COVID-19’s Lockdown and Crime Victimization: The State of Emergency under the Abe Administration

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ABSTRACT
COVID-19 has led many governments to impose lockdowns in efforts to reduce the spread of the virus. One of the many consequences of the lockdown is a reduction in crime. We apply a difference-in-differences approach to the 2018–2020 Crime Statistics to investigate the effect of the 2020 lockdown on crime victimization in Japan. We find that the 2020 lockdown leads to 12.7% and 20.9% declines in violent and property crime victimization rates per 100,000 people, respectively. Moreover, we observe that premeditated crimes, such as breaking-and-entering and sexual assault, decline more than non-premeditated crimes, such as homicide. We also explore the heterogeneous effects of the lockdown by age groups. We observe that there is a significant decline in sexual assault victimization for those between the ages of 0 and 29, and there are significant declines in overall violent and property crime victimizations and their subtypes for those between ages of 30 and 59. Finally, we show that there is an improvement in suicide rates, which suggests that better mental health is the mechanism partially mediating the relationship between lockdown and crime victimization.

Key words: COVID-19, crimes, difference-in-differences, lockdown, pandemic

JEL codes: H12, I12, I18

1. Introduction
COVID-19 has killed more than 1.5 million people worldwide as of December 2020. The pandemic presents an unprecedented challenge to governments across the globe.

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As a consequence of the pandemic, many countries have imposed bans on traveling and lockdowns on various cities and regions in an effort to prevent the spread of the virus. However, these measures have many consequences that can be felt across different levels of society. For example, research has shown that COVID-19 lockdowns significantly increase the number of unemployed and the number of unemployment benefit claims (Campello et al., 2020; Coibion et al., 2020; Lemieux et al., 2020). In addition to the worsening labor outcomes, the measures also increase inequalities, such as racial and income inequalities (Alon et al., 2020; Blundell et al., 2020; Campello et al., 2020).

Any policy can have potential unanticipated spillover effects, which can be either beneficial or detrimental to the society. This is also true for the lockdown policies implemented by various countries in 2020 to combat the COVID-19 pandemic. For instance, the lockdown policies may lead to a significant reduction of crime rates, particularly in urban areas (Hodgkinson & Andresen, 2020; Abrams, 2021). Abrams (2021) shows that crime rates decreased when lockdowns were put in place across various states in the USA. Similarly, Hodgkinson and Andresen (2020) show that the crime rates decrease after the implementation of a lockdown in Vancouver City in Canada.

While many governments have reacted swiftly and decisively to the COVID-19 pandemic, the Abe Administration responded relatively slowly and mildly. In fact, when compared to the USA that has a relatively similar timeline for the COVID-19 pandemic as Japan, the US state governments imposed lockdown measures in March and April, whereas similar measures were put into place sometime in early-to mid-April in Japan. Moreover, other Japanese policies, such as the Go-To-Travel campaign, have a relatively limited effect on business and consumer consumption, since the inconsistent policy attitudes of the local governments and Abe’s central government has led to a significant confusion over whether to apply the policy or not.1 Due to the confusing and delayed responses, the Japanese public began to question the Abe administration’s ability to manage the crisis and criticized these responses as a result of the administration’s long-time failure to establishing an effective and consistent risk management task force (Ohta, 2020).

Despite the relatively delayed (and ineffective) responses, the Abe Administration did declare a “state of emergency” in April and extended it to the end of May. The Japanese “state of emergency” was similar to the state of emergencies in many other countries, except that the enforcement of the rules was not mandatory. In other words, the lockdown measures imposed by the Japanese government were largely voluntary, which was quite different from other countries, such as the USA where the lockdown was mandatory. However, even with a voluntary lockdown, one may expect that it may change individuals’ behaviors (though not to the same extent as a mandatory lockdown).2 That is, a voluntary lockdown may increase individuals’ fear of the pandemic and increase the probability of individuals staying at home.

The objective of our paper is to assess the effect of the voluntary lockdown imposed by the Abe administration on crime victimization rates in Japan. Despite the criticisms from the media and public over the administration’s slow responses, we find significant

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1. Ohta (2020).

