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Measuring the impact of the state of emergency on crime trends in Japan: a panel data analysis

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Abstract

Purpose/Background City-specific temporal analysis has been commonly used to investigate the impact of COVID-19-related behavioural regulation policies on crime. However, these previous studies fail to consider differences in the intensity of intervention among cities and the impact of these behavioural regulation policies on crime trends nationwide. This study performs panel data analyses to examine how the declaration of a state of emergency (SoE) affected ambient population and crime in Japan, taking advantage of the fact that the SoE was implemented at different times in different prefectures.

Methods The current study uses two sets of panel data of 47 prefectures for 22 weeks from February to July 2020: (1) the data on ambient population in five types of locations provided by the Google Mobility Reports, and (2) official crime data of six types of crime: residential burglary, commercial burglary, theft of/from vehicle, bicycle theft, sexual assault, and violence and injury. Firstly, an ordinary least squares regression analysis was performed to examine the impact of the SoE on the ambient population. Then a negative binomial model with fixed effects was adopted to examine the effect of the ambient population on the crime trends.

Findings The SoE declaration was found to increase the ambient population in 'residential', and decrease that in other settings including 'workplaces', 'transit stations', and 'retail and recreation' in targeted prefectures. Spill-over effects of the SoE were observed on the ambient population of non-SoE prefectures. The ambient population have impacted five out of the six types of crime examined, except for sexual assault. After controlling for the ambient population, we observed an increase in commercial burglary and theft of/from the vehicle in all prefectures during the SoE weeks, compared to the weeks when the SoE was not declared.

Conclusions The declaration of the SoE during the COVID-19 pandemic changed the ambient population in the SoE-prefectures, resulting the changes in crime levels as well. In addition, the implementation of the SoE in specific prefectures was found to have a contextual impact on national-level crime trends. Furthermore, the implementation of the SoE caused changes in some crime types that could not be explained by the changes in the ambient population, suggesting that the implementation of the SoE affected offenders' decision-making. It is also worth noting that the changes in ambient population and crime trends during the pandemic were observed in Japan where the behavioural regulation policy without law enforcement was introduced.

Keywords COVID-19, Natural experiment, Panel data analysis, State of emergency, Google Mobility Reports

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Introduction

The COVID-19 pandemic has changed people's lifestyles globally. Various social distancing measures (e.g., stay-at-home orders, lockdowns) have been introduced in many countries (Andresen & Hodgkinson, 2020; Ashby, 2020). These countermeasure policies have been found to affect crime trends in different ways.

The relationship between COVID-19 and crime is theoretically grounded in the routine activity theory (Cohen & Felson, 1979), which states that a crime occurs when three elements converge in time and space: motivated offenders, suitable targets, and the absence of capable guardians. Accordingly, it can be argued that stay-at-home orders reduced the opportunity for street crime and increased that for domestic violence. Likewise, an increase in the number of capable guardians at home and a decrease in guardians on commercial sites could have led to reduced residential burglary and increased commercial burglary opportunities. COVID-19-related social restrictions changed people's routine activities and affected various types of crime outcomes (Stickle & Felson, 2020). As such, different levels of social distancing measures implemented at different times may have influenced the levels of crime differently.

The paradigm of natural experiments has been commonly used in criminological research (Kurland et al., 2018; Vandeviver et al., 2019). Stickle and Felson (2020, pp. 534) called the COVID-19 pandemic 'the largest criminological experiment in history'. Indeed, the natural experimental condition facilitated by the COVID-19 pandemic has allowed researchers to examine the impact of stay-at-home orders on city-level crime trends. In the US, changes in crime trends have been reported in several cities. For instance, Ashby (2020) examined changes among six types of crime in 16 cities and found that during the pandemic, some cities experienced large decreases in burglary and motor vehicle theft. Mohler et al. (2020) also demonstrated that stay-at-home orders and social distancing measures significantly reduced both burglary calls and reported burglary cases in Los Angeles, while they increased domestic violence calls in Los Angeles and Minneapolis. Felson et al. (2020) showed that block-level changes in burglary in Detroit during the pandemic in March 2020 were moderated by land use. Campedelli et al. (2020) reported that only a few communities in Chicago experienced considerable reductions in burglary, assault, drug offences, and robbery during the pandemic. In the UK, Halford et al. (2020) examined daily recorded crime data in one police jurisdiction using an autoregressive integrated moving average (ARIMA) model and found that one week after the nationwide lockdown, shoplifting, theft, domestic violence, theft from vehicle, assault, and burglary declined. Using official crime data from Queensland, Australia, Andresen and Hodgkinson (2020) found that enforcing a lockdown led to immediate reductions in social disorder, violent crime, burglary, theft, and motor vehicle theft; however, these crimes increased soon after the lockdown was relaxed. A few studies using the ARIMA model have examined trends in non-Western countries, such as China (Borrion et al., 2020; Dai et al., 2021) and Bangladesh (Rashid, 2021). Borrion et al. (2020) found that commercial burglary declined by 64% from January to April 2020. Dai et al. (2021) reported that the lockdown introduced between the end of January 2020 and mid-March 2020 reduced the number of county-level police calls. Additionally, several studies have analysed regional variations in crime during the COVID-19 pandemic. For instance, Payne et al. (2021) reported that several types of crime were found to decrease significantly during the COVID-19 pandemic across 77 local governments in Queensland, Australia. Langton et al. (2021b) applied longitudinal k-means clustering by month to examine the changes in clusters of crime throughout the pandemic.

The impact of COVID-19 on crime has been reported in many cities, and most prior studies have relied on the ARIMA model, focusing on crime trends in one or multiple cities (Borrion et al., 2020; Dai et al., 2021; Halford et al., 2020; Kim & Phillips, 2021; Piquero et al., 2020; Rashid, 2021). However, the ARIMA model has some issues. First, it requires multiple testing when simultaneously analysing the crime trends in more than one city. Applying the ARIMA model to crime trends by city would reveal whether the crime trend in a given city changed significantly by the stay-at-home order compared to the trend if the order had not been declared. However, analysing crime trends by city increases the number of significance tests, leading to the type I error. Therefore, applying a single analysis for the changes in crime in multiple cities is preferable to determine the impact of a stay-at-home order.

Second, the city-specific ARIMA approach does not consider differences among cities in the intensity of intervention and the responsiveness of the urban environment. Felson et al. (2020) illustrated that the impact of the stay-at-home order on the levels of crime varies by land use within the city. Thus, different urban contexts may have different effects on the relationship between the stay-at-home order and crime trends.

