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Effects of transport-related COVID-19 policy measures: A case study of six developed countries

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ABSTRACT

This study attempts to provide scientifically-sound evidence for designing more effective COVID-19 policies in the transport and public health sectors by comparing 418 policy measures (244 are transport measures) taken in different months of 2020 in Australia, Canada, Japan, New Zealand, the UK, and the US. The effectiveness of each policy is measured using nine indicators of infections and mobilities corresponding to three periods (i.e., one week, two weeks, and one month) before and after policy implementation. All policy measures are categorized based on the PASS approach (P: prepare-protect-provide; A: avoid-adjust; S: shift-share; S: substitute-stop). First, policy effectiveness is compared between policies, between countries, and over time. Second, a dynamic Bayesian multilevel generalized structural equation model is developed to represent dynamic cause-effect relationships between policymaking, its influencing factors and its consequences, within a unified research framework. Third, major policy measures in the six countries are compared. Finally, findings for policymakers are summarized and extensively discussed.

1. Introduction

The COVID-19 pandemic has lasted for more than one year, resulting in more than 100 million cumulative infections and more than 2 million deaths across the world. These numbers are still growing day by day. Before vaccination is implemented worldwide, control of the current COVID-19 pandemic has had to rely heavily on non-pharmaceutical interventions, from the strictest nationwide lockdowns to “very soft” voluntary social distancing practices. All serious policymakers in the whole world have been struggling to find effective policy measures that can better control the pandemic without seriously damaging their economies. COVID-19 policymaking has been very challenging for various reasons, such as poor data availability, weak collaboration across government sectors, and the limited involvement of non-medical experts in the policymaking process, which has been centered on public health experts. The spread of the invisible SARS-CoV-2 virus needs to be prevented and controlled in a seamless way, by eliminating all possible transmission chances. However, what has been happening in reality? Countries across the world look as if they are competing with various social experiments, which unfortunately gives the impression of putting the general public onto the experiment table.

To date, more and more data has been accumulated worldwide, which, together with more and more relevant research, are helping to design effective COVID-19 policy measures. To date, numerous policy measures against COVID-19 have been taken here and there over time and across geographical locations. However, as discussed in Section 2 below, policymakers seem very far from reaching robust, consistent and widely accepted conclusions on what kinds of COVID-19 policies should be made, how to make such policies, and to what extent they should be implemented.

Therefore, this study attempts to provide alternative ways of evaluating COVID-19 policy measures in order to help make more useful policy recommendations. To this end, this study focuses on the six developed countries of Australia, Canada, Japan, New Zealand, the UK, and the US, and collected about 500 policy measures (both public health measures and measures from the transport sector). Comparisons across countries are useful to confirm the robustness of policy measures by reflecting different patterns of the spread of the SARS-CoV-2 virus.
Developed countries were targeted to assess policy effectiveness, as it was assumed that their governments had advanced policymaking expertise in the field of infectious diseases. The six developed countries are selected because of data availability and the authors’ capacity to check the reliability of data sources within the limited period. Following data cleaning and matching, 418 policy measures are eventually used as the samples in this study, of which 244 are transport measures. Indicators of both infections and mobilities are used to evaluate policy effectiveness. Because there are no widely accepted durations of time suitable for capturing changes before and after policymaking, this study measures the indicators of infections and mobilities with respect to three periods of time: one week, two weeks, and one month before and after policymaking. Data on mobilities come from Google’s COVID-19 Community Mobility Reports and data on infections are extracted from HDX.  For this study, the following research questions are raised.

**Question 1**: How to better measure the effects of COVID-19 policymaking?

**Question 2**: Whether and how are changes in mobilities associated with levels of infections?

**Question 3**: Whether and how do the levels of infections affect COVID-19 policymaking?

**Question 4**: How does COVID-19 policymaking influence changes in mobilities and curb the spread of COVID-19 infections?

To answer Question 1, several methods of measuring policy effects are attempted. It is argued that the effects of COVID-19 policymaking should be properly evaluated from different angles. To answer the remaining three questions, a dynamic Bayesian multilevel generalized structural equation (GSEM) model is developed. The multilevel approach is adopted to address potential cross-sample correlations because the 418 policy measures were collected from six countries, and policy measures in a country may not be independent of others in the same country. This is done by adding an additional country-specific error component into the GSEM model. GSEM is used to better reflect the inherent features of different types of data, without arbitrarily assuming linear relationships between variables. Concretely speaking, policymaking variables are all a dummy variable (0 or 1). Such a binary choice is fully reflected in the modeling estimation. The Bayesian approach is applied to the above model with additional error components specific to all types of policy measures. For COVID-19 policymaking, this study follows the PASS approach proposed by Zhang (2020), which argued that COVID-19 policies (especially related to the transport sector) should be made in a seamless and comprehensive way by classifying policies into four categories: i.e., Prepare-protect-provide (P), Avoid-adjust [A], Shift-share [S], and Substitute-stop [S]. In the paper by Zhang (2020), more than 100 policy measures were proposed and extensively discussed in a conceptual way. This paper further attempts to present empirical evidence of the PASS-based policymaking by answering the above four research questions. The developed model captures the cause-effects dynamics.

In the remaining part of this paper, Section 2 presents a literature review of research on COVID-19 policymaking from a broad perspective. Section 4 describes the data used in the study. Section 5 evaluates policy effects in an aggregate way from several angles. Section 5 evaluates policy effects by estimating the dynamic Bayesian multilevel generalized structural equation (GSEM) model. Section 6 describes and discusses selected policy measures by reflecting the previous aggregate and modeling analysis results. This study concludes in Section 7 with a summary of key findings and discussion about the challenges of the research.

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1. https://www.google.com/covid19/mobility/
2. https://data.humdata.org/dataset/novel-coronavirus-2019-ncov-cases.
measures, such as school closures and lockdowns, on the COVID-19 spread in different states of the US, based on the data of case fatalities from February 29 to April 25, 2020, when some states began reversing their interventions. Model results indicated that lockdowns played a key role in reducing the reproduction number to below 1.0.

2.1.3. School closures

Abdollahi et al. (2020) evaluated the contribution of school closures to reducing the proportion of the infected population throughout the COVID-19 outbreak in Ontario, Canada by using an age-structured agent-based simulation model. They found that school closures reduced infection rates in the range of 7.2%–12.7% if the duration of school closures was increased from 3 to 16 weeks, thereby restricting contacts among school children by 60%–80%. Viner et al. (2020) undertook a systematic review on the effectiveness of school closures and other school social-distancing practices. It was found that school closures were deployed rapidly across China and Hong Kong, but there is no evidence of the relative contribution of school closures to controlling virus transmission. Recent modelling studies of COVID-19 proved that school closures alone would not substantially contribute to the transmission control if they prevented only 2–4% of deaths, exhibiting much fewer positive effects than other social-distancing interventions.

Harli, Wälde and Weber (2020) applied a simple linear trend model to examine the effects of the policy decisions adopted by German authorities on March 13, 2020 to shut down schools and stop major sports events, which were closely followed by further restrictions on restaurants, shops and other facilities. This study identified a trend break on March 20 that is in line with an expected lagged impact of the above policies. Furthermore, it was found that the growth rate of infections fell by 48.2%. While the growth rate was almost halved, the number of infection cases was still doubling every 5.35 days. Focusing on nation-level school closures in 107 countries up to March 18, 2020, Daniele et al. (2021) used a multivariate negative binomial regression with panel data to evaluate the effects of early adoptions of mass gathering bans and school closures on the COVID-19 cumulative mortality during the first pandemic wave for the 37 OECD member countries. This study estimated that a one-day delay in mass gathering bans was associated with an increase in the cumulative mortality by 6.97% (95% CI, 3.45 to 10.5), whilst a one-day delay in school closure was associated with an increase of 4.37% (95% CI, 1.58 to 7.17). If every country had enacted both interventions one week earlier, the cumulative mortality could have been reduced by an average of 44.1% (95% CI, 20.2 to 67.9). It was concluded that mass gathering bans and school closures should be implemented as early as possible.

2.1.4. Face masks and isolation

Heald et al. (2020) used a step-by-step approach to conduct a sequential assessment of the contribution of face coverings to risk reduction. The Infection Risk Score (IRS) associated with several common activities was calculated to analyze the effectiveness of reducing infection and the consequences of wearing a face covering. The effect of face coverings was evaluated when applied to different infection rates over 3 months from July 24, 2020, when face coverings were made compulsory in England on public transport and retail outlets. Results illustrated that the policy on the mandatory use of face coverings in retail outlets and on public transport may have been followed by many in the country but may be of limited value in reducing hospital admissions and deaths, unless infections are rising faster than currently seen. The impact appeared small compared with all other sources of risk, thereby raising questions regarding the effectiveness of the policy.

Bertuzzo et al. (2020) employed a spatially explicit model to estimate the expected unfolding of the outbreak under continuous lockdown and assess the isolation effort required to prevent a resurgence of the outbreak. This study tried to find effective methodologies to selectively loosen containment measures. Results show that a 40% increase in effective transmission would yield a rebound of infections. In addition, a control effort capable of isolating about 5.5% of the exposed and highly infectious individuals on a daily basis proved necessary for maintaining the epidemic curve onto the decreasing baseline trajectory.

2.2. Multi-faceted measures

2.2.1. Temporal comparison

Pan et al. (2020) investigated the association of public health interventions with the epidemiology of the COVID-19 outbreak based on 32,583 laboratory-confirmed COVID-19 cases reported in Wuhan during December 8, 2019 to March 8, 2020. This study classified five periods according to dates that played important roles in the virus transmission: Period 1 - no intervention; Period 2 - massive human movement due to the Chinese New Year holiday; Period 3 - cordon sanitaire, traffic restrictions and home quarantine; Period 4 - centralized quarantine and treatment; and Period 5 - universal symptom survey. Results indicated that the daily confirmed case rate peaked in Period 3. The declining trend in the proportion of severe and critical cases from 53.1% to 10.3% can be observed over the five periods. It was concluded that a series of multifaceted public health interventions were associated with improved control of the outbreak in Wuhan.

Crowling et al. (2020) evaluated the effects of government interventions in Hong Kong, including travel restrictions and bans, flexible working arrangements, and school closures in kindergartens, tertiary and post-tertiary institutions, and tutorial centers, and behavioral changes of the public based on three surveys conducted on Jan. 20–23, Feb. 11–14, and March 10–13, 2020. Results suggested that the daily effective reproduction number remained around the critical threshold of 1.0, implying that policy interventions were effective in tackling the spread.

