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A time-series COVID-19 policy outcome analysis tool to measure human behavior from a herd instinct perspective

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Abstract

Purpose There are 47 municipalities and prefectures in Japan that operate similar COVID-19 policies in a unified manner. There are significant differences regarding their policy outcomes. In order to investigate when the outcomes are different, we made a COVID-19 policy outcome analysis tool, jpcovid for evaluating time-series scores of individual prefectures, not a policy analysis tool.

Methods Scoring policies is based on a single population mortality metric: the number of COVID-19 deaths divided by the population in millions from a demographic perspective.

Results Although uniformed policies have been adopted by the 47 prefectures in Japan, there are significant differences in the calculated scores among the 47 prefectures. This difference can be caused by differences in the herding instincts of the community with COVID-19 variants. The herd instinct is an inherent tendency to associate with others and follow the group's behavior or a behavior wherein people tend to react to the actions of others without considering the reason. The snapshot scoring tool, jpscore showed that Niigata has the best score of 67.9 while Osaka has the worst score of 727.9. jpcovid allows users to identify when herd instincts made changes in time-series scores.

Conclusions This is the world's first large-scale measurement on the herd instinct of prefectures in Japan. The proposed method can be applied to other countries in general.

Keywords Time-series policy analysis · Jpscore · Herd instinct · Jpcovid

1 Introduction

Vaccine efficacy is a snapshot result in the closed laboratory experiment and the vaccine effectiveness wanes over time in the real world with new variants having spike mutations and immune escape. In other words, policymakers must identify the current problem in the pandemic and update their policies to reduce the unnecessary deaths due to COVID-19.

There are 47 municipalities and prefectures in Japan that operate similar COVID-19 policies in a unified manner. There are significant differences regarding their policy outcomes. In order to investigate when the outcomes are different, we made a COVID-19 policy outcome analysis tool, jpcovid for evaluating time-series scores of individual prefectures, not a policy analysis tool.

This outcome difference can be caused by differences in the herding instincts of the individual community with COVID-19 variants in Japan. Therefore, this paper discusses the herd instinct of COVID-19 in Japan along with policy outcomes, not a policy analysis of COVID-19. The herd instinct is an inherent tendency to associate with others and follow the group's behavior or a behavior wherein people tend to react to the actions of others without considering the reason. Community policies and human behavior affect the outcome of COVID-19.

Highlights
- Niigata had three big change points on herd instinct.
- Fukui had the single biggest change point on herd instinct in July 2022.
- The top four prefectures face the Sea of Japan by herd instinct.

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The proposed policy outcome analysis tool is applicable to other countries and areas on COVID-19 and other infections. The policy outcome analysis is based on time-series population mortality which can identify when policymakers made mistakes. The scope of this paper is to analyze and focus on COVID-19 policy outcomes in Japan.

Marton-Alper et al. reported herding in human groups of autistic traits [1]. Anderson studied immunities of the herd in peace, war, and COVID-19 [2]. Anderson only briefly surveyed the herd instinct of Trotter‘s papers [3, 4], Dudley’s study [5], Malinowski [6], Swanson [7], and Canetti [8] respectively. However, Anderson did not study herd instinct quantitatively or qualitatively.

Lee et al. examined how COVID-19 triggers our herding behavior [9]. Lee et al. used the questionnaire result from 180 voluntary participants. However, questionnaire bias is an important problem in public health surveys and needs to be removed [10]. However, they did not alleviate questionnaire bias in herding behavior study. Their result is not conclusive on the herd instinct.

Arafat et al. reported psychological behavior of panic buying during pandemic [11]. They presented the possible hypothetical explanations for the behavior based on a literature survey. However, they did not investigate herd instinct quantitatively or qualitatively.

Aslam et al. studied herding behavior during the COVID-19 pandemic and compared between Asian and European stock markets [12]. However, they did not present the COVID-19 mitigation method. The result of the proposed method should be used for mitigating the pandemic.

To the best of our knowledge, there are no existing methods to measure the large-scale herd instinct quantitatively or qualitatively. This paper proposes a time-series policy outcome analysis tool for evaluating the performance of COVID-19 policies, but it just happens to be used to measure herd instincts because of the uniform policy adopted by all 47 prefectures in Japan. In other words, the proposed time-series policy analysis tool can detect and identify when a prefecture's behavior change with COVID-19 variants has occurred.

There are two types of policy outcome analysis tools: snapshot policy outcome analysis tool and time-series policy outcome analysis tool. Both tools will be used for analysis of 47 municipalities and prefectures in Japan. Time-series policy outcome analysis tool is superior to snapshot policy outcome analysis tool because they allow us to observe the evolution and progress of scores over time.