Third, the city-specific ARIMA model may not control for the contextual effects that occurred nationwide. Since COVID-19 cases in different cities within a country may have increased at different rates, the stay-at-home orders may have been declared at different times across cities. Therefore, a stay-at-home order declared in one city may have affected the routine activities of the citizens

Table 1 Timeline of the state of emergency in Japan

Date	
7 Apr 2020	State of emergency declared in 7 prefectures, requesting 'reducing person-to-person contact by 80%'
11 Apr 2020	PM asked companies in 7 prefectures to reduce the number of employees working at their offices by 70%
16 Apr 2020	Nationwide state of emergency declared, categorising 13 prefectures as 'hardest-hit prefectures'
4 May 2020	Nationwide state of emergency extended to 31st May
14 May 2020	Nationwide state of emergency ended in 39 prefectures
21 May 2020	State of emergency ended in Osaka, Kyoto, and Hyogo
25 May 2020	State of emergency lifted in all prefectures

Adapted from: https://www3.nhk.or.jp/news/special/coronavirus/chronology/

of another city. Such nationwide contextual effects have not been adequately considered in existing city-specific ARIMA analyses.

Against this methodological limitation of the ARIMA approach, the current study uses panel data to examine the impact of behavioural regulation policies (BRPs) on crime in Japan. Panel data analysis allows researchers to analyse crime data based on time-varying factors, including discrete and continuous factors, and area-specific factors (Levitt, 2001) such as sociodemographic characteristics (Hipp, 2007; Levitt, 2001; McDowall & Loftin, 2009) and temperature (Mares & Moffett, 2019). One-time events include residential demolition (Kim & Wo, 2020; Wheeler, 2012), sporting events (Kurland et al., 2018; Vandeviver et al., 2019), and disasters (Kirk, 2009).

In criminological panel research, a fixed-effects panel data model has been used to investigate the distribution of crimes in time and space (Law et al., 2015; Levitt, 2001; Mares & Moffett, 2019; Wheeler, 2012; Wheeler et al., 2018). Panel data analysis has also been adopted to assess the effectiveness of crime prevention measures, such as home security (Vollaard & van Ours, 2011), car immobilisers (Gonzalez-Navarro, 2013), and third-party policing (Hoshino & Kamada, 2020). These evaluation studies take advantage of the fact that the interventions are implemented in different areas at different times. They treat the intervention at a site as a time-varying variable to measure its effect. If BRPs against COVID-19 were implemented at different times in different cities, panel data analysis can be applied to systematically analyse the effect of the BRP on crime in a single analysis, avoiding the multiple testing problem associated with applying the ARIMA model by city.

Another important point which the current study examines is whether the BRP affected crime opportunities, which then led to changes in crime trends. The BRP increased the number of people 'staying at home' and decreased the number of people staying outside. The current study therefore mainly examines the effect of BRPs on the ambient population, and how changes in this population affected crime. BRPs may cause qualitative changes in the opportunity structure of crime (e.g., offender's decision-making and potential victims' awareness) in ways that cannot be explained by quantitative changes in the ambient population. Therefore, this study first examines the impact of the BRP on the ambient population using panel data analysis; second, it examines the impact of the ambient population on crime. We also examine the impact of the BRP on crime, controlling for the impact of the ambient population.

Declaration of the state of emergency in Japan

Various social distancing measures have been introduced as countermeasures against COVID-19 in many countries, including the US (Ashby, 2020; Campedelli et al., 2020; Kim & Phillips, 2021; Mohler et al., 2020; Nix et al., 2020), the UK (Halford et al., 2020; Langton et al., 2021a, 2021b), Australia (Andresen & Hodgkinson, 2020; Payne et al., 2021; Sargeant et al., 2021; Workman et al., 2021), Germany (Nef et al., 2021), and China (Borrion et al., 2020; Dai et al., 2021; Jiang et al., 2020). The Japanese government declared a state of emergency (SoE) as a countermeasure against COVID-19. The Japanese SoE was implemented at different times in different prefectures based on each prefecture's COVID-19 risk estimation (Table 1). The first SoE was implemented in seven major prefectures on 7 April 2020, wherein local authorities asked citizens to avoid unnecessary outings and close local businesses where possible (McCurry, 2020b). On 16 April, the SoE was expanded to all prefectures, with 13 densely populated prefectures with a high estimated risk designated as the 'hardest-hit prefectures' (BBC, 2020; NHK, 2020). In the hardest-hit prefectures, more intensive efforts were made to control the pandemic. From 14 May, the alert level for COVID-19 was gradually reduced, and the nationwide SoE was lifted on 25 May (McCurry, 2020b).

The SoE in Japan was implemented 'without punitive measures or legal force' (BBC, 2020). The SoE requested that people work remotely, maintain social distancing, and stop non-essential travel (McCurry, 2020a). Although the SoE relied on requests, many people refrained from leaving home. The rate of people in Tokyo leaving their homes decreased by 64% by 26 April 2020, compared with that in January 2020 (Watanabe & Yabu, 2021). Additionally, the population by time rate estimated from mobile phone location information in metropolitan areas in Japan showed a substantial drop. Kabuki-cho, one of the most densely populated nightlife spots in Tokyo, had over 55,000 people on weekends in January 2020; however, there were less than 15,000 people on weekends in April 2020 (Agoop Corporation, 2021). Indeed, Watanabe and Yabu (2021) reported that the number of people going out in prefectures under a declared SoE decreased by nearly 9%, rather similar to the estimated impact of lockdowns in the US. However, to the best of our knowledge, how the SoE declaration has systematically affected crime trends via the ambient population has not been examined yet. As the SoE was declared at different times in different prefectures, the current study aims to investigate the impact of SoE declaration on the ambient population and crime trends, based on a natural experiment paradigm.

Further, since SoE declaration was announced by the media nationwide, people living in the prefectures without the SoE may have possibly also tried to 'stay at home' when it was declared only in some specific prefectures. Many studies showed that implementing social restrictions against COVID-19 was associated with crime reductions within the cities where stay-at-home orders were declared. This may have also influenced crime trends in other areas, as the orders also triggered behavioural changes of inhabitants there. Indeed, the impact of area-level governmental orders and information from other areas can spread when disasters such as fires (Knez et al., 2021), floods (Takenouchi, 2020), and tsunamis (Yamabe et al., 2019) occur. Criminological research suggests that people take coping actions based on indirect criminal victimisation (Skogan & Maxfield, 1981). Since the SoE presents indirect information on COVID-19, prefecture-level SoE may have changed people's behaviour in other prefectures since they knew about the virus and attempted to be safe, thereby influencing national-level crime trends. Therefore, the current study examines the impact of the area-specific countermeasures against COVID-19 on people's movement and crime trends nationwide.