Michal et al. (2020) examined whether the anti-COVID-19 policy in Poland would significantly change the mobility on public transport at both regional and country levels by using a one-factor variance analysis and Tukey’s honest significance test between March 2 and July 19, 2020. This study collected data on changes in the transit station usage from Google’s COVID-19 Community Mobility Reports to determine mobility changes in public transport. It is observed that strong and negative correlations existed between mobility changes in public transport and the stringency of government restrictions. Results suggested that government restrictions and ongoing pandemic information campaigns have a greater impact on human mobility than information on daily new infection cases.

2.2.2. Cross-country comparison

Gibney (2020) reviewed COVID-19 policy measures all over the world by summarizing approximately 170 policy interventions collected from 52 countries, ranging from minor measures (e.g., social distancing floor stickers) to large-scale restrictive policies (e.g., school closures) and resumption measures. It was found that aggressive and early control strategies were adopted in Germany and Austria, while Italy, France, and Spain implemented policies later. The study showed that on a per capita basis, Germany and Austria accounted for a smaller proportion of the deaths from COVID-19 than these other countries.

Fitzman et al. (2020) studied the effects of major interventions including school closure orders, case-based measures, bans of public events, social-distancing, and lockdowns decreed across 11 European countries during the period from the start of the COVID-19 epidemics in February 2020, until May 4, 2020 when lockdowns started to be lifted. Results implied that current interventions were sufficient for all selected countries to drive the time-varying reproduction number below 1.0 and achieve the goal of epidemic control.

Bendavid et al. (2021) conducted a comparison analysis of the effects of non-pharmaceutical interventions (NPIs) on infection cases in 10 countries including England, France, Germany, Iran, Italy, the Netherlands, Spain, South Korea, Sweden, and the US. By using first-difference models, it was revealed that implementing any NPIs
could reduce infection cases in most countries, including South Korea and Sweden where only less restrictive NPIs were implemented. However, significant effects of more restrictive NPIs on reducing infection cases were not observed in any country. It was concluded that less restrictive interventions may achieve similar effects as more restrictive NPIs, and that therefore more restrictive NPIs may be unnecessary.

2.2.3. Behavioral comparison

Abouk and Heydari (2021) investigated the impacts of social distancing policies in the US by using difference-in-differences and event-study methodologies. The study considered six common social distancing policies including statewide stay-at-home orders, limited stay-at-home orders, nonessential business closures, bans on large gatherings, school closure mandates, and limits on restaurants and bars. Data were extracted from Google’s COVID-19 Community Mobility Reports, which illustrate changes in mobility levels at six location categories: retail and recreation, grocery stores and pharmacies, parks, transit stations, workplaces, and residences. The mobility changes were identified by comparing the outcome of interest in states adopting the above six policies with states that did not introduce those policies. Results showed that statewide stay-at-home orders were most effective in reducing out-of-home mobilities and increasing the time spent at home by 2.5 percentage points (15.2%), followed by limits on restaurants and bars, which resulted in an increase in in-home activities by 1.4 points (8.5%). On the contrary, a significant reduction in mobility levels was not found when implementing the other four social distancing policies.

Focusing on several policy measures and strategies, ranging from international air travel restrictions, case isolation, home quarantine, social distancing with varying levels of compliance, and school closures, Chang et al. (2020) conducted a fine-grained computational simulation of the ongoing COVID-19 pandemic in Australia by using an agent-based model. The results showed that unless combined with a high degree of compliance with social distancing measures, school closures would not bring decisive benefits in the control of the pandemic. They further found that the pandemic can be controlled within 13–14 weeks by 90% compliance coupled with effective case isolation and international travel restrictions.

2.2.4. Large-scale comparison

Hsiang et al. (2020) established a database by collecting daily infection rates, changes in case definitions and the timing of policy deployments. The subnational database included: (1) travel restrictions, (2) social distancing through the cancellation of events and suspension of educational, commercial and religious activities, (3) quarantines and lockdowns, and (4) additional policies such as emergency declarations and extensions of paid sick leave, from the earliest available dates to April 6, 2020. Then reduced-form econometric methods were employed to empirically evaluate the effects of 1,700 local, regional and national anti-contagion policy deployments on the growth rates of infections across localities within China, South Korea, Italy, Iran, France and the United States. Without any policy actions, the early infections of COVID-19 exhibited exponential growth rates of approximately 38% per day, whereas anti-contagion policies could significantly and substantially slow this growth. Policy interventions prevented or delayed an estimated 61 million confirmed cases, corresponding to averting approximately 495 million total infections in the six countries.

2.2.5. Modeling comparison

Chen et al. (2020) developed a mathematical compartmental model to simulate the spatiotemporal dynamics of state-level infections in the US. The model can reflect the geographic variations of the 51 administrative units and their spatial interactions. Modeling results revealed that curtailing interstate travel would not work significantly if the pandemic had already become widespread across the country. Instead, enhancing testing capacity to facilitate the early identification of infected individuals (and subsequent isolation), and strict social-distancing and self-quarantine rules, work effectively to abate the outbreak of COVID-19. Furthermore, modeling results also suggested state specific effects: individuals exposed to the virus needed to be isolated within 2 days in New York and Michigan, whereas the isolation period could be 3.6 days for other states.

Chen and Qiu (2020) employed a dynamic panel SIR model to investigate how non-pharmaceutical interventions including travel restrictions, mask wearing, lockdowns, social distancing, school closures, and centralized quarantine would impact the COVID-19 transmission dynamics with panel data from nine countries (Italy, Spain, Germany, France, UK, Singapore, South Korea, China, and the US) from January 22 to April 3, 2020. Research findings suggested that school closures, mask wearing, and centralized quarantine would generate positive outcomes for controlling COVID-19 infections, which can help avoid lockdown policies.

2.3. Effects of COVID-19 policies on the transport sector

The above review revealed some effects of COVID-19 policies on the transport sector in terms of out-of-home mobility indicators. Here, some key additional observations are summarized. Guo et al. (2021) developed a Community Activity Score (CAS) based on inter-community traffic volume and travel frequency/distance to capture changes in travel-related activity levels caused by COVID-19 in Honolulu county in the State of Hawaii. Based on negative binomial models, they found that the detected changes are significantly correlated with the spread of COVID-19, in association with social distancing measures of stay-at-home orders, face-covering orders, and self-quarantine for out-of-county travels. Meng et al. (2021) built a hybrid seasonal ARIMA (autoregressive integrated moving average) intervention model to evaluate and compare the impacts of different control measures implemented in China, the USA and Singapore on air passenger and air freight traffic. They revealed the mildest economic impact on the air transport industry in China, far-reaching negative impacts in the USA, and more uncertain impacts in Singapore. Furthermore, they concluded that the short-term negative impacts of stricter and more effective measures are large, but the long-term impacts would be relatively mild. By targeting New York City and Seattle, Bian et al. (2021) examined the time lag effects of COVID-19 policies on the use of road system, mass transit, and micromobility, and found a lead effect of stay-at-home and reopening policies, but no lag effects of the national declaration of emergency.

2.4. Transport policy measures

The above-mentioned travel restrictions and bans are not only part of general COVID-19 policies, but also an important part of transport policy measures. Other transport-focused studies can also be found. Based on an observational study of several selected transportation stations in the Greater Accra region of Ghana between March 27 and 29, 2020, Bonful et al. (2020) found that many people did not follow COVID-19 prevention measures (social distancing, handwashing) and argued that transport operators need support and guidance to enforce prevention measures. By building a modified susceptible-exposed-infected-removed (SEIR) model, Maji et al. (2020) estimated the train and bus fleet sizes required for transporting the repatriating migrant workers in several selected states with high outflux of migrants in India. They found that reducing the flow of migrant workers can help to lower the surge in confirmed and active infection cases. Meanwhile, rebuilding confidence in public transport has been a challenge (Zhang et al., 2021). In the context of Italy, Maltese et al. (2021) observed that infrastructural interventions were used to encourage active transport; however, they are skeptical about the effects. Focusing on airlines, Abate et al. (2020) observed that maintaining air transport connectivity was given a high but uneven priority by most governments from the perspective of protecting economic activities and jobs on one hand, while they further raised serious concerns about
possible re-orientation of aviation policy related to climate change and the environment on the other. Abate et al. further pointed out that governments should be deeply involved in post-pandemic interventions by introducing stringent environmental goals. In China, some cities have introduced fare-free policies to encourage people to use public transport as usual. In this regard, however, Dai et al. (2021) found no effects of the peak-hours free-ride policy in Hangzhou on subway ridership, and positive but limited effects on transit ridership in Ningbo (“more rides, more discounts” and off-peak-hours free-ride policies) and Xiamen (a rest day free-ride policy). These findings may suggest the necessity of exploring non-economic measures to rebuild confidence in using public transport.

2.5. How to position this study in the literature

First, existing studies have not confirmed consistent effects of COVID-19 policies in either public health or transport sectors. This suggests the need for more research to provide more scientifically sound evidence on COVID-19 policymaking, which this study attempts to do. Second, policy comparisons could have been made better by paying more attention to simultaneous comparisons across countries and over time. In this regard, this study collected more than 400 policy measures that were taken in different periods of 2020 in six developed countries. Third, there is still limited knowledge on what indicators can be used to assess policy effects, as well as on what duration of time should be used to capture changes before and after policy implementation. This study adopted nine types of indicators, measured with respect to three periods: one week, two weeks, and one month. Thus, 27 indicators are used to evaluate whether, how and how much COVID-19 policy measures work in an expected or unexpected way. Fourth, various policy measures have been compared in other studies; however, comparisons tend to be made arbitrarily, without a comprehensive consideration. To overcome this shortcoming, this study follows the PASS approach (Zhang, 2020) to systematically categorize various policies for guaranteeing seamless comparisons. Fifth, existing studies have mainly adopted single-equation modeling approaches, which have neglected various cause-effect relationships, while cross-sample correlations have not been well addressed either. Therefore, this study will develop a dynamic Bayesian multilevel generalized structural equation model, which can incorporate various complicated cause-effect relationships in a dynamic way, without sacrificing the inherent features of different types of data.

