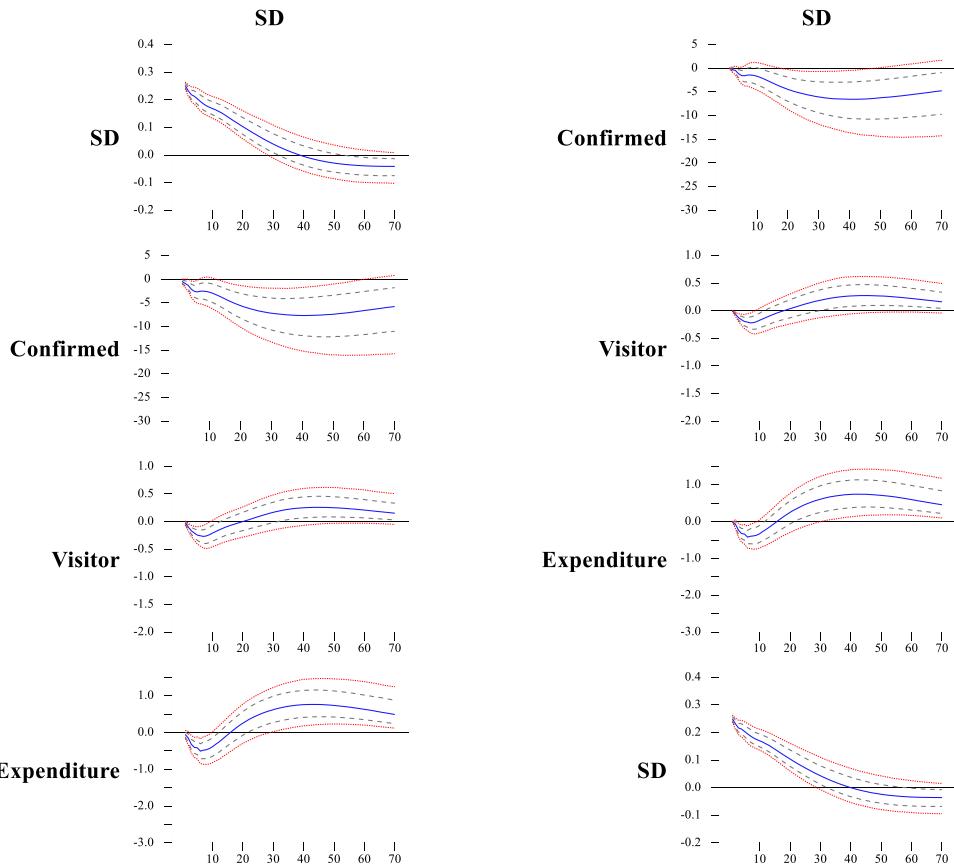
Source: Authors based on the government press releases

**Table A2**

Description on adjustments to the normalized social distancing index.

Adjustment	Description
+0.5	To strengthen the basic quarantine rules to seven and expand the scope of application; and adopt special infection control measures for a spring outing.
+0.2	Seoul Metropolitan Government ordered to ban on social gatherings in the entertainment facilities such as discotheques, nightclubs, and cabarets. To ban gatherings in the entertainment facilities. General restaurants, cafes, bakeries, franchise-type bakeries, and ice cream/shaved ice specialty stores are only allowed for packaging and delivery. To adopt special infection control measures for the autumn trip season. To adopt special infection control measures for Halloween day. To adopt special infection control measures for New Year's Day. Mask rule reinforced. Outdoor drinking in parks and riverside is prohibited after 22:00. Enforcement of strengthened social distancing measures for the Seoul metropolitan area. To restrict the operation of public facilities, and multi-purpose facilities.
+0.1	To adopt special infection control measures for Chuseok. To introduce KI-PASS, digital customer register, quick response (QR) code-based entry logs. Vocational training institutions are also subject to a ban on gathering. To prohibit entering major densely populated areas such as Yeouido, Ttukseom Island, and Banpo Han river park. To adopt special infection control measures for the public bath business. No personnel exceptions are applied for the composition of sports games. To prohibit the operation of shower rooms in outdoor sports facilities. To reinforce and adjust special infection control measures for the public bath business.
-0.1	Allowing 10% of spectators to return to professional sports. To allow indoor meals in restaurants.
-0.2	To expand the contact visits in the nursing hospital to those who have been vaccinated. To resume the operation of public outdoor sports facilities, outdoor facilities, religious facilities, and entertainment facilities. Easing social gatherings in the entertainment facilities. Public facilities such as museums, art galleries, and libraries resume operation in the Seoul metropolitan area while complying with quarantine rules. Re-operate the social welfare facilities in stages. Easing the collective restriction on mandatory core quarantine rules for churches. To start the discount event for domestic travel. Easing the special infection control measures for Halloween day. To start a discount coupon program for travel, amusement park, and hotel. To adjust infection control policies of private gatherings.
-0.5	To start applying vaccine incentives. To resume the operation of the multi-purpose facilities, indoor sports facilities, karaoke, private educational institute, and small performance hall.

Source: Authors based on the government press releases



**Fig. A6.** Impulse-Response: Daily, Seoul Metropolitan Area, Total Visitors, SVAR—Alternative Identifying Assumptions

SD = social distancing policy index, SVAR = structural vector autoregression.

Note: The dashed and dotted lines are 68% and 90% probability bands, respectively. we assume that (i) social distancing policy is contemporaneously exogenous to the number of confirmed cases, visitors, and expenditure, and (ii) these three variables are contemporaneously exogenous to social distancing policy.

Source: Authors' calculations.

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