Current study

Utilising Google mobility reports (GMRs) and police-recorded data, a panel data analysis is performed to investigate how social restrictions, particularly the SoE declared to prevent the spread of COVID-19, affected crime trends in Japan. Specifically, this study aims to answer the following research questions:

1) Did the declaration of the SoE in a prefecture change people's mobility in the prefecture where it was declared?

2) Were the changes in mobility observed in every prefecture regardless of the SoE declarations?

3) Did the changes in people's mobility in each prefecture affect crime trends in each prefecture?

4) Did the SoE affect crime trends even when people's mobility was controlled?

To overcome the methodological challenges of prior research described above, this study introduces prefectural panel data analysis, which takes advantage of the fact that in Japan, the SoEs were declared in different prefectures at different times.

Data and methods

This study uses two sets of panel data. The analysis first examines the impact of the SoE on ambient population. The first analysis uses data compiled from the GMRs to examine mobility changes during the SoE in Japan. The GMRs comprise anonymised cell phone location data provided by Google Apps that demonstrate mobility trends during the COVID-19 pandemic. The GMRs have been used in criminological research on the relationship between mobility and crime trends during the COVID-19 pandemic (Halford et al., 2020; Mohler et al., 2020). The GMRs in Japan provide data on the daily changes in activities compared to a baseline (the median value for the corresponding day of the week, during the 5-week period from 3 January to 6 February) in six types of locations (grocery and pharmacy, residential, transit stations, parks, retail and recreation, and workplaces) by prefecture. In this study, we aggregated the raw data by prefecture and by week from the second week of February to that of July 2020. The current study focuses on five locations except for 'park'. 'Park' in the GMR refers to public garden, castle, national forest, camp ground and observation deck, and in Japan these large-scale tourist attractions do not exist in all 47 prefectures. Therefore, 'park' is excluded in the study because this would make the model estimation unstable.

The second analysis deals with national crime data compiled for the period between the second week of February to that of July 2020 for six types of crime: residential burglary (n = 6285), commercial burglary (n = 7182), theft of and from vehicle[1] (n = 18,187), bicycle theft (n = 39,151), sexual assault (n = 1325), and violence and injury (n = 17,117). The dependent variable is the weekly number of cases in each prefecture.

[1] Theft from vehicle includes vehicle load theft (stealing items placed on the vehicle) and vehicle part theft (stealing parts of the vehicle).

Table 2 Descriptive statistics predicting ambient population and crime trends

Variables	Mean	SD	Minimum	Maximum	Source	Year
Temperature	14.32	6.93	-3.10	28.90	Japan Meteorological Agency	2010
Population	2,711,565.17	2,735,383.69	566,052.00	13,740,732.00	The Basic Resident Registration, Ministry of Internal Affairs and Communications	2019
Number of households (in thousand)	1,134.60	1,251.58	216.00	6691.00	Statistics Bureau, Ministry of Internal Affairs and Communications	2015
Number of cars	1,672,467.43	1,142,145.17	459,209.00	5,102,653.00	Automobile Inspection and Registration Information Association	2020
Number of bicycles	1405.75	1610.98	262.00	8168.00	Japan Bicycle Promotion Institute	2018
SoE period	0.32	0.47	0	1		
SoE period x intensity	0.07	0.25	0	1		

Prior panel data studies on crime have adopted different spatial units of analysis, such as state (Mares & Moffett, 2019), county (Difurio & Lewis, 2017), city (Piza & Gilchrist, 2018; Shayegh & Malpede, 2020; Vandeviver et al., 2019; Wheeler, 2012; Wheeler et al., 2018; Ye & Wu, 2011), district (Kurland et al., 2018), and block (Hipp, 2007; Kim & Wo, 2020). The present study uses prefectures as the unit of analysis. Japan has an area of approximately 378,000 km^2, with a population of approximately 126 million, including 47 prefectures, the largest administrative entities (size: 1877-83,424 km^2, population: 0.56-13.92 million; Statistics Bureau of Japan, 2021). Each prefecture has a local government and a police department. Prefectural governments are responsible for public administration, including health, welfare, commerce, and industry. Prefectural police departments are responsible for public safety and they conduct police activities, such as crime investigation, policing, and road traffic safety. Although the central government's power in Japan is considered stronger than that in the US, prefectures have autonomy over social services and policing (Roberts & Lafree, 2004). The prefecture has been commonly used as a unit of analysis in crime studies in Japan.[2]

This study introduces two independent variables: SoE period and intensity of the SoE. The SoE period was coded 1 for all prefectures if the SoE was declared in more than one prefecture to identify the effect of the SoE on all the prefectures. The variable that represents the intensity of the SoE intervention is added in our analysis.Specifically, the variable is coded 1 if (1) the prefecture is under the SoE when the SoE was declared only in some prefectures or (2) the prefecture is designated as among the 'hardest-hit prefectures' when the nationwide SoE was declared. The SoE period represents its impact on the ambient population and crime trends nationwide. The interaction variable 'SoE period x intensity' represents the additional impact of the SoE on the prefectures where the SoE was declared.

The control variables used in this study are trend and temperature. The trend variable is included to capture the COVID-19 pandemic expansion effects. The temperature of each month is used as a time-varying variable since both crime trends and people's mobility demonstrate seasonality.

In the first step, an ordinary least square regression analysis is performed to examine the impact of the SoE on people's mobility. In the second step, a negative binomial model with fixed effects is adapted to model the effect of the mobility and SoE on crime trends, since crime estimates are characterised by over-dispersed count data due to low crime rates in Japan. Different types of exposure variables are introduced for different types of crime: population (commercial burglary, street robbery, violence, and injury), number of households (residential burglary), number of cars (theft of/from vehicle), and number of bicycles (bicycle theft). These variables have been acquired from the census and aggregated by prefecture to append the prefecture-week datasets for the panel data analysis. With regard to bicycle theft, the data for the year 2018 is appended to the datasets due to data availability (Table 2).

Results

Ambient population

Figure 1 presents the data on people's mobility for 22 weeks in the 13 hardest-hit prefectures and other 34 prefectures derived from the GMRs. We weighted the data extracted from the GMRs so that they reflect the population of each prefecture. During the SoE period, substantial changes in people's mobility were observed in 'residential', 'workplaces', 'transit stations', and 'retail and recreation', especially in the hardest-hit

[2] For example, Hoshino and Kamada (2020) conducted a quasi-experiment to test the impact of prefectural-level organised crime group exclusion ordinances on the number of group members.