3. Data

Table 1 shows the numbers of PASS-based policy measures taken in the six target countries. In total, 418 policy measures were found from various online sources, of which there are 235 “Prepare-protect-provide” measures (prepare: 56; protect: 126; provide: 53), 66 “Avoid-adjust” measures (avoid: 31; adjust: 35), 48 “Shift-share” measures (shift: 39; share: 9) and 69 “Substitute-stop” measures (substitute: 6; stop: 63). Most of these measures were taken before July 2020 (Table 1(a)). Japan has the largest number of policy measures, while the UK, New Zealand and Australia have similar small numbers. The US has 88 measures and Canada has 51 measures. Concerning policy measures by type, the largest number were “Prepare-protect-provide” measures (235), followed by “Substitute-stop” measures (69) and “Avoid-adjust” measures (66). The “Shift-share” measures have the smallest number (48). Concerning the original nine types (Table 1(b)), the “protect” measures show the largest number (126), followed by “stop” (63), “prepare” (56), and “provide” measures (53). In total, there are 244 transport measures, which distributions across the six countries and across the four P-A-S-S measures are similar to those of the 418 measures: the share differences range only between −5.1 and 3.1 percentage points (share: the share of transport measures in each country or the share of each policy measure in all transport or non-transport measures).

In the later modeling analyses, the analysis unit is each policy measure, so the sample size of policy measures is 418 from the six developed countries. Because policy measures from each country may not be taken independently, modeling tasks need to better address potential cross-sample correlations.

4. Evaluation of policy effects: an aggregate perspective

Here, it is assumed that a policy measure is effective if it is associated with a decline in either an infection indicator, an out-of-home mobility indicator, or an increase in an in-home mobility indicator. It is difficult to specify what length of period should be used to compare the effects of a policy measure before and after its implementation. There are no universally accepted criteria, either. Here, three time periods are selected: one week, two weeks, and one month. The above assumption is made by recognizing that changes in infections and/or mobilities within a certain period can be caused by many factors, including policy measures. In other words, when comparing a certain indicator to evaluate the effectiveness of a policy before and after its implementation, the influences of some other policies may exist. To date, various policies have been made and implemented worldwide as if they were social experiments in COVID-19 policymaking, but without proper control. All policies in practice may have some effects on changes in people’s behaviors and the resulting infection levels in a certain place. Thus, it is impossible to identify the pure effects of any single policy measure taken in practice. However, for example, if a policy is associated with a decline in the number of infection cases, at least, the policy does not increase the number. It is therefore possible to argue that the policy is effective during the comparison period.

A data set is built by linking each policy measure (as a sample) with three indicator sets of infections and mobilities: i.e., one week, two weeks, and one month before and after the implementation of the measure. Infection indicators include daily new infection cases, cumulative deaths, and cumulative infection cases, which are divided by the population of each country (per million). Indicators of mobilities are collected from Google’s COVID-19 Community Mobility Reports, which include changes in activities in six typical places of daily life: retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential areas.3 Parks include public gardens, castles, national forests, campgrounds, observation decks, etc. Transit stations include subway stations, seaports, taxi stands, highway rest stops, car rental agencies, etc. Thus, a policy measure is judged to be effective if the measure is associated with a decline in one of the above three infection indicators and five out-of-home activities, or an increase in in-home activities. This can help to answer Question 1. Table 2 shows the shares of effective policy measures using indicators of infections and mobilities.

Looking at the 418 policy measures, none of them is associated with declines in cumulative deaths and cumulative infection cases in any country. This observation is very striking, considering that there are 63 “stop” measures (e.g., travel bans, border closures, lockdowns, closures of schools and offices) including 32 transport measures in the data set. On the other hand, the policy measures show a certain level of effectiveness in terms of other indicators. Concretely speaking, as seen in the three rows related to all policy measures in Table 2, 41.1%–43.3% of policy measures are effective in terms of declines in daily new cases. Focusing on mobility indicators, more than 50% (many are more than 60%) of the policy measures seem effective in the sense that they are associated with declines in out-of-home activities and increases in in-home activities (except one case with 49.0%).

In Table 2, nine indicators of infections and mobilities at three time periods are used: i.e., 27 indicators in total. Here, we interpret a policy to be more effective if there are more indicators which suggest it to be

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3 https://www.google.com/covid19/mobility/ (Accessed on January 30, 2021).
Table 1
PASS-based policy measures by country collected in 2020.

(a) PASS-based policy measures per month

| Country     | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | Total |
|-------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-------|
| Australia   | 8   | 4   | 3   | 7   | 1   | 3   |     |     |     |     |     | 26    |
| Canada      | 20  | 9   | 1   | 7   | 8   | 4   | 2   |     |     |     |     | 51    |
| Japan       | 43  | 76  | 74  | 14  | 1   |     |     |     |     |     |     | 208   |
| New Zealand | 12  | 5   | 1   | 1   | 2   | 1   | 1   | 2   | 5   |     |     | 25    |
| UK          | 5   |     | 6   | 2   | 2   |     |     |     |     |     |     | 20    |
| USA         | 1   | 48  | 26  | 5   | 2   | 3   | 2   | 1   | 88  |     |     |       |
| Total       | 1   | 136 | 120 | 90  | 26  | 21  | 9   | 3   | 4   | 6   | 3   | 418   |

(b) PASS-based policy measures by type

| Country | Prepare | Protect | Provide | Avoid | Adjust | Shift | Share | Substitute | Stop |
|---------|---------|---------|---------|-------|--------|-------|-------|------------|------|
| Australia | 5      | 8       | 4       | 2     | 1      | 2     |       |            | 4    |
| Canada   | 4      | 20      | 3       | 2     | 5      | 4     | 3     | 1          | 9    |
| Japan    | 18     | 65      | 33      | 24    | 14     | 22    | 5     |            | 27   |
| New Zealand | 1   | 6       | 1       | 1     | 5      | 9     |       |            | 2    |
| UK       | 11     | 1       | 5       | 1     | 1      |       |       |            | 1    |
| USA      | 17     | 26      | 7       | 4     | 8      | 3     | 3     |            | 20   |
| Total    | 56     | 126     | 53      | 31    | 35     | 39    | 9     | 6          | 63   |

effective. If this is the case, it is found that New Zealand has the largest average number (13.0) of indicators showing policy measures to be effective, followed by the US (12.7), Australia (12.0), Japan (11.4), Canada (9.7), and the UK (7.9).

As a new evaluation indicator, a dummy variable (1 or 0) for each policy is calculated to indicate whether more than half of the 27 indicators show the policy to be effective or not. The higher the average value of this dummy variable, the more effective the corresponding policy category is. Looking at this average value, the most effective country is also New Zealand (60.0%), followed by the US (50.0%), Japan (47.1%), Australia (42.3%), Canada (37.3%), and the UK (25.0%).

The features of each country are illustrated below.

Japan [March 6 – July 22, 2020]
In this study, the largest number of policy measures were found in Japan (208; note that some measures were taken several times), but only with respect to the period of March 6 to July 22, 2020 (Fig. 1 shows daily new cases observed in this period). As a whole, 39.4%–78.8% of policy measures were deemed to be effective.

In terms of daily new cases, 51.0%–60.1% of policy measures in Japan were found to be effective in reducing daily new cases. Comparing the four types of policy measures, there are more effective “Avoid-adjust” measures (63.2%–73.7%) out of the total 38 measures, while the effective shares for the 32 “Substitute-stop” measures are smallest, but still range between 43.8% and 50.0%. The second highest effective shares are found with respect to the “Shift-share” measures (59.1%–68.2%) out of the total 22 measures. The shares of effective “Prepare-protect-provide” measures are 47.4%–57.8% out of the total 116 measures.

In the case of mobility indicators, the shares of effective policy measures show larger variations than the shares measured by daily new cases. In-home activities show stable shares, indicating that the most effective measures are the “Prepare-protect-provide” measures (62.5%–69.8%) and the least effective measures are the “Shift-share” measures (31.8%). The other two types of policy measures display similar effective shares: 53.1%–65.6% for the “Substitute-stop” measures and 56.8%–60.5% for the “Avoid-adjust” measures.

As shown in Fig. 2, the “Avoid-adjust” measures seem most effective in reducing out-of-home activities and increasing in-home activities, followed by the “Substitute-stop” and “Prepare-protect-provide” measures. The “Shift-share” measures show mixed effects in reducing activities involving face-to-face social contacts, and tend to increase transit ridership and workplace activities.

The US [February 29 – December 16, 2020]
In the case of the US, 88 policy measures were found between February 29 and December 12, 2020. Fig. 3 shows daily new cases observed in this period. The 88 measures include 50 “Prepare-protect-provide” measures, 12 “Avoid-adjust” measures, 6 “Shift-share” measures, and 20 “Substitute-stop” measures. As a whole, the effectiveness of policy measures in the US is very low compared to Japan in terms of daily new cases (10.2%–26.1%), but very high in terms of changes in out-of-home and in-home activities, as suggested by the effective shares of more than 70% (except one case of 48.9%).

As for the “Prepare-protect-provide” measures, daily new cases show that the effective shares are 14.0%–28.0%, while changes in both out-of-home and in-home activities suggest that more than 70% of these measures are effective, except three cases. Looking at the 12 “Avoid-adjust” measures, only 0.0%–16.7% are effective according to data on the daily new cases; however, most of them (more than 80.0%) are effective according to changes in out-of-home and in-home activities. Concerning the 6 “Shift-share” measures, 66.7%–83.3% are effective in terms of changes in out-of-home and in-home activities, but the effective shares drop to 0.0%–66.7% in terms of daily new cases. Concerning the 20 “Substitute-stop” measures, more than 70% are effective, as shown by changes in out-of-home and in-home activities, while daily new cases reveal that the effective shares are 5.0%–15.0%.

As shown in Fig. 4, all four types of policy measures play a role in mitigating the spread of the virus, i.e., reducing out-of-home activities and increasing in-home activities. In most cases, the “Avoid-adjust” and “Substitute-stop” measures seem most influential while the “Shift-share” measures are least influential. The effects of the “Prepare-protect-provide” measures are moderate.

Australia [March 1 to October 5, 2020]
In Australia, 26 policy measures were found between March 1 and October 5, 2020, including 17 “Prepare-protect-provide” measures, two “Avoid-adjust” measures, three “Shift-share” measures, and four “Substitute-share” measures. Fig. 5 shows daily new cases observed in this period. Daily new cases indicate that the effective shares are 38.5%–50.0%, while changes in out-of-home and in-home activities reveal a 42.3%–70.8% effective share. The “Prepare-protect-provide” measures show similar effective shares, because they account for 65.4% of the total 26 measures.

As for the limited numbers of the other three policy types, most changes in out-of-home and in-home activities show a 100% effectiveness, while daily new cases indicate that the effective shares are 25.0% for the “Substitute-stop” measures and 50.0% for the “Avoid-adjust” measures. A different effective pattern is observed for the “Shift-share” measures, which are judged to be 66.7%–100.0% effective in terms of daily new cases, but to be only 33.3% effective according to changes in out-of-home and in-home activities.