Japan has a unique COVID-19 policy such that the 47 individual prefectures have adopted the same uniform policy controlled by the government. In other words, Japan has a golden opportunity to observe the large-scale herd instinct of COVID-19 or the community behavior due to the uniform COVID-19 policy. Therefore, the difference of the COVID-19 outcomes can be caused by the herd instinct with COVID-19 variants. The vaccination situation is almost the same in all prefectures.

We have developed a snapshot policy outcome analysis tool, jpscore to score individual policies of the 47 prefectures and generate a list of sorted scores [13]. The lower the score, the better the policy. The list of sorted scores allows policymakers to identify the best prefecture to learn the best strategy or policy.

In order to run jpscore, you must install Python and jpscore on the system. To install jpscore, run the following command. ($) character indicates the prompt from the system terminal.

```
$ pip install jpscore
```

To run jpscore, run the following command.

```
$ jpscore
```

Figure 1 indicates that Niigata has the best score of 203.8 while Osaka has the worst score of 969.7 as of April 26, 2023. Niigata’s score is nearly 5 times better than Osaka’s score. As noted above, similar policies have been adopted in all prefectures for COVID-19, but herding instincts make a significant difference in COVID-19 outcomes.

This paper will show and visualize when herding behaviors have changed in prefectures. The role of time-series policy outcome analysis tool, jpcovid will be introduced in this paper and the contribution of the jpcovid tool will be discussed. Since the source code for jpcovid is released

prefecture	deaths	population	score
Niigata	453	2.223	203.8
Fukui	200	0.768	260.4
Toyama	321	1.044	307.5
Yamagata	367	1.078	340.4
Tokushima	421	0.728	578.3
…	…	…	…
Miyazaki	777	1.073	724.1
Kumamoto	1314	1.748	751.7
Kochi	602	0.698	862.5
Hokkaido	4592	5.250	874.7
Osaka	8542	8.809	969.7

Fig. 1 Result of jpscore as of April 26. 2023

in public, the proposed method can generally be applied to other countries in general to observe the herding behavior.

2 Methods

jpcovid is a new Python Package Index (PyPI) application. The PyPI application is composed of three files such as README.md, setup.py and jpcovid.py. README.md is usually generated by GitHub site. setup.py and jpcovid.py files are attached in APPENDIX. This paper will disclose source codes in Python. The setup.py file is a Python script, usually included in a library or app written in Python, to indicate that the module or package you are about to install may be packaged. jpcovid.py is a main Python program. Time-series scoring policy outcome is based on the daily population mortality rate: dividing the number of daily cumulative COVID-19 deaths by the population in million. The latest dataset is automatically scraped over the Internet and jpcovid can calculate and visualize the time-series scores. The higher the score, the worse the policy. In other words, the lower the score, the better the policy.

Remember that jpscore is a snapshot scoring tool while the proposed jpcovid is a time-series scoring tool to be able to identify when policymakers made mistakes against COVID-19.

PyPI allows users to install the target library via pip command. As long as Python is installed on the system, the installed library can run on Windows, MacOS, and Linux operating systems without being aware of the installed operating system.

According to Wikipedia, as of 17 January 2022, more than 350,000 Python packages can be accessed through PyPI. In other words, PyPI offers the largest packages in public which means that it is for programmers to maximize the dissemination of software in the world. The contribution of this paper is the release of source codes, which can be applied in other countries to evaluate COVID-19 policies and measure herd instincts through datasets. In other words, once the dataset is prepared, the researcher can calculate and identify when the policymaker made mistakes or behavioral change points of communities were observed.

3 Results

Two policy outcome analysis tools such as jpscore for generating a snapshot list of sorted scores and jpcovid for visualizing time-series scores and identifying when policymakers made mistakes. While jpscore can reveal a better ordered list of sorted scores, it cannot identify when a policymaker made a mistake. However, a new time-series policy analysis tool, jpcovid is presented in this paper. The jpcovid tool allows policymakers to visualize and identify when they made mistakes or herding behaviors changed. Identified mistakes or herding behaviors can be corrected by policymakers for updating policies in the near future.