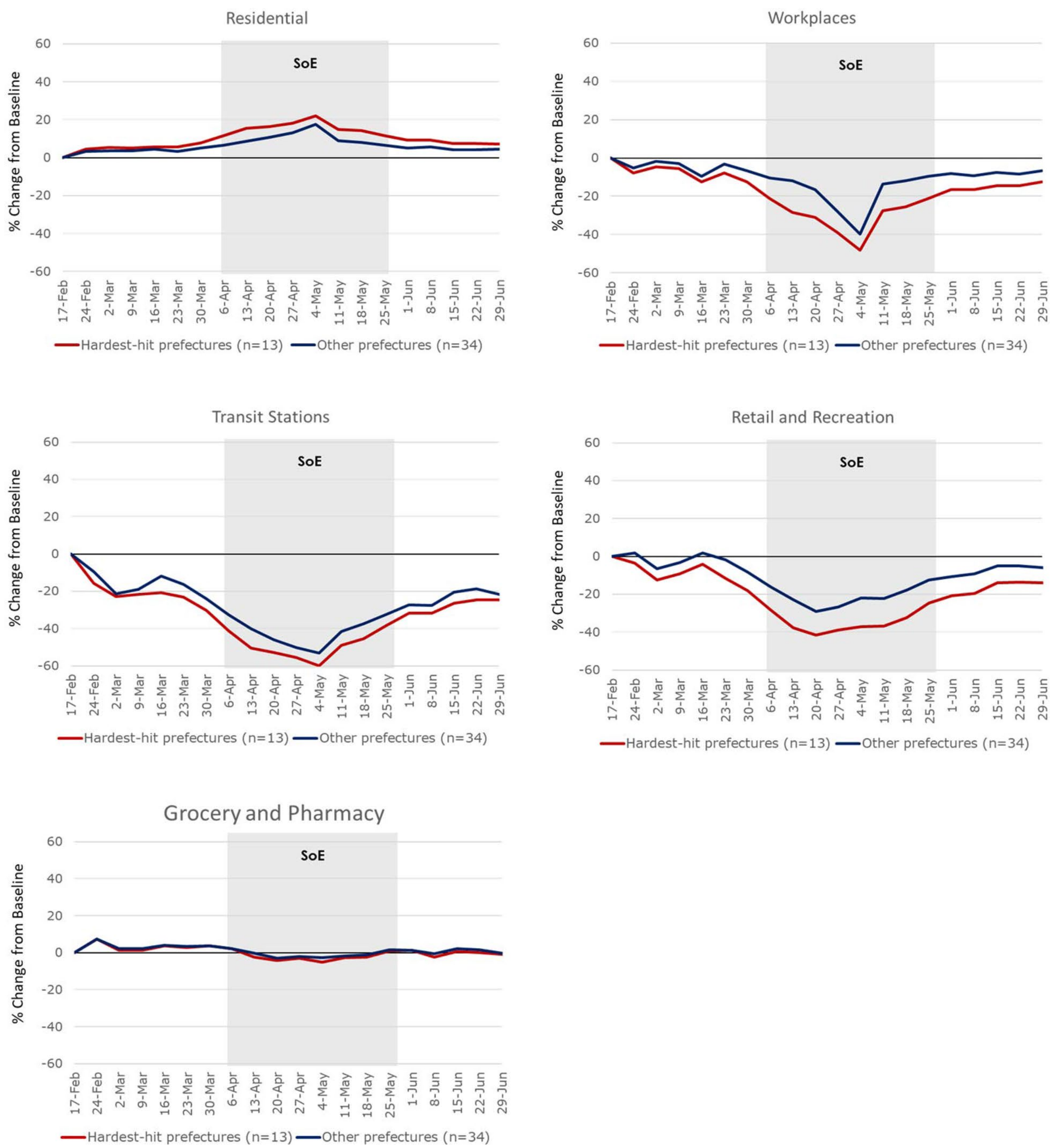

Fig. 1 Changes in ambient population during the pandemic based on intensity of the state of emergency

prefectures. Those who were in 'residential' in the 13 hardest-hit prefectures increased by 22%, compared to an increase of 18% in other prefectures. Similarly, in other locations, the 13 hardest-hit prefectures showed larger reductions than other prefectures (workplaces: - 28.5% in the hardest-hit prefectures, - 12.0% in other prefectures; transit stations: - 60.0% in the hardest-hit prefectures, - 12.0% in other prefectures; retail and recreation: - 41.5% in the hardest-hit prefectures, - 29.0% in other prefectures). While large changes in people's mobility were observed in these four locations, the extent of change in people's mobility in 'grocery and pharmacy' was relatively smaller (- 5.2% in the hardest-hit prefectures, - 2.8% in other prefectures).

Table 3 shows the impact of SoE on people's mobility as calculated by panel data analysis. Model 1 addresses the effect of two control variables on people's mobility, derived from the GMRs; Model 2 includes additional variables related to the SoE, by which an increase in R-squared compared to Model 1 can be noted. For the five location types, the R-squared for Model 1 was 0.087 at the lowest (residential) and 0.236 at the highest (grocery and pharmacy). In contrast, in Model 2, where the variables on SoE was included, the R-squared increased to a minimum of 0.415 (grocery and pharmacy) and a maximum of 0.695 (transit stations).

Controlling for the two control variables, SoE declaration increased the population in 'residential spaces' and decreased those in workplaces, transit stations, retail and recreation spaces, and grocery stores and pharmacies. Additionally, an intensive operation of the SoE brought about significant changes in the population in these types of places (other than grocery stores and pharmacies) in the relevant weeks and prefectures.

Official crime statistics

Figure 2 displays the crime trends between February and July 2020 according to the type of crime and by the hardest-hit prefecture. The red line depicts the crime trend in the hardest-hit prefecture and the blue line depicts that in other prefectures. During the SoE period, declined crime rates were observed compared to the baseline in residential burglary, commercial burglary, and bicycle theft. Additionally, crime trends during the SoE were different depending on whether the prefectures are categorised as hardest-hit or not. The decrease in residential burglary was larger in hardest-hit prefectures than other prefectures. Similarly, sexual assault and violence and injury decreased only in hardest-hit prefectures; the number of such crimes remained unchanged or even increased in other prefectures. Conversely, the decrease in commercial burglary was larger in other prefectures compared to the hardest-hit prefectures.