As shown in Fig. 6, the “Substitute-stop” measures seem most
Table 2
Shares of effective policy measures, classified based on the PASS approach.

| Policy measures by country | Indicators of infections | Indicators of mobilities |
|----------------------------|--------------------------|--------------------------|
|                            | daily new cases          | cumulative deaths        | cumulative cases |
|                            | retail & recreation      | groceries and pharmacies | parks          |
|                            | workplace                |                          | residential areas |
| All policy measures (418)  | 41.7% 0.0% 0.0%         | 58.4%                    | 65.5% 68.5%    |
|                            | 43.3% 0.0% 0.0%         | 52.6%                    | 63.4% 55.7%    |
|                            | 41.1% 0.0% 0.0%         | 50.0%                    | 49.0% 53.1%    |
| Australia [AU] (26)        | 50.0% 0.0% 0.0%         | 58.3%                    | 70.8% 54.2%    |
|                            | 50.0% 0.0% 0.0%         | 61.5%                    | 53.8% 63.5%    |
| Prepare-protect-provide (17)| 38.5% 0.0% 0.0%         | 61.5%                    | 42.3% 62.9%    |
|                            | 47.1% 0.0% 0.0%         | 50.0%                    | 68.8% 50.0%    |
|                            | 52.9% 0.0% 0.0%         | 52.9%                    | 47.1% 52.9%    |
| Shift-share (3)            | 29.4% 0.0% 0.0%         | 53.9%                    | 29.4% 58.8%    |
|                            | 50.0% 0.0% 0.0%         | 100.0%                   | 100.0% 100.0%  |
| Avoid-adjust (2)           | 50.0% 0.0% 0.0%         | 100.0%                   | 100.0% 100.0%  |
|                            | 50.0% 0.0% 0.0%         | 100.0%                   | 100.0% 100.0%  |
| Substitute-stop (4)        | 33.3% 0.0% 0.0%         | 33.3%                    | 33.3% 33.3%    |
| Canada [CA] (51)           | 25.0% 0.0% 0.0%         | 100.0%                   | 100.0% 100.0%  |
| Prepare-protect-provide (27)| 44.8% 0.0% 0.0%         | 44.8%                    | 51.9% 48.1%    |
|                            | 18.5% 0.0% 0.0%         | 37.0%                    | 59.3% 33.3%    |
|                            | 29.6% 0.0% 0.0%         | 20.0%                    | 40.0% 20.0%    |
| Avoid-adjust (7)           | 42.9% 0.0% 0.0%         | 42.9%                    | 42.9% 28.6%    |
|                            | 42.9% 0.0% 0.0%         | 42.9%                    | 42.9% 28.6%    |
| Shift-share (7)            | 28.6% 0.0% 0.0%         | 14.3%                    | 42.9% 28.6%    |
|                            | 57.1% 0.0% 0.0%         | 0.0%                     | 42.9% 28.6%    |
| Substitute-stop (10)       | 10.0% 0.0% 0.0%         | 88.9%                    | 88.9% 77.8%    |
| Japan [JP] (208)           | 10.0% 0.0% 0.0%         | 90.0%                    | 90.0% 80.0%    |
| Prepare-protect-provide (116)| 58.7% 0.0% 0.0%         | 56.0%                    | 62.8% 76.4%    |
|                            | 60.1% 0.0% 0.0%         | 43.3%                    | 61.1% 47.6%    |
|                            | 51.0% 0.0% 0.0%         | 39.4%                    | 48.1% 42.3%    |
|                            | 56.9% 0.0% 0.0%         | 61.5%                    | 70.2% 78.8%    |
| Prepare-protect-provide (116)| 57.8% 0.0% 0.0%         | 63.9%                    | 63.3% 60.7%    |
|                            | 47.4% 0.0% 0.0%         | 35.3%                    | 48.4% 34.5%    |
|                            | 68.4% 0.0% 0.0%         | 54.1%                    | 59.5% 81.1%    |
| Shift-share (22)           | 73.7% 0.0% 0.0%         | 50.0%                    | 68.4% 65.8%    |
|                            | 63.2% 0.0% 0.0%         | 60.5%                    | 65.8% 65.8%    |
| Substitute-stop (32)       | 63.6% 0.0% 0.0%         | 27.3%                    | 27.3% 50.0%    |
|                            | 59.1% 0.0% 0.0%         | 31.8%                    | 50.0% 40.9%    |
|                            | 46.9% 0.0% 0.0%         | 60.7%                    | 67.9% 81.1%    |
|                            | 50.0% 0.0% 0.0%         | 40.6%                    | 59.4% 46.9%    |
|                            | 43.3% 0.0% 0.0%         | 34.4%                    | 37.5% 43.8%    |

Note: Upper row refers to one-month indicator; Middle row refers to two-week indicator; Lower row refers to one-week indicator. Value in each parenthesis means the number of policy measures.
effective in reducing out-of-home activities and increasing in-home activities, followed by the “Avoid-adjust” measures, while the “Prepare-protect-provide” measures show the least influence. In contrast, all of the “Shift-share” measures did not reduce activities involving face-to-face social contacts.

Canada [March 2 to September 16, 2020]

In Canada, there are 51 policy measures found from accessible sources, consisting of 27 “Prepare-protect-provide” measures, seven “Avoid-adjust” measures, seven “Shift-share” measures, and ten “Substitute-stop” measures between March 2 and September 16, 2020. Fig. 7 shows the daily new cases observed in this period. The effective shares are 19.6%–25.5%, as shown by daily new cases, while the shares in increase to 43.1%–65.2%, as indicated by changes in out-of-home and in-home activities.

Daily new cases reveal that the most effective measures are the “Shift-share” measures (28.6%–57.1%), while the least effective measures are the “Substitute-stop” measures with only a 10.0% effective share. In contrast, changes in out-of-home and in-home activities show a completely different picture: the “Substitute-stop” measures work most effectively (80.0%–90.0%) and the “Shift-share” measures function least effectively (only 14.3%–42.9%).

As shown in Fig. 8, the “Substitute-stop” measures seem most effective in reducing out-of-home activities and increasing in-home activities, followed by the “Prepare-protect-provide” measures, while the “Avoid-adjust” measures show the least influence. Unexpectedly, all the “Shift-share” measures did not reduce activities causing face-to-face social contacts. Concerning the “Avoid-adjust” measures, they are more likely to increase visiting park activities.

New Zealand [March 14 to December 18, 2020]

Only 25 policy measures are found in New Zealand, which includes eight “Prepare-protect-provide” measures, six “Avoid-adjust” measures, nine “Shift-share” measures, and only two “Substitute-stop” measures between March 14 and December 18, 2020. Fig. 9 shows daily new cases observed in this period. Changes in out-of-home and in-home activities show that a majority of the policy measures are effective; however, daily new cases suggest that most of the measures are not effective.

Among the four types of policy measures, most of them are more than 60.0% effective and there are quite a few mobility indicators suggesting 100% effectiveness, except the “Shift-share” measures.

As shown in Fig. 10, all the four types of policy measures play an expected role in mitigating the spread of the virus, i.e., reducing out-of-home activities and increasing in-home activities. The “Substitute-stop” measures seem most influential and the “Shift-share” measures are the least influential. The effects of the other two types of measures are similar.

The UK [March 16 to November 26, 2020]

The number of policy measures found in the UK is 20, between March 16 and November 26, 2020. Fig. 11 shows daily new cases observed in Japan (March 6 – July 22, 2020).
Daily new cases suggest that the effective shares are 65.0%–70.0%. On the other hand, the mobility indicators show that there are only 15.0%–55.0% effective measures. Similar shares are observed for the “Prepare-protect-provide” measures, because it makes up a large proportion of the measures.

As shown in Fig. 12, most of the “Prepare-protect-provide” measures seem effective in mitigating the spread of the virus; however, most of the other measures play an unexpected role. After policymaking, there are more people visiting parks than before.

4.1. Relevance to existing studies

It is difficult to expect that COVID-19 policy measures would take effect immediately. This is because the incubation period of the SARS-CoV-2 virus can be as long as 14 days (WHO; USA-CDC). Wang et al. (2020) found that there is a lag of 8–11 days between changes in human mobility and declines in COVID-19 transmission. The lag between the onset of symptoms and deaths in Wuhan was assumed to be 15–22 days (Linton et al., 2020; Yang et al., 2020). The above analyses compared policy effectiveness with respect to three periods of one week, two weeks, and one month. There are 63 “stop” measures under study, which are confirmed to be insensitive to deaths. This observation may suggest that these “stop” measures could not reduce deaths within one month, and/or that the timing of implementing these measures was not appropriate. In terms of daily new cases and mobility indicators, both expected and unexpected effects of COVID-19 policy measures (transport and non-transport measures) are observed. Such mixed effects are also found by McKenzie and Adams (2020), who focused on general pandemic measures. These mixed effects are probably related to the timing of policy implementation. For example, focusing on China, Aleta et al. (2020) found that early travel restrictions should be recommended to effectively control the COVID-19 pandemic. Daniele et al. (2021) also

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4 https://www.who.int/news-room/commentaries/detail/transmission-of-sars-cov-2-implications-for-infection-prevention-precautions (Accessed on March 27, 2021).
5 https://www.cdc.gov/coronavirus/2019-ncov/hcp/clinical-guidance-management-patients.html#:~:text=The%20incubation%20period%20for%20COVID,from%20exposure%20to%20symptoms%20onset.&text=One%20study%20reported%20that%2097.5,SARS%2DCoV%2D2%20infection (Accessed on March 27, 2021).
showed that strict measures should be implemented as early as possible. Hsiang et al. (2020) empirically found a constant delayed effect of all non-pharmaceutical interventions on reducing infections in their study on China, South Korea, Italy, Iran, France and the United States. Zhang et al. (2020) found that existing COVID-19 policies may be taken too late to reduce infections and deaths, based on data from several Asian countries. Bian et al. (2021) confirmed both lag (2–83 days) and lead (1–59 days) effects of general pandemic measures on the use of different transport modes in New York City and Seattle. The effectiveness of a policy may also differ depending on how people respond to it. For example, Gargoum and Gargoum (2021) empirically revealed using a case study of 10 countries that people who are slow to respond to COVID-19 have a significantly high mortality rate.

5. Evaluation of policy effects: a modeling analysis

Here, the modeling analysis framework shown in Fig. 13 is described. It is assumed that the levels of mobilities affect rate of infection, which in turn motivates policy implementation. As a result of policy implementation, changes in mobilities are expected and eventually result in changes in infections. Such sequential connections of events are logical. This part of the study tries to answer Question 2 – Question 4.