2. Shen et al. (2021).
reductions in both violent and property crime victimization rates after the implementation of the voluntary lockdown in April and May in Japan using data from the 2018–2020 Crime Statistics and a difference-in-differences (DD) approach, which is consistent with findings from the previous studies in other countries. Moreover, we examine whether there are heterogeneous effects of the lockdown on crime victimization rates across age groups. We find that the victimization due to sexual assault significantly declined for individuals between the ages of 0 and 29 during the lockdown, while the victimization for all types of violent and property crimes for individuals between the ages of 30 and 59 are declined during the lockdown, though the magnitudes and significances of the effect differ across the type of crime victimization. Finally, we explore the mental health mechanism by proxying the channels with suicide rates. We find that the lockdown significantly reduced suicide rates. Specifically, the decline in the suicide rates due to economic/living conditions is driving our results. However, our results do not suggest that the Abe administration anticipated the crime reduction effect of their lockdown policies, but rather our results show that a lockdown, whether it is voluntary or mandatory, would have negative spillover effects on the crime victimization rates, regardless of the intention.

Section 2 discusses the conceptual framework underlying our analysis and a brief description of COVID-19 pandemic in Japan. Section 3 states the empirical strategy and Section 4 describes the data used in this paper. Section 5 shows the results, while Section 6 discusses the policy implications of our results.

2. Conceptual Framework and Background

2.1 Conceptual framework

Becker’s (1968) framework of the crime of economics envisions a crime as a rational choice for an agent weighing up the benefits and costs of committing a crime at the margin. Ehrlich (1996) emphasizes that crime can be explained by a “market model” that consists of multiple parties, such as offenders and victims, interacting based on their rational expectations of costs and benefits. The “market,” however, should not be simply understood as a physical setting where illegitimate (or stolen) goods are transacted, but as a concept in which the aggregated behavior of suppliers and demanders is coordinated and readjusted based on relevant prices for each side in equilibrium. On the supply side, the offender’s participation in criminal behavior can be thought of as a function of the certainty and severity of criminal punishment. On the demand side, the victim’s “demand” for crime is a function of the marginal costs and benefits of investing in protection or precaution, such as door alarms or changes in outdoor behavior like outings into slum areas.

In particular, the framework shows how a lockdown could affect the costs and benefits of crime on both sides through direct and indirect channels.3 We focus on the demand side rather than the supply side, given that our data are based on victimization records. A lockdown would reduce the crime victimization by reducing the costs and benefits associated with precautions and protection. For instance, a lockdown would
significantly increase the benefits associated with taking precautionary behaviors such as outings into unsafe areas or engaging with criminals, since victims are concerned with being infected with the SARS-CoV-2 virus when going outdoors and interacting with other people. Moreover, given that some people working in areas such as information technology and finance services are shifted to working remotely (for instance, telework) in order to comply with the lockdown (Okubo, 2020), the cost of staying at home as a deterrent to certain crimes, for example breaking-and-entering, would decrease naturally (Angelucci et al., 2020; Brynjolfsson et al., 2020).

In addition to direct channels, a lockdown could also affect crime on the demand side through indirect channels, such as mental health, family, and labor market outcomes. Research for Japan has shown that the lockdown had a positive effect on mental health when proxied by suicide rates (Ueda et al., 2020a; Tanaka & Okamoto, 2021). An improvement in mental health would lead victims to be more alert to potential criminals and take more precautions. On the other hand, a lockdown has also been shown to increase family-related conflicts and issues, such as domestic violence and child abuse (Griffith, 2020; Leslie & Wilson, 2020; Piquero et al., 2020). More family conflicts (and issues) would lead to more violent crimes, such as homicide. Finally, it is also possible that a lockdown significantly reduces employment rates and leads to a higher level of poverty (Bargain & Ulugbek, 2020; Han et al., 2020; Jain et al., 2020). As a result, an increase in the poverty level may be positively correlated with some types of property crimes, such as shoplifting, in order to compensate for income losses.