Table 4 displays the impact of SoE and ambient population on official crime statistics by crime type. Model 1 introduces two control variables (trend and temperature). In Model 2, the dummy variable indicating whether SoE is declared in a given week and prefecture was introduced. The results in Model 2 support the visual inspection of crime trends in the hardest-hit prefectures and other prefectures, as shown in Fig. 2. SoE declaration was found to reduce bicycle theft and increase commercial burglary across prefectures in Japan. However, significant interaction effects between the SoE period and intensity were found in residential burglary, commercial burglary, bicycle theft, and violence and injury. These significant interactions imply that intensive SoE operation in the hardest-hit prefectures resulted in the reduction of these four crime types during the SoE period (Fig. 2).

In Model 3, instead of the SoE variables in Model 2, four types of measures of people's mobility from the GMRs were added, though 'workplaces' was excluded due to strong collinearity with 'residential'. Model 3 revealed that the increase in the population in residential dwellings was associated with the significant decrease in residential burglary, bicycle theft, and violence and injury. Further, the increase in population in transit stations was found to be related to the significant decrease in commercial burglary, bicycle theft, and violence and injury. Additionally, the increase in population in retail and recreation spaces was related to the significant increase in violence and injury. The population in grocery stores and pharmacies was positively related to the crime types other than sexual assault.

In Model 4, the full model including the control variables, ambient population, and SoE was estimated. Some of the significant effects of the SoE on crime, shown in Model 2, are replaced by the effect of the ambient population on crime in Model 4. For example, the interaction effect of the SoE period and intensity on residential burglary in Model 2 was replaced by the population of residential dwellers in Model 4. Further, the effects of SoE on bicycle theft in Model 2 diminished in Model 4, where the effects of four types of ambient population were considered.

Several significant relationships between ambient population and crime were identified. The increase of populations in residential spaces was associated with the reduction of residential burglary. The reduction of customers visiting grocery stores and pharmacies was associated with a decrease in commercial burglary and theft of/from vehicle. Increased rates of ambient populations in residential spaces and transit stations were associated with a reduction in bicycle theft. Increased rates of ambient populations in retail and recreation spaces and grocery stores and pharmacies were associated with an increase in bicycle theft. Further, an increased use of public transportation decreased violence and injury, whereas grocery and pharmacy customers increased violence and injury.

Even after controlling for the changes in the ambient population, SoE declaration was found to affect crime trends. Specifically, intensive BRPs in targeted prefectures were associated with significant reductions in commercial burglary, and violence and injury. Moreover, theft of/from vehicle increased in all prefectures during the SoE period, controlling for other variables.

Table 3 The effect of the state of emergency on ambient population measured by Google Mobility Reports in Japan

	Residential					
	Model 1			**Model 2**		
	B	**S.E.**		**B**	**S.E.**	
Trend	-0.363	0.087	***	0.227	0.052	***
Temperature	0.559	0.085	***	-0.058	0.051	
State of Emergency						
SoE period				6.148	0.179	***
SoE period × intensity				3.903	0.356	***
Constant	1138.719	272.971		-706.862	162.260	
sigma_u	1.998			1.490		
sigma_e	4.033			2.314		
rho	0.197			0.293		
R^2	0.087			0.651		
	Workplaces					
	Model 1			**Model 2**		
	B	**S.E.**		**B**	**S.E.**	
Trend	0.630	0.199	**	-0.589	0.136	***
Temperature	-1.115	0.194	***	0.158	0.133	
State of Emergency						
SoE period				-12.347	0.468	***
SoE period × intensity				-9.652	0.930	***
Constant	-1971.535	621.178		1839.536	423.768	
sigma_u	4.205			2.834		
sigma_e	9.179			6.043		
rho	0.173			0.180		
R^2	0.088			0.595		
	Transit stations					
	Model 1			**Model 2**		
	B	**S.E.**		**B**	**S.E.**	
Trend	0.825	0.293	**	-1.270	0.162	***
Temperature	-1.694	0.285	***	0.499	0.158	**
State of Emergency						
SoE period				-23.503	0.558	***
SoE period × intensity				-6.178	1.108	***
Constant	-2590.326	914.940		3959.803	505.118	
sigma_u	5.313			4.651		
sigma_e	13.519			7.204		
rho	0.134			0.294		
R^2	0.138			0.695		
	Retail and recreation					
	Model 1			**Model 2**		
	B	**S.E.**		**B**	**S.E.**	
Trend	0.985	0.210	***	-0.561	0.103	***
Temperature	-1.431	0.204	***	0.185	0.101	†

Table 3 (continued)

	Retail and recreation					
	Model 1			**Model 2**		
	B	**S.E.**		**B**	**S.E.**	
State of Emergency						
SoE period				-16.764	0.355	***
SoE period × intensity				-7.170	0.705	***
Constant	-3081.507	654.591		1750.265	321.330	
sigma_u	5.011			4.505		
sigma_e	9.672			4.583		
Rho	0.212			0.492		
R^2	0.105			0.682		
	Grocery and pharmacy					
	Model 1			**Model 2**		
	B	**S.E.**		**B**	**S.E.**	
Trend	0.319	0.056	***	0.056	0.049	
Temperature	-0.494	0.055	***	-0.219	0.048	***
State of Emergency						
SoE period				-2.848	0.168	***
SoE period × intensity				-169.565	151.857	
Constant	-992.619	176.356		2.166		
sigma_u	1.400			1.411		
sigma_e	2.606			2.166		
Rho	0.224			0.298		
R^2	0.236			0.415		

***:$p < .001$, **:$p < .01$, *:$p < .05$, †:$p < .10$

Number of observations = 1034; number of prefectures = 47; number of weeks = 22

Discussions and conclusion

This study explored the impact of the SoE on ambient population and different types of crime across Japan using weekly GMR and crime data. Although city- or regional-level research on the impact of COVID-19 on crime trends has been conducted, whether COVID-19 affects country-level crime trends (based on a nationwide systematic analyses) remains unclear. To fill this gap, the current study examined the influence of the COVID-19 SoE declaration on crime trends at the local and national levels by utilising nationwide panel data. Specifically, we examined how the SoE declared at different times in different prefectures had varying influences on people's mobility and crime rates, and proposed four research questions investigating the relationship between the SoE, ambient population, and crime.

Regarding the first research question, the SoE declaration in hardest-hit prefectures was found to increase the ambient population in 'residential', and to decrease the ambient population in other settings including 'workplaces', 'transit stations', and 'retail and recreation' in targeted prefectures. Thus, the BRP in Japan did affect people's mobility, even though the policy lacks punitive measures or legal force.