A dynamic Bayesian multilevel generalized structural equation model was built to estimate the above modeling framework. The dynamic Bayesian multilevel modeling approach is applied because the 418 policy measures are collected from six countries and decisions on policy measures within a country may be interrelated. From such a consideration, a country-specific error component is introduced. This study adopts three sets of time periods for measuring policy effectiveness: one month, two weeks, and one week. Since these three sets do not generate significant differences in the effective shares, the following modeling analyses only focus on the two-week data.

We first tried to estimate the whole modeling framework jointly, but failed. It seems that the sample size of 418 was not sufficient. Then, we decided to estimate a whole model in a sequential way. Concerning the multi-level modeling tasks, a country-specific error component is introduced for each sub-model. It is found that the error component is not statistically significant in the "from before policy implementation" to "policy implementation" and "from mobilities to infections" sub-models, but it is significant in the "from policy implementation to mobilities" sub-model.

As shown in Table 3 (for answering Questions 2 & 3), the "from
before policy implementation’ to ‘policy implementation’” sub-model suggests that there is only one statistically significant parameter representing the influence of the number of cumulative deaths (before policy implementation) on the implementation of the 69 “Substitute-stop” measures. Unexpectedly, no other influential relationships are found. For this unique parameter with statistical significance, however, the negative sign indicates that more deaths discourage decisions on the “Substitute-stop” policy measures. This is very unexpected. It is also surprising that the remaining 349 measures were taken without any significant relationship with infections. On the other hand, all mobility indicators are statistically influential for daily new cases and cumulative deaths before policy implementation. It is found that before policy implementation, an increase in in-home activities is associated with a reduction in both daily new cases and cumulative deaths. Similar effects are also observed with respect to declines in grocery and pharmacy activities (for both daily new cases and cumulative deaths) and declines in visiting parks (but only for cumulative deaths). Other mobility indicators work in an unexpected way.

Table 4 (for answering Question 4) presents an encouraging picture, which shows that all policy measures are associated with a decline in all out-of-home mobility indicators and increase in in-home activities. Comparing the parameter values, the “Substitute-stop” measures are most influential, followed by “Avoid-adjust” and “Prepare-protect-provide” measures, while the “Shift-share” measures are least effective (set to be zero as a reference for estimating the parameters of other policies). This is true for all six mobility indicators.

Concerning the influence of changes in mobilities on changes in infections (see Table 5 which relates to Question 4), there is only one significant parameter, “Difference of changes in grocery and pharmacy activities before and after policy implementation”. However, its negative sign indicates that lower shares after policy implementation led to an increase in daily new cases after policy implementation. This expected influence is also observed with respect to cumulative deaths and cumulative infection cases.

In the case of “Difference of changes in retail and recreation activities before and after policy implementation”, its parameters are positive and statistically significant with respect to cumulative deaths and cumulative infection cases. This implies that a decline in retail and recreation activities after policy implementation is linked to a decline in cumulative deaths and infection cases. “Difference of changes in activities visiting parks before and after policy implementation” and “Difference of changes in transit ridership before and after policy implementation” are estimated to be significant. However, the parameter signs suggest
that these two indicators after policy implementation did not curb the spread of COVID-19 infections, but instead, led to a worsening situation. Fortunately, “Difference of changes in in-home activities before and after policy implementation” plays an expected role in reducing cumulative infection cases in a statistically meaningful way, even though its parameter interval values include a small portion of positive values.

6. Featured COVID-19 policy measures

The modeling estimation results in Section 5 confirm that on average, all PASS-based policy measures are effective in terms of the six mobility indicators. Here, for each country, some featured policy measures are selected and discussed, based on the number of indicators showing effectiveness.

It was found that there are 192 out of all 418 measures (i.e., 45.9%) where more than half of the corresponding indicators showed effectiveness. Among the 192 measures, 79 (41.1%) were taken in March 2020 and 97 (50.5%) in April 2020. In contrast, only 35.3% of less effective measures (i.e., less than half of the indicators showing effectiveness) were taken in March and April 2020. Thus, more than 90% of more effective policy measures were taken at the early stages of the pandemic. This may suggest that COVID-19 policy measures should be taken as early as possible to enhance their effectiveness.

Hereafter, the most featured policy measures are selected and discussed. The selection is made based on the largest two numbers of indicators showing effectiveness. In the following tables showing policy measures, the date indicates the day when a policy measure was announced and/or was taken. All the dates refer to the year 2020.

6.1. Declaration

Note that detailed contents of each policy measure were directly copied or translated from original sources to avoid any misunderstanding. It is declared here that the authors do not have any intention of plagiarism.

6.1.1. Japan

The two numbers of indicators showing the largest degree of effectiveness are 20 and 21, out of the total 27 indicators. Policy measures corresponding to these two numbers are shown below, which were taken mainly in the middle of April. There are 13 policy measures, including seven “Avoid-adjust” measures, three “Prepare-protect” measures, one “Shift” measure, and two “Substitute-stop” measures. “Avoid” measures

![Fig. 8. Differences in mobility indicators before and after policymaking in Canada.](image1)

![Fig. 9. Daily new cases in New Zealand (March 14 to December 18, 2020).](image2)
emphasize self-restraint of inter-regional travel and encourage public transport users to avoid unnecessary and non-urgent trips.

There are two “Adjust” measures and one “Stop” measure about construction projects and the maintenance of transportation infrastructure. It is difficult to assume that such “Adjust” measures could significantly reduce infections and/or out-of-home mobilities, but when they were announced, people may have perceived that infection risks had already spread to construction sites, making them pay more attention to proper social-distancing measures. This argument is also applied to the “Substitute” measure of “allow taxi to transport goods”.

As for preparedness, the basic policy for measures against COVID-19 issued by the central government on April 16 is ranked as a top measure. The “Protect” measures are featured with respect to bus operations and Haneda Airport. The “Shift” measures requesting railway employees to practice telework and staggered commuting are highly evaluated.

### Table 1: PASS policy measures

| Date       | PASS policy measures                                      | Type       | Detailed contents                                                                 |
|------------|----------------------------------------------------------|------------|-----------------------------------------------------------------------------------|
| 2020/4/14  | Avoid Self-restraint of inter-regional travel to organizational bodies administered by the Ministry of Land, Infrastructure, Transport and Tourism | Avoid      |                                                                                   |
| 2020/4/14  | Adjust Regular inspection can be postponed due to presence of infected employees or susceptible employees | Adjust     |                                                                                   |
| 2020/4/15  | Avoid Self-restraint of inter-regional travel to organizational bodies administered by the Ministry of Land, Infrastructure, Transport and Tourism | Avoid      |                                                                                   |
| 2020/4/16  | Prepare Basic policy for measures against COVID-19        | Prepare    |                                                                                   |
| 2020/4/16  | Adjust Postponing the deadlines of submissions for bidding projects | Adjust     |                                                                                   |
| 2020/4/16  | Adjust Adjust the declaration of a state of emergency to cover the whole country | Adjust     |                                                                                   |
| 2020/4/16  | Stop Temporal cancellation measures of ongoing projects upon request from contractors | Stop      |                                                                                   |
| 2020/4/17  | Protect Body temperature check via thermography: Haneda Airport | Protect   |                                                                                   |
| 2020/4/17  | Avoid Call for self-restraint of inter-regional travel at major transport facilities | Avoid     |                                                                                   |
| 2020/4/17  | Avoid Avoid unnecessary trips via in-platform announcement to railway users | Avoid     |                                                                                   |
| 2020/4/17  | Shift Shift to pandemic-sensitive working styles - to request railway operators to promote telework and staggered commuting among their employees | Shift     |                                                                                   |
| 2020/4/21  | Protect Request bus operators and organizations to take physical-distancing measures inside vehicles | Protect   |                                                                                   |
| 2020/4/21  | Substitute Allow taxis to transport goods                | Substitute |                                                                                   |
6.1.2. New Zealand

The two numbers of indicators showing the largest degree of effectiveness are 18 and 17, out of the total 27 indicators. There are 15 policy measures corresponding to these two numbers, as shown below. The 15 measures include four “Protect” measures and one “Provide” measure, one “Avoid” measure and three “Adjust” measures, four “Shift” measures and one “Share” measure, and one “Stop” measure. The
Table 3
Estimation results of Bayesian multilevel GSEM model: The “from ‘before policy implementation’ to ‘policy implementation’” sub-model.

| Parameter | Sig. | [95% Conf. Interval] |
|-----------|------|----------------------|
| Prepare-protect-provide measures | | |
| Daily new cases before policy implementation | 0.001 | −0.006 | 0.007 |
| Cumulative deaths before policy implementation | 0.002 | −0.001 | 0.004 |
| Country-specific error component | 1.000 | | |
| Avoid-adjust measures | | |
| Daily new cases before policy implementation | −0.002 | −0.014 | 0.011 |
| Cumulative deaths before policy implementation | −0.001 | −0.006 | 0.003 |
| Country-specific error component | 1.20E−05 | −1.97E+06 | 2.21E+06 |
| Substitute-stop measures | | |
| Daily new cases before policy implementation | 0.007 | −0.003 | 0.017 |
| Cumulative deaths before policy implementation | −0.004 | + | 0.000 |
| Country-specific error component | 1.18E+05 | −1.93E+06 | 2.17E+06 |
| Daily new cases before policy implementation | | |
| Changes in in-home activities | −2.733 | ** | −3.714 | −1.751 |
| Changes in workplace activities | 1.702 | ** | 0.615 | 2.788 |
| Changes in activities visiting parks | −0.307 | * | −0.562 | −0.052 |
| Changes in transit ridership | −0.946 | * | −1.865 | −0.026 |
| Changes in workplace activities | −4.481 | ** | −5.998 | −2.964 |
| Changes in in-home activities | −17.209 | ** | −23.248 | −11.170 |
| Cumulative deaths before policy implementation | | |
| Changes in in-home and recreation activities | −10.887 | ** | −12.923 | −8.850 |
| Changes in grocery and pharmacy activities | 3.188 | ** | 0.933 | 5.442 |
| Changes in activities visiting parks | 1.304 | ** | 0.775 | 1.833 |
| Changes in transit ridership | −1.610 | + | −3.518 | 0.297 |
| Changes in in-home activities | −8.451 | ** | −11.600 | −5.303 |
| Changes in in-home activities | −44.051 | ** | −56.581 | −31.520 |
| Variance of country-specific error component | 2.15E−10 | - | 1.56E−25 | 2.98E+05 |
| Variance of cumulative deaths before policy implementation | 1.90E+03 | ** | 1.66E+03 | 2.18E+03 |
| Variance of cumulative deaths before policy implementation | 8.18E+03 | ** | 7.14E+03 | 9.37E+03 |

Note: + 10% significant; * 5% significant; ** 1% significant.