This framework also suggests that different crimes will respond differently to a lockdown. Some types of crimes, like homicide, may not be as affected as other crimes. Crimes like homicide are generally not premeditated and are highly situational. Given a lockdown significantly affects the costs and benefits of the “demand” for crime, one would expect that premeditated crimes would be more affected by a lockdown than non-premeditated crimes, as one would have time to plan and research the costs and benefits of taking precautions and protection for crimes, such as motor vehicle theft, compared to crimes that are unplanned, such as homicide.

2.2 Background
The first case of COVID-19 emerged in China between late December 2019 and early January 2020, and the virus quickly spread across the globe through international travel. In Japan, the first confirmed case of COVID-19 was detected sometime around mid to late January. However, the virus was eventually spread to other prefectures through both internal and external travel. On February 5th, the Diamond Princess cruise liner docked in the Yokohama Port and was quarantined in the port due to an outbreak, causing a political debate on the emergency measures that could be taken by Japanese government. Given the unprecedented crisis, the laws were amended by the Diet to allow the government to declare a “state of emergency” in order to combat the COVID-19 virus. The “state of emergency” gives governments many powers including the ability: to request people to refrain from going-out for unnecessary services, unless
they are workers in essential areas such as health care; to request restrictions on the use of public spaces, such as schools and businesses, temporarily; to expropriate private spaces, such as hotels, for use as emergency medical areas; and to request the sale and seizure of medical or other goods. The laws were amended on March 13th (Prime Minister’s Office of Japan [PMOJ], 2020). On April 7th, the Abe Administration issued a 1-month state of emergency for seven prefectures: Tokyo, Saitama, Chiba, Osaka, Hyogo, Fukuoka, and Hokkaido (PMOJ, 2020). The state of emergency was eventually extended to all prefectures on April 16th (PMOJ, 2020). On May 4th, the state of emergency was further extended until the end of May (PMOJ, 2020).

Given that we are interested in the effects of Japan’s COVID-19 lockdown on crime victimization rates, we leverage the temporal difference before the declaration of the state of emergency. That is, we implement a DD approach with the differences between the months prior to the lockdown and the months after the lockdown and between the nonpandemic years and the pandemic year. We elaborate on the strategy further in the empirical section (see Section 3). However, an important problem with this strategy is the trends in crime/crime victimization rates in Japan. It is important to note whether the crime situation worsens or improves before the pandemic and Abe Administration as a whole. Figure 1 shows the number of crime victims for total, violent, and property crimes from 2016 to 2020 using data from the Crime Statistics between January and May. Panel a shows the aggregate number of crimes year by year. We can see that the number of victims seems to mildly decline for violent crime from 2016 to 2019, but decline sharply in 2020. Similarly, the property crime victim numbers decline between 2016 and 2020, though the decline is much milder than for violent crime before 2020. The figures point to the fact that the crime situation has improved, although mildly, during Abe’s tenure as a prime minister, which may cast some doubt on the effect of the lockdown on crime victimization. We further decompose the trends by the months before the lockdown (January to March) and the months after the lockdown (April and May) from 2016 to 2020. Panels b and c show the number of victims of violent and property crime, respectively. For violent crime victims, there is a decline in 2018 for April and May, but the number increases in 2019. Corresponding to the lockdown, there is a sharp decline in 2020 for April and May cohort. For property crime victims, the number of victims in the two cohorts is relatively similar before 2020, but the April and May cohort declines sharply in 2020. Although panel a seems to show that there are some declines in crime victimizations before 2020, our panels b and c seem to suggest that the trends between the cohort before the lockdown and the cohort during the lockdown before 2020 are relatively similar (no strong declining trends) to warrant concerns over our results being driven being pre-existing declining trends.