Further, the analysis revealed spill-over effects of the SoE on ambient population in other than the SoE prefectures, regarding the second research question. Taken into specific effect of the SoE on ambient population in targeted prefectures, significant changes caused by the SoE were still observed in all prefectures including non-SoE prefectures during the SoE periods. At pandemic onset, it is likely that the residents outside the target prefectures saw and heard those public announcements which changed their behaviour.

Regarding third research question, significant associations between population and crime were found for five of the six types of crime examined in this study, with the exception of sexual assault. The increase in the population in 'residential' was found to be associated with a decrease in residential burglary and bicycle theft. The

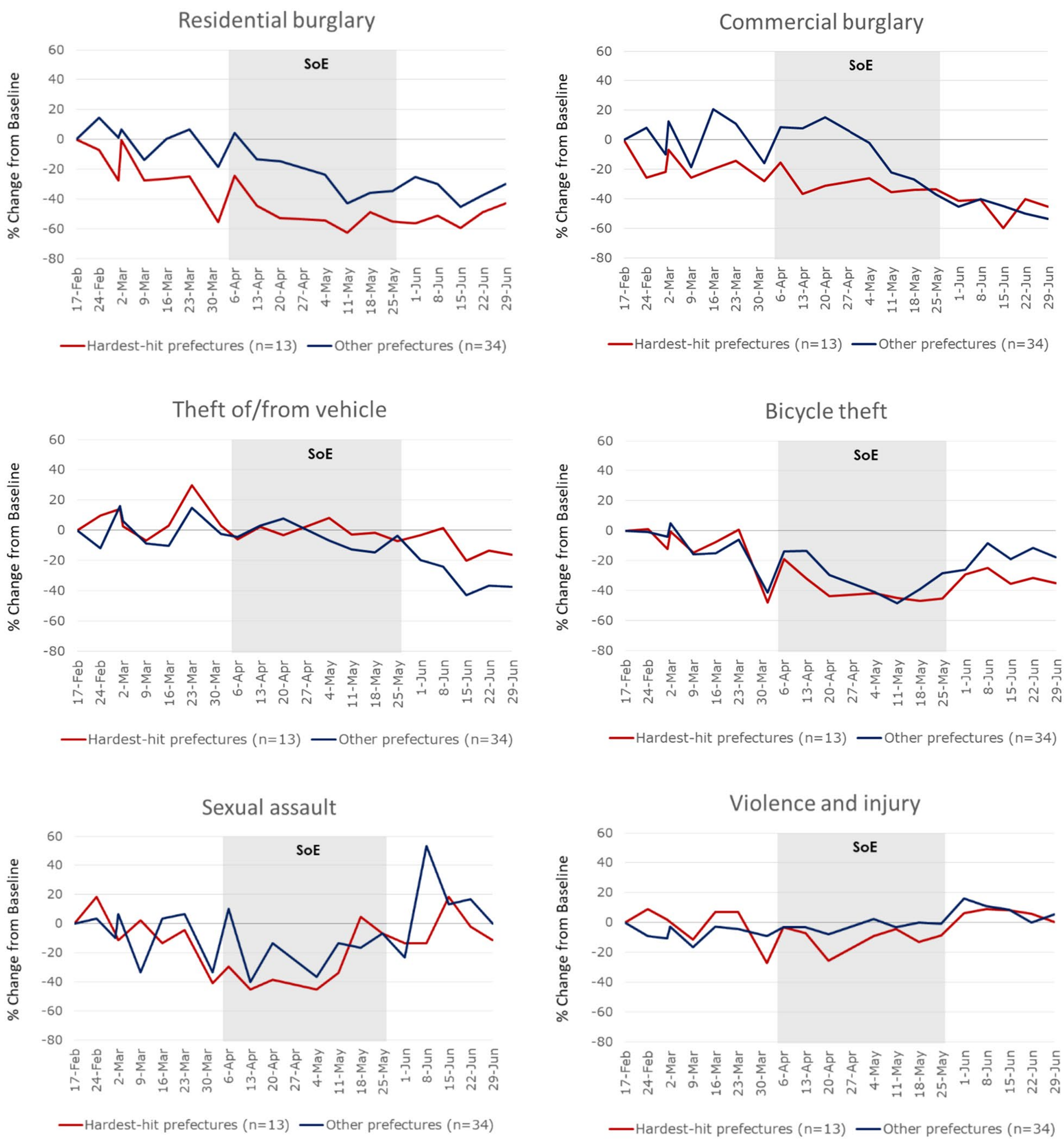

Fig. 2 Changes in penal code crime during the pandemic by intensity of state of emergency

increase in the population in 'transit stations' was found to be associated with a decrease in bicycle theft, and the increase in the population in 'retail and recreation' was found to be associated with an increase in bicycle theft.

These relationships between the ambient population and crime can be explained by the routine activity theory. With respect to residential burglary, the increase in the ambient population in residential dwellings, through the SoE stay-at-home request, may have reduced crime opportunities due to the increased capable guardianship. Routine visits to the grocery store are considered to increase crime opportunities for burglars by increasing the amount of time they are absent from their homes. Opportunities to go out, as typified by routine shopping