Table 4
Estimation results of Bayesian multilevel GSEM model: The “from policy implementation to mobilities” sub-model.

| Parameter | Sig. | [95% Conf. Interval] |
|-----------|------|----------------------|
| Difference of changes in retail and recreation activities before and after policy implementation | | |
| Prepare-protect-provide measures | −9.398 | ** | −12.417 | −6.379 |
| Avoid-adjust measures | −12.095 | ** | −16.645 | −7.546 |
| Substitute-stop measures | −16.477 | ** | −20.966 | −11.988 |
| Country-specific error component | 1.000 | | |
| Difference of changes in grocery and pharmacy activities before and after policy implementation | | |
| Prepare-protect-provide measures | −4.939 | ** | −6.622 | −3.256 |
| Avoid-adjust measures | −6.092 | ** | −8.703 | −3.482 |
| Substitute-stop measures | −7.859 | ** | −10.431 | −5.286 |
| Country-specific error component | 0.524 | ** | 0.383 | 0.665 |
| Difference of changes in activities visiting parks before and after policy implementation | | |
| Prepare-protect-provide measures | −3.364 | ** | −5.659 | −1.070 |
| Avoid-adjust measures | −6.753 | ** | −10.501 | −3.006 |
| Substitute-stop measures | −8.655 | ** | −12.340 | −4.970 |
| Country-specific error component | 0.610 | ** | 0.418 | 0.803 |
| Difference of changes in transit ridership before and after policy implementation | | |
| Prepare-protect-provide measures | −10.890 | ** | −13.913 | −7.867 |
| Avoid-adjust measures | −12.059 | ** | −16.593 | −7.524 |
| Substitute-stop measures | −17.866 | ** | −22.341 | −13.391 |
| Country-specific error component | 1.010 | ** | 0.756 | 1.264 |
| Difference of changes in workplace activities before and after policy implementation | | |
| Prepare-protect-provide measures | −10.699 | ** | −13.605 | −7.793 |
| Avoid-adjust measures | −11.492 | ** | −15.836 | −7.148 |
| Substitute-stop measures | −16.615 | ** | −20.904 | −12.327 |
| Country-specific error component | 0.972 | ** | 0.729 | 1.216 |
| Difference of changes in in-home activities before and after policy implementation | | |
| Prepare-protect-provide measures | 3.801 | ** | 2.719 | 4.883 |
| Avoid-adjust measures | 4.259 | ** | 2.616 | 5.902 |
| Substitute-stop measures | 6.268 | ** | 4.647 | 7.889 |
| Country-specific error component | −0.351 | ** | −0.441 | −0.260 |
| Variance of country-specific error component | 1.41E+02 | + | 4.29E+01 | 4.65E+02 |
| Variance of changes in retail and recreation activities | 2.82E+02 | ** | 2.46E+02 | 3.23E+02 |
| Variance of changes in grocery and pharmacy activities | 9.69E+01 | ** | 8.46E+01 | 1.11E+02 |
| Variance of changes in activities visiting parks | 2.13E+02 | ** | 1.86E+02 | 2.45E+02 |
| Variance of changes in transit ridership | 2.78E+02 | ** | 2.43E+02 | 3.19E+02 |
| Variance of changes in workplace activities | 2.55E+02 | ** | 2.22E+02 | 2.92E+02 |
| Variance of changes in in-home activities | 3.73E+01 | ** | 3.26E+01 | 4.27E+01 |

Note: + 10% significant; * 5% significant; ** 1% significant.
Table 5
Estimation results of Bayesian multilevel GSEM model: The “from mobilities to infections” sub-model.

| Parameter | Sig. | [95% Conf. Interval] |
|-----------|------|---------------------|
| Difference of changes in daily new cases before and after policy implementation | 0.284 | –1.134 – 1.703 |
| Difference of changes in retail and recreation activities before and after policy implementation | 1.094 | –0.402 – 2.590 |
| Difference of changes in grocery and pharmacy activities before and after policy implementation | 4.185 | –1.594 – 9.663 |
| Country-specific error component | 1.000 | |
| Difference of changes in cumulative deaths before and after policy implementation | 1.445 | ** 0.554 – 2.335 |
| Difference of changes in retail and recreation activities before and after policy implementation | 1.789 | ** –2.414 –1.165 |
| Difference of changes in grocery and pharmacy activities before and after policy implementation | 0.231 | –0.140 – 0.601 |
| Difference of changes in transit ridership before and after policy implementation | 0.883 | –2.120 – 0.455 |
| Difference of changes in workplace activities before and after policy implementation | 0.294 | –1.000 – 1.588 |
| Difference of changes in in-home activities before and after policy implementation | 1.540 | –6.667 – 3.586 |
| Country-specific error component | 4.92E+05 | ** –8.37E+06 – 7.39E+06 |

Table 5 (continued)

| Parameter | Sig. | [95% Conf. Interval] |
|-----------|------|---------------------|
| Country-specific error component | –1.17E+07 | –1.99E+08 – 1.76E+08 |
| Variance of country-specific error component | 1.58E-08 | 1.90E-22 – 1.32E+06 |
| Variance of difference of changes in daily new cases before and after policy implementation | 1.26E+03 | ** 1.10E+03 – 1.44E+03 |
| Variance of difference of changes in cumulative deaths before and after policy implementation | 8.34E+02 | ** 7.28E+02 – 9.56E+02 |
| Variance of difference of changes in cumulative infection cases before and after policy implementation | 9.09E+05 | ** 7.93E+05 – 1.04E+06 |

Note: + 10% significant; * 5% significant; ** 1% significant.

The strictest “Stop” measure was to close borders to all travelers on March 19, but New Zealand citizens and permanent residents were exempt. The “Shift” measures were mainly about the shift of alert levels. Avoiding use of public transport during peak hours was recommended on March 23. Essential workers and trips were well defined and announced at the end of March and the beginning of April. Free use of public transport was allowed for essential workers and for essential trips, essential workers were allowed to travel domestically by air and essential trips were not restricted.

| Date | PASS policy measures | Type | Detailed contents |
|------|----------------------|------|-------------------|
| 2020/3/19 | Stop | Borders close to all but New Zealand citizens and permanent residents |
| 2020/3/21 | Protect | Provide | Government announces COVID-19 alert system, and the country is initially set at Alert Level 2 (face coverings required on public transport and domestic flights [Measure 1], appropriate physical distancing on public transport and aircrafts) |
| 2020/3/23 | Shift | Government moves country from Alert Level 2 to Alert Level 3 |
| 2020/3/23 | Protect | Avoid | Alert Level 3 (Measure 1: passengers and workers in transport stations and on public transport services should comply with the 1-m physical distancing rule; Measure 2: people traveling on public transport should avoid peak times unless going to work or school) |
| 2020/3/25 | Shift | Government moves to Alert Level 4 (Measure 1; Measure 2: personal travel is only permitted within territorial authority), and the entire nation goes into self-isolation |
| 2020/3/25 | Protect | Government moves to Alert Level 4 (Measure 1; Measure 2: personal travel is only permitted within territorial authority), and the entire nation goes into self-isolation |
| 2020/3/26 | Adjust | Public transport becomes free but can only be used by essential workers or for essential trips |
| 2020/3/26 | Share | Shared e-scooter services suspended |
| 2020/3/27 | Adjust | Domestic air travel and Cook Strait passenger services restricted to essential workers only |
| 2020/4/3 | Adjust | Foreign nationals returning home are deemed “essential travel” and allowed to travel domestically (by air or land). |
| 2020/4/10 | Protect | Every New Zealand national boarding a flight to return home will have to go into mandatory quarantine for 14 days |
| 2020/8/11 | Shift | Auckland region moves to Alert Level 3. The rest of New Zealand moves to Alert Level 2 |
| 2020/8/14 | Shift | Auckland moves to Alert Level 2, with extra restrictions on travel and gatherings. The rest of New Zealand remains at Alert Level 2 |

6.1.3. Australia

The two numbers of indicators showing the largest degree of effectiveness are 21 and 20, out of the total 27 indicators. Policy measures corresponding to these two numbers are shown below. Four types of
“Protect”, “Stop”, “Adjust”, and “Share” are found, which are ordered in sequence. Closures of entertainment facilities, sports facilities and other public places were imposed. All passengers returning home from overseas were required to be quarantined for 14 days. Essential services were allowed. The rules of protective measures remained consistent.

| Date       | PASS policy measures | Detailed contents                                                                 |
|------------|----------------------|----------------------------------------------------------------------------------|
| 2020/3/29  | Protect              | All travelers returning home from overseas will be quarantined in a hotel or designated facility for 14 days. |
| 2020/3/30  | Stop                 | Pubs, licensed clubs and hotels, gyms, skateparks, cinemas, outside playgrounds and other public places must be closed. |
| 2020/3/30  | Adjust               | Allow roadhouse and rest stop facilities to continue supplying their services to heavy vehicle drivers. |
| 2020/8/7   | Share                | Freight Movement Code for Domestic Border Controls: delivering consistency between states about COVID-19 testing, self-isolation requirements, and reporting requirements to facilitate contact tracing. |

6.1.4. The UK

The two numbers of indicators showing the largest degree of effectiveness are 18 and 17, out of the total 27 indicators. There are only three policy measures corresponding to these two numbers, as shown below. All are “Prepare” measures about guidance on international travel, drivers, and maritime transport.

| Date       | PASS policy measures | Detailed contents                                                                 |
|------------|----------------------|----------------------------------------------------------------------------------|
| 2020/3/16  | Prepare              | Guidance on coronavirus (COVID-19) for shipping and sea ports                     |
| 2020/3/17  | Prepare              | Freight industry guidance on international travel during the coronavirus (COVID-19) pandemic. |
| 2020/3/20  | Prepare              | Guidance on the relaxation of drivers’ hours rules in the context of coronavirus (COVID-19) and Brexit. |

6.1.5. The US

The two numbers of indicators showing the largest degree of effectiveness are 19 and 18, out of the total 27 indicators. Policy measures corresponding to these two numbers are shown below. In total, 30 measures are applied, including two “Prepare” measures, 12 “Protect” measures, and three “Provide” measures; two “Avoid” measures and four “Adjust” measures; two “Share” measures; and five “Stop” measures. Thus, the top measures in the US emphasize protective measures.