3. Empirical Strategy

To examine the effect of the COVID-19 lockdown on crime victimization rates, we implement a specification similar to Leslie and Wilson’s (2020) model. We regress the following DD model:
Figure 1  Crime victimization rates: 2016–2020.
Source: 2016–2020 Crime Statistics. Notes: For panel A, The left hand vertical axis is the scale for the number of victims of property crime and the right-hand vertical axis is the scale for the number of victims of violent crime.
$Y_{amt} = \beta_0 + \beta_1 Post_m + \beta_2 2020t + \beta_3 Post_m \times 2020t + \gamma_m + \omega_t + u_{amt}, \quad (1)$

where $Y_{amt}$ is the natural logarithm of violent or property crime victimization rates per 100,000 people by age group $a$ in month $m$ and year $t$. Similar to Leslie and Wilson (2020), our treatment variable is $2020t$, which is a 0-1 dummy variable that is equal to one if the year of the observation is 2020, and zero otherwise. The treatment period variable, $Post_m$ is also a 0-1 variable that equals one if the month of observation is either April or May, and zero otherwise. $Post_m \times 2020t$ is the interaction term between $Post_m$ and $2020t$, and $\beta_3$ is the main coefficient of interest, measuring the effect of the COVID-19 lockdown on crime victimization rates. $\lambda_a, \gamma_m$, and $\omega_t$ are age group, month, and year fixed effects, respectively. $u_{amt}$ is the error term. Note that $Post_m$ and $2020t$ are perfectly collinear with $\gamma_m$ and $\omega_t$, so that $\beta_1$ and $\beta_2$ cannot be identified.

Our DD model in Equation (1) relies on the common trend assumption. That is, the systematic differences between treated and control groups do not differ (or are not declining) before the implementation of the policy, in this case, the COVID-19 lockdown. In other words, the parameter, $\beta_3$, from Equation (1) is not driven by pre-existing declining trends of victimization rates. In order to show the crime victimization rates before the lockdown are not declining, we estimate the event study model specified in Equation (2):

$Y_{amt} = \delta_0 + \sum_{m=1}^{5} \delta_m Month_m \times 2020t + \lambda_a + \gamma_m + \omega_t + u_{amt}, \quad (2)$

where all the dependent variables and fixed effects are identical to those in Equation (1), except for the interaction terms. Our interest lies in the interaction terms, $Month_m \times 2020t$, and their associated parameters, $\delta_m (m = 1, \ldots, 5)$. The baseline (or omitted) category is March which corresponds to the month prior to the lockdown. Compared to the baseline, if the magnitude, sign, and significance of the estimates for January and February are small, opposite, and/or insignificant, we may conclude that the common trend assumption is plausible.

The lockdown can affect different populations differently. For example, older individuals who are already retired and do not commute to work may be less affected by the lockdown, whereas younger individuals who are supposed to commute to work and school may be more strongly affected. Given our data set is stratified by age group, we can examine the age heterogeneity by interacting our DD interaction term with a three-level category variable of age, similar to a triple-differences (DDD) approach. Specifically, we estimate the following model:

$Y_{amt} = \alpha_0 + \alpha_1 Post_m + \alpha_2 2020t + \alpha_3 Age0 - 29a + \alpha_4 Age30 - 59a + \alpha_5 Post_m \times 2020t$

$+ \alpha_6 Post_m \times Age0 - 29a + \alpha_7 Post_m \times Age30 - 59a + \alpha_8 2020t \times Age0 - 29a$

$+ \alpha_9 2020t \times Age30 - 59a + \alpha_{10} Post_m \times 2020t \times Age0 - 29a + \alpha_{11} Post_m \times 2020t$

$\times Age30 - 59a + \lambda_a + \gamma_m + \omega_t + \gamma_m \lambda_a + \omega_t \lambda_a + u_{amt}, \quad (3)$
where Age0 \(-29\) is a 0-1 dummy variable that equals one if the age group is between 0 and 29, and zero otherwise. Age30 \(-59\) is a 0-1 dummy variable that equals one if the age group is between 30 and 59, and zero otherwise. Note that Postm, 2020t, Age0 \(-29\), and Age30 \(-59\) are perfectly collinear with \(\gamma_m\), \(\omega_t\), and \(\lambda_a\), so that \(\alpha_1\), \(\alpha_2\), \(\alpha_3\), and \(\alpha_4\) cannot be identified. The baseline level is the age group for individuals who are 60 years old and above. We use these cutoffs, because these individuals who are 60 years old are more likely to be retired and/or widowed (or divorced). Thus, they would not be as severely affected by labor market shocks or family shocks associated with the COVID-19 pandemic as those who are younger than 60 years old. Moreover, we stratify those who are below 60 into two groups (0–29 and 30–59), since we expect those between the ages of 30 and 59 to be more vulnerable to the labor market and family shocks, given that they are in the prime working-age. \(\gamma_m\lambda_a\) and \(\omega_t\lambda_a\) control for time-specific age trends.