Table 4 The effects of the state of emergency and ambient population on crime

	Residential burglary							
	Model 1		**Model 2**		**Model 3**		**Model 4**	
	B	**S.E.**	**B**	**S.E.**	**B**	**S.E.**	**B**	**S.E.**
Trend	-0.004	0.011	0.012	0.011	-0.015	0.011	-0.008	0.012
Temperature	-0.038	0.011***	-0.029	0.011*	-0.021	0.011†	-0.026	0.012*
State of Emergency								
SoE period			-0.002	0.049			0.134	0.074†
SoE period x intensity			-0.180	0.064**			-0.047	0.074
Ambient population								
Residential					-0.030	0.010**	-0.028	0.011*
Transit stations					-0.006	0.004	-0.004	0.004
Retail and recreation					0.000	0.004	0.001	0.005
Grocery and pharmacy					0.015	0.007*	0.015	0.007*
Constant	9.871	34.110	33.833	35.216	43.645	35.055	19.762	38.294
Log Likelihood	-2025.79		-2017.98		-2010.24		-2008.57	
AIC	4057.57		4045.97		4034.48		4035.14	
BIC	4072.40		4070.68		4069.07		4079.61	
	Commercial burglary							
	Model 1		**Model 2**		**Model 3**		**Model 4**	
	B	**S.E.**	**B**	**S.E.**	**B**	**S.E.**	**B**	**S.E.**
Trend	-0.025	0.011*	-0.008	0.011	-0.031	0.011**	-0.025	0.012*
Temperature	-0.019	0.011†	-0.040	0.011***	-0.022	0.011*	-0.027	0.012*
State of Emergency								
SoE period			0.308	0.048***			0.181	0.075*
SoE period x intensity			-0.165	0.062**			-0.231	0.073**
Ambient population								
Residential					0.004	0.010	0.016	0.011
Transit stations					-0.009	0.004*	-0.003	0.004
Retail and recreation					0.002	0.004	0.000	0.005
Grocery and pharmacy					0.015	0.007*	0.017	0.007*
Constant	66.444	34.378	13.740	35.424	83.586	34.806	67.190	38.207
Log Likelihood	-2253.43		2231.75		-2230.08		-2223.27	
AIC	4512.86		4473.51		4474.16		4464.54	
BIC	4527.68		4498.21		4508.75		4509.01	
	Theft from/of vehicle							
	Model 1		**Model 2**		**Model 3**		**Model 4**	
	B	**S.E.**	**B**	**S.E.**	**B**	**S.E.**	**B**	**S.E.**
Trend	-0.010	0.008	0.007	0.009	-0.010	0.008	-0.004	0.009
Temperature	-0.016	0.008†	-0.036	0.009***	-0.021	0.008*	-0.026	0.009**
State of Emergency								
SoE period			0.213	0.035			0.125	0.057*
SoE period x intensity			-0.034	0.046			-0.066	0.053
Ambient population								
Residential					0.003	0.008	0.006	0.008
Transit stations					-0.006	0.003†	-0.003	0.003
Retail and recreation					-0.002	0.003	-0.001	0.004
Grocery and pharmacy					0.015	0.006**	0.015	0.006**
Constant	18.915	26.462	-34.538	27.012	21.052	26.347	0.945	28.783

Table 4 (continued)

	Theft from/of vehicle							
	Model 1		**Model 2**		**Model 3**		**Model 4**	
	B	**S.E.**	**B**	**S.E.**	**B**	**S.E.**	**B**	**S.E.**
Log Likelihood	-2725.55		-2698.97		-2694.22		-2691.36	
AIC	5457.10		5407.94		5402.44		5400.72	
BIC	5471.92		5432.65		5437.03		5445.19	
	Bicycle theft							
	Model 1		**Model 2**		**Model 3**		**Model 4**	
	B	**S.E.**	**B**	**S.E.**	**B**	**S.E.**	**B**	**S.E.**
Trend	-0.036	0.007***	-0.054	0.007***	0.050	0.007***	-0.047	0.008***
Temperature	0.006	0.007	0.026	0.007***	0.033	0.007***	0.031	0.007***
State of Emergency								
SoE period			-0.184	0.035***			0.009	0.050
SoE period x intensity			-0.100	0.044*			0.077	0.050
Ambient population								
Residential					-0.023	0.007**	-0.028	0.008***
Transit stations					-0.006	0.003*	-0.007	0.003*
Retail and recreation					0.005	0.003†	0.007	0.003*
Grocery and pharmacy					0.035	0.005***	0.034	0.005***
Constant	107.380	23.199	163.602	22.508	153.065	21.964	142.711	24.333
Log Likelihood	-3338.23		-3286.16		-3223.70		-3222.36	
AIC	6682.46		6582.32		6461.41		6462.72	
BIC	6697.28		6607.02		6496.00		6507.19	
	Sexual assault							
	Model 1		**Model 2**		**Model 3**		**Model 4**	
	B	**S.E.**	**B**	**S.E.**	**B**	**S.E.**	**B**	**S.E.**
Trend	0.011	0.020	-0.036	0.021†	-0.021	0.020	-0.029	0.022
Temperature	0.005	0.020	0.032	0.021	0.026	0.021	0.030	0.021
State of Emergency								
SoE period			-0.127	0.097			-0.023	0.138
SoE period x intensity			-0.236	0.120†			-0.250	0.137
Ambient population								
Residential					0.001	0.020	0.014	0.021
Transit stations					0.009	0.007	0.011	0.008
Retail and recreation					0.000	0.008	-0.005	0.008
Grocery and pharmacy					0.008	0.013	0.009	0.013
Constant	21.603	63.175	99.634	64.165	54.831	63.769	80.185	67.800
Log Likelihood	1-064.61		-1053.81		-1054.60		-1052.66	
AIC	2135.21		2117.62		2123.20		2123.32	
BIC	2150.04		2142.33		2157.79		2167.79	
	Violence and injury							
	Model 1		**Model 2**		**Model 3**		**Model 4**	
	B	**S.E.**	**B**	**S.E.**	**B**	**S.E.**	**B**	**S.E.**
Trend	-0.005	0.007	-0.009	0.007	-0.014	0.007*	-0.016	0.007*
Temperature	0.000	0.006	0.005	0.007	0.011	0.007	0.012	0.007†

Table 4 (continued)

	Violence and injury							
	Model 1		**Model 2**		**Model 3**		**Model 4**	
	B	**S.E.**	**B**	**S.E.**	**B**	**S.E.**	**B**	**S.E.**
State of Emergency								
SoE period			0.029	0.029			0.003	0.044
SoE period x intensity			-0.140	0.038***			0.100	0.042*
Ambient population								
Residential					0.013	0.006*	-0.008	0.007
Transit stations					-0.009	0.002***	-0.008	0.003**
Retail and recreation					0.006	0.002*	0.004	0.003†
Grocery and pharmacy					0.013	0.004**	0.014	0.004**
Constant	3.285	20.330	17.746	21.008	31.259	20.510	38.621	21.968
Log Likelihood	-2657.95		-2648.60		2637.59		-2634.71	
AIC	5321.91		5307.19		5289.18		5287.42	
BIC	5336.73		5331.90		5323.77		5331.89	

***:p < .001, **:p < .01, *:p < .05, : †p <.10

Number of observations = 1034; number of prefectures = 47; number of weeks = 22

trips to the grocery store, are thought to increase the chances of theft of/from vehicle and assault and injury, by increased chances of contact with perpetrators.