| Date       | PASS policy measures | Detailed contents                                                                 |
|------------|----------------------|----------------------------------------------------------------------------------|
| 2020/3/16  | Protect              | Recommendations of the US government to avoid the spread of the virus             |
| 2020/3/17  | Avoid                | The US CDC issued a warning (Warning - Level 3, Avoid Nonessential Travel Widespread Ongoing Transmission) on travel with cruise ships. |
| 2020/3/17  | Stop                 | The US Embassy Monctevideo Consular Section is closed for all routine consular services until further notice. |
| 2020/3/17  | Protect              | Hawaii: screening of all passengers disembarking cruise ships will be screened; airports are working on implementation plans for screening arriving visitors. |
| 2020/3/18  | Stop                 | Travelers prohibited from entry to the United States                             |
| 2020/3/18  | Protect              | - The Defense Department will massively expand medical resources, making 5 million respirator masks and 2,000 ventilators available for use. - Federal Emergency Management Agency is now activated in every region of the country and at the highest level. - Navy hospital ships are being deployed to impacted areas. |
| 2020/3/19  | Protect              | Florida governor announced “Executive Order 20-80, which requires those who travel to Florida from New York, New Jersey and Connecticut to self-isolate for 14 days upon entering the state” (beginning March 24) |
| 2020/3/23  | Provide              | Financial support for Disadvantaged Business Enterprises (DBEs) to maintain economic stability - guidance on appropriate flexibilities are provide to the DBE and Airport Concession DBE Program. |
| 2020/3/24  | Provide              | Provided Guidance and information on facilities affected by the outbreak of COVID-19 |

(continued on next column)
### 6.1.6. Canada

The two numbers of indicators showing the largest degree of effectiveness are 18 and 16, out of the total 27 indicators. Policy measures corresponding to these two numbers are shown below. Totally, 16 measures are applied, including 7 “Protect” measures and 1 “Provide” measure, 1 “Adjust” measure, 1 “Substitute” measure and 6 “Stop” measures. Thus, the top measures in Canada emphasize protective measures and the strictest “Stop” measures.

| Date       | Type  | Detailed contents                                                                                                                                 |
|------------|-------|--------------------------------------------------------------------------------------------------------------------------------------------------|
| 2020/3/25  | Protect | **US President Trump announces $16 billion will be provided for the purchase of personal protective equipment, such as masks and respirators, through the Strategic National Stockpile** |
| 2020/3/25  | Stop   | **All travel is prohibited, including but not limited to, travel on scooter, motorcycle, automobile, or public transit, except essential travel and essential activities, respectively** |
| 2020/3/25  | Stop   | **People must use public transit only for the purpose of performing essential activities or to travel to and from work to operate essential businesses or maintain essential governmental functions** |
| 2020/3/25  | Stop   | **All travel must comply with social distancing requirements** |
| 2020/3/27  | Provide | **CDC posted a global pandemic travel health notice, advising against all nonessential international travel** |
| 2020/3/27  | Protect | **Florida Governor issues an executive order directing the establishment of appropriate checkpoints on the roadways for travelers and vehicles entering the State of Florida and to require those persons to provide information, including a written form, regarding the origin of their travel and the address of their location of isolation or quarantine for a period of 14 days** |
| 2020/3/27  | Protect | **Rhode Island - New York travel: Anyone returning to Rhode Island after traveling to New York state by any mode of transportation must self-quarantine for 14 days** |
| 2020/3/29  | Adjust  | **US President Trump extends Social Distancing Guidelines through end of April** |
| 2020/4/6   | Share  | **Arizona: Increased access to public medical records for the government. This is in order to have more accurate information regarding the pandemic** |
| 2020/4/7   | Prepare | **The Centers for Medicare & Medicaid Services (CMS) issues New Wave of Infection Control Guidance Based on CDC Guidelines to Protect Patients and Healthcare Workers from COVID-19, under the leadership of President Trump** |
| 2020/4/7   | Prepare | **Department of Health and Human Services (HHS) Office of the Assistant Secretary for Health (OASH) temporarily suspended a number of rules so that hospitals, clinics, and other healthcare facilities can boost their frontline medical staffs as they fight to save lives during the COVID-19 pandemic** |
| 2020/4/8   | Adjust  | **At US President Trump’s direction, the Centers for Medicare & Medicaid Services (CMS) temporarily suspended a number of rules so that hospitals, clinics, and other healthcare facilities can boost their frontline medical staffs as they fight to save lives during the COVID-19 pandemic** |
| 2020/4/9   | Adjust  | **April 9, the Office for Civil Rights at the US Department of Health and Human Services (HHS) announced that it will exercise its enforcement discretion and will not impose penalties for violations of the HIPAA Rules against covered entities or business associates in connection with the good faith participation in the operation of COVID-19 testing sites during the COVID-19 nationwide public health emergency** |

| Date       | Type  | Detailed contents                                                                                                                                 |
|------------|-------|--------------------------------------------------------------------------------------------------------------------------------------------------|
| 2020/3/16  | Stop   | **The Transportation Ministry: Cruise ships that are capable of carrying 500 or more persons, including crew members, will be prohibited from accessing ports managed by port authorities, public ports, public port facilities, and within the Seaway** |
| 2020/3/16  | Stop   | **Prime Minister Trudeau announces that Canada will bar foreign nationals from all countries except the United States from entering until June 30** |
| 2020/3/18  | Provide | **Prime Minister Trudeau announced new economic measures to help stabilize the economy and help Canadians affected by the impacts of this challenging period. The $82 billion in support represents more than 3 percent of Canada GDP** |
| 2020/3/18  | Protect | **Health Canada is facilitating access to products (hand sanitizers, disinfectants, and personal protective equipment) that may not fully meet current regulatory requirements, as an interim measure** |
| 2020/3/18  | Protect | **Health Canada expedites access to COVID-19 diagnostic laboratory test kits and other medical devices** |
| 2020/3/18  | Protect | **The Honorable Patty Hajdu, Minister of Health, announced an Emergency Order under the Quarantine Act that requires any person entering Canada by air, sea or land to self-isolate for 14 days whether or not they have symptoms of COVID-19** |
| 2020/3/18  | Protect | **The barring of foreign nationals from all countries, except the US, from entering has been instituted by the Government of Canada until June 30, 2020** |
| 2020/3/18  | Stop   | **The eating of food in restaurants, dining rooms, and any location where food is consumed has been suspended until further notice** |
| 2020/3/18  | Stop   | **The government announced that from March 27, 2020, all in-person Service Canada locations will be closed until further notice. Services will still be available via phone or online** |
| 2020/3/20  | Substitute | **Prime Minister Justin Trudeau announced that from March 30, 2020, domestic travel by plane or train will not be allowed for anyone exhibiting symptoms of coronavirus** |
| 2020/3/25  | Protect | **The Government of Canada is investing $2 billion to support diagnostic testing and to purchase ventilators and protective personal equipment, including for bulk purchases with provinces and territories. Personal protective equipment includes things like masks and face shields, gowns, and hand sanitizer** |
| 2020/3/25  | Stop   | **Prohibit all commercial marine vessels with a capacity of more than 12 passengers from entering Canada by air, sea or land to self-isolate for 14 days whether or not they have symptoms of COVID-19** |
| 2020/3/26  | Protect | **The House of Commons of Canada passes a bill on March 31, 2020, to prevent drug shortages in the country due to COVID-19** |
| 2020/3/28  | Stop   | **Prohibit all commercial marine vessels with a capacity of more than 12 passengers from entering Canada by air, sea or land to self-isolate for 14 days whether or not they have symptoms of COVID-19** |
| 2020/3/31  | Adjust  | **Require ferries and essential passenger vessel operators to immediately reduce by 50% of the maximum number of passengers to support the 2-m physical distancing rule, or implement alternative practices to reduce the risk of spreading COVID-19 (consistent with Public Health Agency of Canada guidelines) among passengers on board their vessels, such as keeping people in their vehicles, when feasible, or enhanced cleaning and hygiene measures** |
| 2020/4/14  | Protect | **Regulatory amendments under the Contraventions Act came into force: these changes provide increased flexibility for law enforcement activities** |
7. Conclusions

Recognizing the lack of scientifically sound evidence for COVID-19 policymaking, this study examined 418 policy measures taken by Australia, Canada, Japan, New Zealand, the UK, and the US. The effectiveness of each policy measure is evaluated by checking whether each of nine indicators of infections and mobilities with respect to three time periods (one week, two weeks, and one month before and after policymaking) is associated with a reduction of infections, out-of-home activity, or an increase in in-home activity.

In this way, policy effects have been extensively evaluated in an objective way. Furthermore, a dynamic Bayesian multilevel modeling framework was developed to quantify the relationships between mobilities and infections before policymaking, the relationships between before-policymaking infections and policymaking (i.e., whether a certain type of PASS-based policy measures is taken or not), the relationships between policymaking and changes in mobilities after policymaking, and the relationships between changes in mobilities and infections after policymaking. Findings from this study can be summarized below.

[1] None of the 418 COVID-19 policy measures in public health and transport is associated with a decline of either cumulative deaths or cumulative infection cases. The continuing growth of global infections during the whole of 2020 may support this observation.

[2] In terms of daily new cases, about 40% of all 418 measures can be judged to be effective. Among the six countries, the UK showed the best performance, followed by Japan and Australia. This is probably because all the measures found in these three countries were mostly taken before August 2020.

[3] In terms of mobility indicators, the US has the highest shares (mostly 70%–80%) of effective measures, followed by New Zealand (mostly 60%–77%) and Japan (mostly 54%–76%). The UK performed the worst, with the effective shares of only 15%–40% (mostly).

[4] Concerning the four types of PASS policy measures, “Prepare-protect-provide” policy measures have been dominating in practice. The effective shares of the four types vary largely across countries. Firstly, daily new cases show that Japan’s “Avoid-adjust” measures performed the best (the effective shares range between 63% and 74%), followed by “Shift-share” measures (59%–68%), while the effective shares of the other two types are between 44% and 58%. With one exception, the US’s effective shares are all below 30% and its “Prepare-protect-provide” measures performed better than the other measures. In the case of Canada, the “Shift-share” and “Avoid-adjust” measures show a better performance (the effective shares are mostly 29%–43%) than the other measures. The “Prepare-protect-provide” measures of Australia, Canada, New Zealand, and the UK are judged to be 29%–53%, 15%–22%, 13%–25%, and 59%–65% effective, respectively. In New Zealand, the “Avoid-adjust” and “Shift-share” measures are mostly 30% effective. Secondly, the mobility indicators show a different picture, and different indicators with different time windows show varying levels of policy effectiveness, mostly ranging between 15% and 90%.