One potential mechanism that can mediate the relationship between the lockdown and becoming a crime victim is mental health. Some papers show that COVID-19 has a direct effect on mental health (Ueda et al., 2020a; Tanaka & Okamoto, 2021). Moreover, COVID-19 can also have indirect effects on mental health through various channels related to family, physical health, and economic/living conditions. To examine the effect of the lockdown on mental health, we proxy mental health by the suicide rate. We estimate the following model:

\[
S_{amt} = \phi_0 + \phi_1 Post_m + \phi_2 2020_t + \phi_3 Post_m \times 2020_t + \lambda_a + \gamma_m + \omega_t + u_{amt}
\]

where all independent variables are the same as in Equation (1). \(S_{amt}\) is the natural logarithm of the suicide rate per 100,000 people for age group \(a\) in month \(m\) and year \(t\). We also estimate the effect on the suicide rate by the reason for the suicide – family, physical health, or economic/living conditions – to further explore the mechanisms. Note that Postm and 2020t are perfectly collinear with \(\gamma_m\) and \(\omega_t\), so that \(\phi_1\) and \(\phi_2\) cannot be identified.

We cluster the standard errors at the age levels. Recent research by Cameron et al. (2008) and MacKinnon and Webb (2017) shows that the inferences based on clustered standard errors with less than 50 observations in the cluster would lead to an over rejection of the null hypothesis. Given the number of groups for our ages is only 10, our inferences may suffer from the issue of too “few” clusters. One strategy is to use wild bootstrapping. This method has been shown to work reasonably well (Cameron et al., 2008; Cameron & Miller, 2015). We wild bootstrap our cluster inferences with 1000 replications with Webb’s weights (Webb, 2013). \(P\)-values are reported instead of standard errors (Roodman et al., 2019). All regressions are weighted with population by age group and estimated using ordinary least squares (OLS).
4. Data Sources

Our primary data source is the 2018–2020 Crime Statistics (Hanzai Toukei). The statistics collect various information on all types of crime victims reported monthly by each Prefectural Police affiliated with the National Police Agency in Japan. To generate dependent variables, we extract the number of confirmed cases of violent and property crime victims by age groups. Violent crime victims are defined as individuals who suffered from crimes that generally involve the use of force, such as homicide and robbery. Property crime victims are defined as individuals who suffered from crimes that do not use force, such as breaking-and-entering and pickpocketing. There are 10 age groups, and they are 0–12, 13–19, 20–29, 30–39, 40–49, 50–59, 60–64, 65–69, 70–79, and ≥80 for each year. We also obtain the four most prevalent subtypes of violent and property crime victim: homicide, sexual assault, breaking-and-entering, and motor vehicle theft. The total number of observations is 150.

To examine the mental health mechanism, we leverage the 2018–2020 Suicide Statistics (Jisatsu no Toukei). The statistics collect the total number of suicides and suicides due to various reasons. The data are stratified into eight age groups which are 0–19, 20–29, 30–39, 40–49, 50–59, 60–69, 70–79, and ≥80 for each survey year. We extract the number of total suicides, suicides due to family circumstances, suicides due to physical health issues, and suicides due to economic and living condition issues. The total number of observations is 120. To normalize the number of crime victims and suicide rates, we acquire the age-level population data from the 2018 and 2019 Population Estimates (Jinko Suikei). However, one particular issue is the lack of data on population estimate for 2020. To alleviate this problem, we fix the 2020 population to be the same as in 2019, given that the populations in 2018 and 2019 are relatively similar. We obtain the population for each 1-year age group and collapse them into each corresponding age group for each dependent variable.