Bicycles are a major means of transportation in urban areas in Japan, and the number of bicycle theft is the highest among all crime types. This study revealed that the risk of bicycle theft was associated with increased opportunities to go out ('retail and recreation' and 'grocery and pharmacy') and reduced hours spent at home. Additionally, avoiding the use of crowded public transportation was found to increase the risk of bicycle theft. A possible explanation is that the decrease in the use of congested public transport, which is unique to Japan, may have increased bicycle use, leading to an increase in criminal opportunities for bicycle theft.

SoE declaration was found to impact the ambient population in some settings, and the change in ambient populations impacted crime levels. The most specific example is that the increase in the number of people at home due to the SoE increased guardianship of residential properties, which in turn reduced residential burglary. Other examples include that increased hours at home and decreased outings reduced bicycle theft, and decreased use of public transportation reduced injury and assaults. These results are consistent with those of other COVID-19-related social restrictions and quarantines backed by legal power introduced in other countries (Andresen & Hodgkinson, 2020; Ashby, 2020; Felson et al., 2020; Halford et al., 2020; Mohler et al., 2020). The results of this study are novel because they showed that relatively 'soft' orders without any law enforcement are associated with reductions in crime rates.

The reduction in commercial burglary needs some considerations. According to panel data analysis of the GMRs, the SoE reduced the ambient population in retail and recreation spaces. This could be related to a decrease in guardianship in commercial facilities, which led to an increase in crime. Contrary to our expectations, commercial burglary was found to be associated with the nationwide decrease during the SoE. According to the routine activity theory, commercial burglary should have increased during the SoE due to the lack of capable guardianship; however, this result was not confirmed in our study.

Violence and injury also require careful interpretation since they involve different types of victim-offender relationships (e.g., between strangers caused by fights in public spaces such as bars and domestic or family violence that occurs in households). The decrease in violence and injury between strangers during the COVID-19 pandemic can be supported by the results of the analysis of the GMRs, which showed a decrease in the ambient population at transit stations and retail and recreation spaces. A possible explanation for the decrease in violence and injury in households is that although the SoE increased victimisation in the household due to an increase in the number of members in households, the SoE, simultaneously, made it more difficult for victims to report to the police during the COVID-19 pandemic due to the presence of the offenders in the same households.

Different from the other five crime types, sexual assault was not affected by the SoE or ambient population variables. This may be due to the small number of cases (Halford et al., 2020). Another interpretation is that because sexual assaults are less likely to be reported to the police, the structural effects of changes in SoE and population did not clearly emerge in the official statistics.

Regarding fourth research question, Model 4 in Table 4 allows us to consider the qualitative changes in criminal opportunities caused by the SoE. After controlling for changes in the ambient population and other variables, we observed an increase in commercial burglary and theft of/from vehicle in all prefectures in Japan during the SoE weeks, compared to the week the SoE was not declared. Meanwhile, commercial burglary and assault and injuries decreased in prefectures where stricter behavioural restrictions were implemented.

There are some possible explanations for these qualitative effects of the SoE on crime opportunities. First, SoE declaration boosted a perpetrator's choice to commit crime. Because commercial burglary and theft of/from vehicle were considered more rewarding compared to other minor theft such as bicycle theft, professional thieves were more inclined to commit these crimes during SoE declaration, when the actions of capable guardians were more restricted. The second possible explanation is the spatial displacement. During the SoE period, commercial burglary increased for all prefectures, while it decreased in prefectures where the SoE was more strictly administered. Notably, offenders of store theft may avoid prefectures where emergency declarations are implemented and choose prefectures where they are not. Third, SoE declaration may have changed the behaviour of potential victims in contexts other than going out. For example, security measures against burglary may have been taken by shop owners in SoE prefectures where stores were asked to close to prevent the spread of COVID-19. Furthermore, SoE declaration may have also reduced the opportunities for assault and injury since it made people avoid contact with each other.

The present study provides two valuable insights on the influence of the COVID-19 pandemic on crime. First, by introducing panel data analysis, the impact of the BRP against COVID-19 on people's mobility was systematically identified; its introduction in a prefecture impacted crime mediated by changes in mobility in that prefecture, even after controlling for the impact of the policy's nationwide effect. Second, we found that requests without enforcement changed people's behaviour and impacted crime trends. Unlike stay-at-home orders declared in other countries, the SoE in Japan had no legal power to restrict peoples' activities. Yet, the SoE had an additional effect on people's mobility and crime in the prefectures where it was declared, even after controlling for its overall impact on the country. This study is, of course, a natural experiment, noting that the timing of the SoE differs across prefectures, and not a randomised experiment to analyse the impact of the SoE on people's mobility and crime. However, it can be argued that policies with no legal enforcement during the pandemic period changed people's behaviours.

This study has some limitations. The first limitation is related to crime classification. It has been reported that domestic violence showed an increasing trend during the pandemic in other countries (Nix & Richards, 2021; Piquero et al., 2020). Domestic violence was included in violence and injury in the present study. Due to this classification issue, this study was unable to distinguish domestic violence from other violent crimes. Therefore, further studies should examine trends in domestic violence during the COVID-19 pandemic in Japan. Second, the unit of analysis (prefecture) was much larger than those used in previous studies, such as the district level (Campedelli et al., 2020; Shayegh & Malpede, 2020). Since different levels of geographical aggregation can result in different outcomes (Hipp, 2007), further COVID-19 research that uses a smaller unit of analysis is recommended.

Japan has not received much attention from criminologists, and criminological research there has been limited. his might be partially because Japan has one of the lowest crime rates among industrialised countries. However, Japan is considered an interesting research setting. Several studies have demonstrated that criminological theories based on Western countries are, to some extent, applicable to the Japanese context. Amemiya and Ohyama (2019) tested whether the Law of Crime Concentration could be found at the census-unit level by using police-recorded crime data in Japan. They revealed that, although the degree of concentration varied depending on crime type, crime concentration was observed. Regarding recent crime trends, Japan reportedly experienced a crime drop similar to developed Western countries (Sidebottom et al., 2018). The current study provides additional support for the applicability of the environmental criminology (routine activity approach) to Japan by showing that crime reductions similar to those in developed Western countries during the COVID-19 pandemic were observed at both the local and national levels.

Abbreviations

ARIMA	Autoregressive integrated moving average
BRP	Behavioural regulation policy
COVID-19	Coronavirus disease
GMR	Google mobility report
SoE	State of emergency

Competing interests
The authors declare that they have no competing interests.

Authors' contribution
TS conceived the idea for this study, led data analysis, and produced the first draft of the manuscript. AS led on literature review and assisted in data analysis, interpretation of statistical analysis and revision of the manuscript. MA assisted in data analysis and revision of the manuscript. All authors read and approved the final manuscript.

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