[5] Changes in mobility levels suggest that in Australia, Japan and the US, their “Avoid-adjust” and “Substitute-stop” measures performed better than the other measures, respectively, while the “Substitute-stop” measures are more effective in Canada and New Zealand and the “Prepare-protect-provide” measures are more effective in the UK than the other measures. In New Zealand, except for the “Shift-share” measures, the other three types of measures performed similarly.

[6] Modeling analyses indicate that infection indicators before policymaking did not affect decisions on the PASS policy measures, with one exception. Fortunately, all the PASS policy measures had, as expected, an influence on changes in mobilities after policymaking. However, after policymaking, the effects of changes in mobilities on changes in infections are mixed. i.e., both expected and unexpected effects are observed.

The above finding [1] implies that both policymakers and citizens as well as other stakeholders should be aware of the insensitivity of actual policymaking to deaths and re-consider their decisions and behaviors. Focusing on the finding [2], the ineffectiveness of more than half of the measures should be recognized by policymakers. COVID-19 policymaking should be revisited by paying more serious attention to scientifically sound evidence. Looking at the infection situations in these countries, the finding [3] suggests that it is important to inform people that a reduction in mobility does not automatically lead to declines in infections, and that it is therefore necessary for people to take active measures to protect themselves and other persons. The findings [4], [5] and [6] indicate that an effective policy measure in one country does not guarantee that it will also be effective in other countries, suggesting that policy assessment is crucial before its implementation.

The significant contributions of this study are as follows. First, this study is one of a very limited number of comparative studies based on a large set of COVID-19 transport-related and public health policy measures. This study has presented new ways of evaluating COVID-19 policies based on multiple indicators, which allow policymakers to directly measure the effectiveness of a certain policy from different angles. Furthermore, building the database with the afore-mentioned indicators allows policymakers in different countries to easily compare policy effectiveness in their own ways. For example, policy effectiveness in other countries can serve as a benchmark to evaluate their own policies. Second, the dynamic Bayesian multilevel generalized structural equation model developed in this study has provided another new way of evaluating COVID-19 policymaking, which can quantify the size of influence of each policy by reflecting dynamic cause-effect relationships between policymaking, its influencing factors and its consequences. Third, the comparison of policies in six developed countries of Australia, Canada, Japan, New Zealand, the UK and the US, which constitute a substantial number of global cases, makes the findings from this study important from a global perspective. Fourth, the research framework developed in this study is general and can be easily expanded to incorporate more factors and more relationships that are useful to evaluate COVID-19 policymaking in a comprehensive way, as long as a sufficient number of policy measures can be collected.

What can be learned from this study? The following are some examples of policy recommendations. First, various ineffective policy measures suggest that existing COVID-19 policymaking should be revisited seriously in order to enhance policy effectiveness and efficiency. The “social experiment”-like or trial-and-error policymaking could have been better designed. Failure of COVID-19 policymaking is understandable, considering the difficulties arising from the many unknowns and uncertainties. The problem is whether policymakers quickly recognize the issues and modify their policymaking in a timely way. It is important to reach immediate consensus building with the general public and all stakeholders about a flexible approach to COVID-19-
sensitive policymaking. Second, there are too many “Prepare-protect-provide” policy measures in practice. COVID-19 policies should be made as early and as quickly as possible, in order to mitigate the rebound effects caused by the fatigue from long-lasting social distancing practices. It is extremely important to quickly accumulate more and more scientific evidence about such strict policy measures. Third, top-down (or centralized) institutional design can help guarantee consistent and effective policy implementation, with the cooperation of various stakeholders. Finally, while it is crucial to strictly protect privacy in COVID-19 policymaking, the trajectory information of personal infection and spatio-temporal social contacts should be made publicly accessible. This is an extremely important public policy to support the implementation of effective COVID-19 policies, based on the scientifically sound evidence derived from research in various disciplines. Data availability has seriously hindered the accumulation of such evidence.

This study focuses on only six developed countries and 418 policy measures. More countries and policy measures should be compared. Policy assessment tools should be further improved by considering the fact that multiple policies are taken simultaneously in a certain period. Research on developing countries is especially needed to address how to overcome various barriers and constraints of COVID-19 policymaking in low-income settings. In this regard, it is important to further promote international collaboration and develop more publicly acceptable robust policy recommendations based on collective wisdom.

Declaration of competing interest

There is no conflict of interest.

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References

Abdollahi, E., Haworth-Brockman, M., Keynan, Y., Langley, J.M., Moghadas, S.M., 2020. Simulating the effect of school closure during COVID-19 outbreaks in Ontario, Canada. BMC Med. 18 (1), 230. https://doi.org/10.1186/s12916-020-01705-0.

Ahate, M., Christidis, P., Purwanto, A.J., 2020. Government support to airlines in the COVID-19 pandemic: an evaluation of the OAG proposals. medRxiv 10. https://doi.org/10.1101/2019-08-0044-3. Article No. 22429.

Chen, X., Qiu, Z., 2020. Scenario Analysis of Non-pharmaceutical Interventions on Global COVID-19 Epidemics. Cogent Econ. and Finan. 7, 160420. https://doi.org/10.1080/17403457.2020.18050-2. Article No. 4264.

Guo, Y., Yu, H., Zhang, G., Ma, D.T., 2020. Exploring the impacts of travel-implied policy factors on COVID-19 spread within communities based on multi-source data interpretations. Health Place 69. https://doi.org/10.1016/j.healthplace.2021.102538. Article No. 102538.

Hartil, T., Wälde, K., Weber, E., 2020. Measuring the Impact of the German Public Shutdown on the Spread of COVID-19. Covid Economics: Vetted and Real-Time Papers. Centre for Economic Policy Research (CEPR). https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3682830.

Huang, L.N.Y., Hultgren, A., Krasovich, E., Lau, P., Lee, J., Rolf, E., Tseng, J., Wu, T., Yang, S., 2020. The effect of large-scale anti-contagion policies on the COVID-19 pandemic. Nature 584 (7820), 262–267.

Kraemer, M.U.G., Yang, C.-H., Gutierrez, B., Wu, C.-H., Klein, B., Pigott, D.M., du Plessis, L., Faria, N.R., Li, R., Huang, E., Phan, S., Lauer, S.A., Laeyendecker, O., Wu, J.T., 2020. The effect of scale-wide anti-contagion policies on the COVID-19 pandemic. Nature 584 (7820), 262–267.

Lin, X.H., Wei, S., Wu, T.C., 2020. Association of public health interventions with the COVID-19 epidemic in Australia: evaluating the effectiveness of international travel restrictions related to the spreading of the novel COVID-19 within mainland China. Chaos. Solit. Fractals 139. https://doi.org/10.1016/j.chaos.2020.110068. Article No. 10068.

Linton, N.M., Kobayashi, T., Yang, Y., Hayashi, K., Akhmetzhanov, A.R., Jung, S., Whittaker, C., Zhu, H., Berah, T., Eaton, J.W., Monod, M., Ghani, A.C., Donnelly, C.A., Riley, S., Vollmer, M.A.C., Ferguson, N.M., Ollell, L.C., Bhatt, S., 2020. Estimating the effects of non-pharmaceutical interventions on COVID-19 on Europe. Nature 584 (7820), 257–261.

Maji, A., Chaudhari, T., Yang, S., Choudhari, T., Yung, J., Hayashi, K., Akhmetzhanov, A.R., Jung, S., Whittaker, C., Zhu, H., Berah, T., Eaton, J.W., Monod, M., Ghani, A.C., Donnelly, C.A., Riley, S., Vollmer, M.A.C., Ferguson, N.M., Ollell, L.C., Bhatt, S., 2020. Estimating the effects of non-pharmaceutical interventions on COVID-19 on Europe. Nature 584 (7820), 257–261.

Riley, S., Donnelly, C.A., Ghani, A.C., Yang, S., Yung, J., Hayashi, K., Valleroy, L.A., Whittaker, C., Zhu, H., Berah, T., Eaton, J.W., Monod, M., Ghani, A.C., Donnelly, C.A., Riley, S., Vollmer, M.A.C., Ferguson, N.M., Ollell, L.C., Bhatt, S., 2020. Estimating the effects of non-pharmaceutical interventions on COVID-19 on Europe. Nature 584 (7820), 257–261.

Wu, J.T., Macken, C.J., Wu, T.C., 2020. The effect of large-scale anti-contagion policies on the COVID-19 pandemic. Nature 584 (7820), 262–267.

Xu, J., Li, X., Gao, S., Kang, Y., Shi, X., 2020. State-specific projection of COVID-19 spread in the United States and evaluation of the impact of major control measures. medRxiv 10. https://doi.org/10.1101/2019-08-0044-3. Article No. 22429.

Xu, J., Qiu, Z., 2020. Scenario Analysis of Non-pharmaceutical Interventions on Global COVID-19 Epidemics. Cogent Econ. and Finan. 7, 160420. https://doi.org/10.1080/17403457.2020.18050-2. Article No. 4264.
Wang, X., Pei, T., Liu, Q., Song, C., Liu, Y., Cheng, X., Ma, J., Zhang, Z., 2020. Quantifying the time-lag effects of human mobility on the COVID-19 transmission: a multi-city study in China. IEEE Access 8, 216752–216761.

Yang, X., Yu, Y., Xu, J., Shi, H., Xia, J., Liu, H., Wu, Y., Zhang, L., Yu, Z., Fang, M., Yu, T., Wang, Y., Pan, S., Zou, X., Yuan, S., Shang, Y., 2020. Clinical course and outcomes of critically ill patients with SARS-CoV-2 pneumonia in Wuhan, China: a single-centered, retrospective, observational study. The Lancet Respiratory Medicine 8 (5), 475–481.

Zhang, J., 2020. Transport policymaking that accounts for COVID-19 and future public health threats: a PASS approach. Transport Pol. 99, 405–418.

Zhang, J., Ding, H., Dinglass, M.G.A., Do, C.X., Namgung, H., Nguyen, H.T.A., Nugroho, S., Renita, R.V., Virakvichetra, L., Yoshida, H., Hayashi, Y., 2020. Comparisons of PASS-based transport policy measures for addressing the impacts of COVID-19 in Asian countries. In: Presented at the International E-Conference on Pandemics and Transport Policy (ICPT2020), December 7-11.

Zhang, J., Hayashi, Y., Frank, L.D., 2021. COVID-19 and transport: findings from a world-wide expert survey. Transport Pol. 103, 68–85.