Then, we log-transformed the crime and suicide rates with log(1 + y) due to presence of zero for some observations in our data set. To test the robustness of our results to a different transformation, we also transform our dependent variables with the inverse hyperbolic sine transformation. The inverse hyperbolic sine transformation has the advantage of not generating missing observations when transforming zeroes, but the interpretation of the results is relatively similar to those for the logarithm transformation (Burbidge et al., 1988). The results of the transformations are reported in panel D of Table 5. Finally, given we are only interested in the effect of the state of emergency on criminal behavior, we focus on the data between January and May of each year (2018–2020), because the state of emergency ended in May 2020.

5. Results

5.1 Summary statistics

Table 1 reports the means and standard deviations of the dependent variables by treatment groups and treatment periods. Column (1) report the descriptive statistics for all
the data; whereas columns (2) and (3) report them for the January–March and April–May cohorts in 2018–2019; and columns (4) and (5) report them for January–March and April–May cohorts in 2020. Panel A reports the crime victimization rates and panel B reports the suicide rates. First, property crime victimization rates are overall higher than violent crime victimization rates. For instance, the property crime victimization rate per 100,000 people is 1.397, whereas the violent crime victimization rate per 100,000 people is 0.393. Second, the means of violent and property crime victimization rates increase between January–March cohort and April–May cohort in 2018–2019, whereas the means decrease between the two cohorts in 2020. Finally, there is significant heterogeneity across the subtypes of crimes. For example, homicide victimization rates between the two cohorts decline less than (1.6% in 2018–2019 vs. −15.9% in 2020) sexual assault victimization rates do (21.8% in 2018–2019 vs. −21.5% in 2020). In sum, the statistics suggest that the lockdown has a negative effect on crime victimization rates, but a more comprehensive analysis is required.

For suicide rates, the mean log of total suicide rates for all years is 0.354. For each respective reason for suicide, the means are 0.076 for familial issues, 0.154 for physical health issues, and 0.061 for economic/living conditions, respectively. Similar to crime victimization rates, we find that the total suicide rates increase between January–March cohort and April–May cohort in 2018–2019, whereas the total suicide rates decrease between January–March cohort and April–May cohort in 2020. We observe that the total suicide rates increase from 0.350 to 0.366. For the same rates in 2020, we find that the total suicide rates decrease from 0.352 to 0.341, indicating a significant decline in total suicide rates compared to 2018–2019. When their reasons for committing suicide are examined, we find that only suicides due to economic/living conditions have similar patterns in 2018–2020 as the total suicide rates. We find that suicide rates due to economic/living condition increase from 0.061 to 0.060 in 2018–2019 and decrease from 0.068 to 0.055 in 2020.

5.2 Main results
Table 2 reports the estimated effect of the lockdown on crime victimization rates from estimating Equation (1). Columns (1)–(3) report the estimates for violent crimes, and columns (4)–(6) report the estimates for property crimes. Each column reports the results for a different dependent variable. Overall, we find that the lockdown is associated with a decline in violent and property crime victimization rates. The lockdown leads to 12.7% and 20.9% declines in violent and property crime victimization rates, respectively. Although there is no statistically significant effect on homicide, the lockdown leads to a decline in the sexual assault victimization rate by 9.0%. For the subtypes of property crimes, we find that breaking-and-entering reduced by 16.4% and motor vehicle theft reduced by 6.1%, respectively.\textsuperscript{12}

Figure 2 reports the estimates of $\delta_m$ obtained from estimating the event study model in Equation (2) for violent, property crime victimizations, and their respective subtypes. The baseline category is March, 1 month prior to the lockdown, so $\delta_3$ is set
equal to zero. Panels A–C report the estimates for violent crime victimization rates and its subtypes, while panels D–F report the estimates for property crime victimization rates and its subtypes. We observe that the estimates for January (month 1) and February (month 2) are statistically insignificant for violent crime and its subtypes. Moreover, the magnitudes of these estimates are trivial compared to the estimates in April (month 4) and May (month 5), suggesting that the common trend assumption is plausible for violent crime victimization rates. For property crime, we find that the estimates for January (month 1) and February (month 2) are positive but statistically significant. The statistically significant estimates before March seem to suggest a

| Table 1 Summary statistics |
|----------------------------|
| (1) | (2) | (3) | (4) | (5) |
|-----|-----|-----|-----|-----|
| All | January–March | April–May | January–March | April–May |
| (N = 150) | (N = 100) | (N = 50) |