To run jpcovid, you must install it by the following command.

```
$ pip install jpcovid
```

To run jpcovid, you must type the following command for Niigata with the best score and Osaka with the worst score in Japan.

```
$ jpcovid Niigata Osaka
```

Figure 2 shows the result of the above command. The flat graph indicates that the policy with herd instinct suppressed COVID-19 and it is successful. The steeper the diagonal

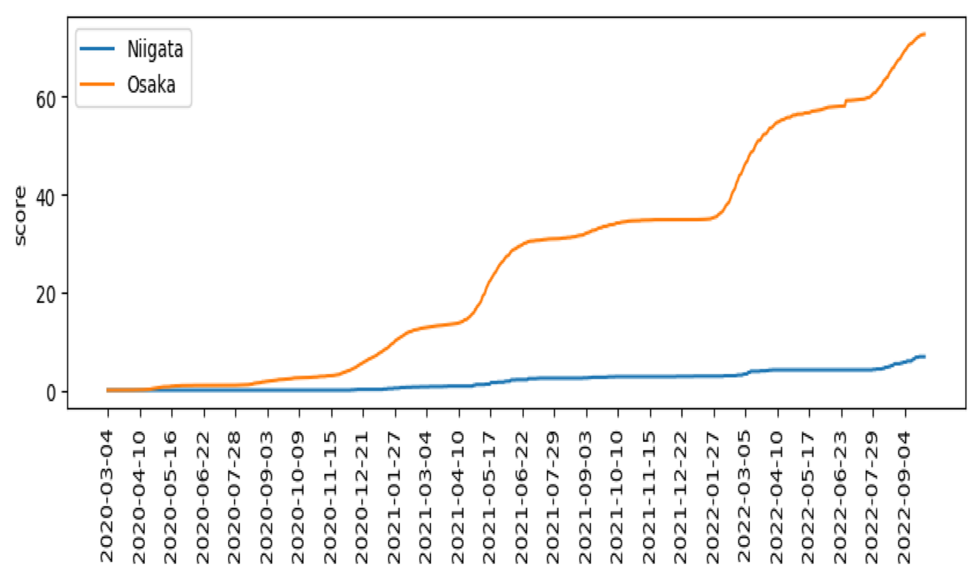

Fig. 2 Result of jpcovid of Niigata and Osaka

graph, the worse the herding behavior. Fig. 2 indicates that Osaka made 4 big change points on herd instinct in November 2020, April 2021, February 2022, and July 2022 respectively. Figure 2 shows that Niigata has a gentle graph with no steep change points.

Figure 3 shows the result of jpcovid with the best four prefectures such as Niigata, Fukui, Toyama and Yamagata. Four prefectures are located on the Sea of Japan side. Figures 2 and 3 include Niigata, but only Fig. 3 indicates that Niigata had three big change points on herd instinct in April 2021, February 2022, and July 2022 respectively. Fukui has the single biggest change point on herd instinct in July 2022. We must analyze why such biggest change points were generated. The proposed tool, jpcovid can only identify the herd instinct change points. In other words, we must investigate why herding behaviors changed.

4 Discussions

All 47 prefectures in Japan have adopted the uniform policy. Thus, for COVID-19, herd instincts and herd behaviors may influence different outcomes.

The snapshot COVID-19 policy analysis tool, jpscore can generate a better ordered list of sorted scores which allows policymakers to learn the good strategies from prefectures with excellent scores. In other words, all prefectures except Niigata should learn the good strategies from Niigata. We should know and learn how the Niigata community behaves against COVID-19. jpscore discovered that Niigata has the best score of 203.8 while Osaka has the worst score of 969.7 as of April 26, 2023. Two scores indicate that Niigata is nearly 5 times better than Osaka. This means that Osaka caused unnecessary COVID-19 deaths due to herding behavior. The lower the score, the better the policy. Or the lower the score, the better the herding behavior.jpcovid allows policymakers to identify major herd behavior changes and when they occurred. Niigata had three big change points on herd instinct. Fukui had the single biggest change point on herd instinct in July 2022.

In Japan, face masks are often worn with or without the government recommendation. In Japan, greetings do not include handshakes, kisses, or hugs. To conduct handshakes, kisses, or hugs, the social distance must be shorter.

The majority of the general public in *Japan* keep a greater *social distance* from individuals [14]. Japanese tend not to talk since silence is golden [15].

According to the Japan Meteorological Agency, the significant climate difference such as snowfall may nurture herding behavior on human mobility. From 2008 to 2017 of 10 years snowfall data such as the total number of snowfall days, the total snowfall amount and the total maximum snow depth in prefecture capitals such as Niigata and Osaka are as follows: 501 days, 1470cm, 360cm of Niigata; and 16 days, 17cm, 14cm of Osaka respectively.

Wei et al. reported that regional ambient temperature is associated with human personality [16]. Temperature is an extremely important factor that affects an individual's personality.

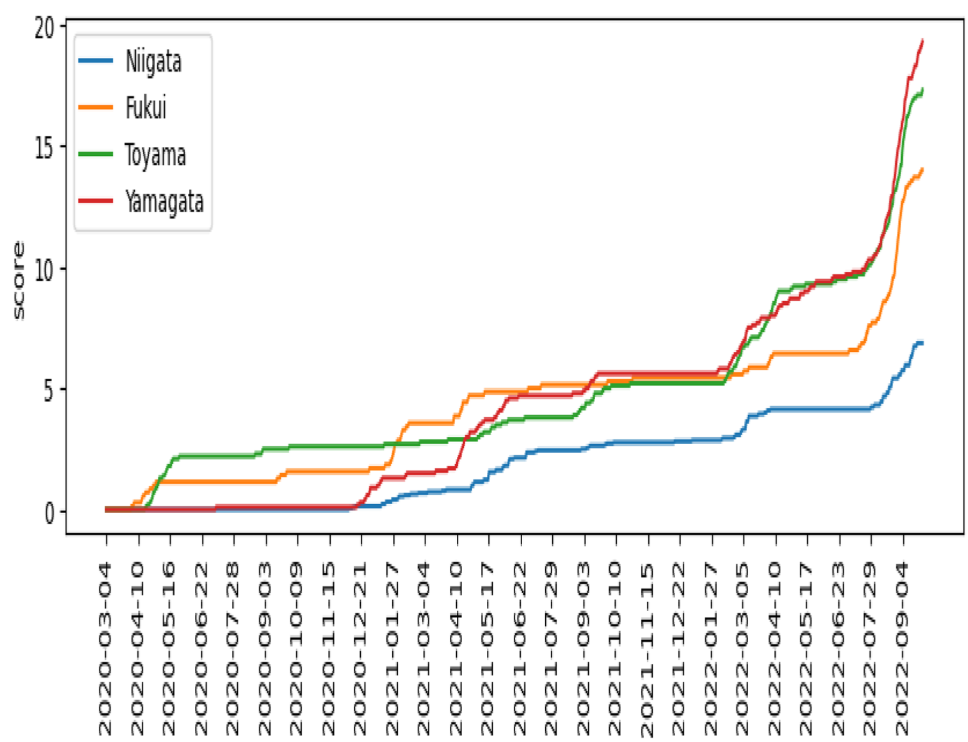

Fig. 3 Result of jpcovid with Niigata, Fukui, Toyama and Yamagata

The hypothesis in this paper is that Niigata's harsh winters will foster herd instinct or human resistance, so that during a pandemic, the Niigata community will be able to withstand with less human mobility, but Osaka will have little snow, so there will be more human mobility to spread COVID-19. This is because top four prefectures such as Niigata, Fukui, Toyama and Yamagata have cold winters with heavy snow on the Sea of Japan side and in mountainous areas. However, Hokkaido has cold winters with the poor score which contradicts with the hypothesis. This is because Hokkaido has the highest indoor temperature in winter among all prefectures in Japan [17]. In other words, Hokkaido communities did not develop their herding instinct and human resistance with harsh winters against COVID-19 as Niigata did.

According to the climatic zones of prefectures, because the Japanese archipelago is long from north to south, it contains various climate zones: subarctic in the north and subtropical in the south. In addition, the Japanese archipelago has a series of high mountain ranges in the center, so the climate varies between the Sea of Japan side and the Pacific side. the Japan Meteorological Agency divides prefectures by climatic zones [18]. According to the climatic zoning, the top 4 of jpscore are on the Sea of Japan side, but especially the top 3 belong to the Hokuriku region.

5 Conclusion

The proposed time series COVID-19 policy analysis tool jpcovid allows policymakers to detect and identify when herd behavior has changed in order to modify community behavior or update policies. The jpcovid discovered three facts:

1. Niigata had three big change points on herd instinct.
2. Fukui had the single biggest change point on herd instinct in July 2022.
3. The top four prefectures face the Sea of Japan due to herding behavior.

Policymakers need to use jpcovid or similar tools to control COVID-19 for pandemic mitigation. Time-series policy analysis tools are important and indispensable for policymakers to identify behavior changes. The proposed method can be applied to other countries in general. The result of jpscore showed that Niigata is nearly 5 times better than Osaka from the viewpoint of herding behavior. Remember that all 47 prefectures in Japan have adopted the uniform COVID-19 policy. There remain unresolved questions as to why herd behavior has changed.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s12553-023-00759-x.

Author contributions TM wrote Python programs and YT wrote the article.

Data availability Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

Declarations

Ethics Not applicable.

Conflict of interest The authors have no conflict of interest.

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