Panel A: Crime victimization

| Violent crime victimization rates | 0.393 | 0.384 | 0.436 | 0.400 | 0.326 |
|----------------------------------|-------|-------|-------|-------|-------|
| Homicide victimization rates     | 0.061 | 0.061 | 0.062 | 0.063 | 0.053 |
| Sexual assault victimization rates | 0.195 | 0.187 | 0.239 | 0.185 | 0.147 |
| Property crime victimization rates | 1.397 | 1.432 | 1.492 | 1.340 | 1.191 |
| Break-and-enter victimization rates | 1.240 | 1.267 | 1.315 | 1.194 | 1.078 |
| Motor vehicle theft victimization rates | 0.340 | 0.359 | 0.372 | 0.311 | 0.263 |
| (0.240) | (0.229) | (0.267) | (0.242) | (0.209) |
| (0.027) | (0.025) | (0.028) | (0.031) | (0.024) |
| (0.225) | (0.211) | (0.278) | (0.205) | (0.165) |
| (0.608) | (0.617) | (0.634) | (0.583) | (0.550) |
| (0.562) | (0.572) | (0.593) | (0.536) | (0.506) |
| (0.234) | (0.245) | (0.245) | (0.219) | (0.188) |

Panel B: Suicide

| Total suicide rates | 0.354 | 0.350 | 0.366 | 0.352 | 0.341 |
|---------------------|-------|-------|-------|-------|-------|
| (0.104) | (0.106) | (0.105) | (0.103) | (0.102) |
| Suicide rates due to family issues | 0.076 | 0.075 | 0.078 | 0.078 | 0.070 |
| (0.029) | (0.030) | (0.030) | (0.030) | (0.024) |
| Suicide rates due to physical health issues | 0.154 | 0.149 | 0.163 | 0.148 | 0.157 |
| (0.067) | (0.067) | (0.070) | (0.064) | (0.070) |
| Suicide rates due to economic/living conditions | 0.061 | 0.061 | 0.060 | 0.068 | 0.055 |
| (0.042) | (0.043) | (0.042) | (0.046) | (0.036) |

Notes: Columns (1)–(5) report the means and standard deviations of the total sample, and the 2018–2019, and 2020 samples. The standard deviations are reported in brackets. The variables are untransformed victimization and suicide rates per 100,000 people. All statistics are weighted by the appropriate population.
violation of the common trend assumption. However, this may be attributed to the effect of the pandemic, as people may be more likely to stay at home due to the fear of pandemic in March. This can be seen when we decompose the property crimes into subtypes: breaking-and-entering and motor vehicle theft. The trends only appear in breaking-and-entering but not motor vehicle theft, suggesting there may be some stay-at-home behavior in March though the effect is not strong. Overall, our event study model suggests that the common trend assumption is plausible in our study.

Table 3 reports the estimated effect of lockdown on crime victimization rates by age group. The baseline category is individuals who are 60 years old and over. Each column reports the estimates using a different dependent variable. Overall, our estimates suggest that different age groups are affected differently between violent and property crime by the lockdown. Based on results in columns (1)–(3), we find that lockdown significantly reduces violent crime victimization rates by 19.8% and 9.5% for those between the ages of 0 and 29 and those between the ages of 30 and 59, respectively. We do not find any effect on homicide regardless of age group, but we find that sexual assault is significantly reduced; however, the effect is much larger for those between the ages of 0 and 29. That is, the sexual assault victimization rates are reduced by 25% for those between the ages of 0 and 29 versus 6.5% for those between the ages of 30 and 59. For the total property crime victimization rates, we find the lockdown decreases the rates by 11.9% only for those between the ages of 30 and 59. The estimates on breaking-and-entering and motor vehicle theft suggest that only breaking-and-entering decreases by 11.6% after the lockdown for those between the ages of 30 and 59. In sum, the estimates suggest there is a significant heterogeneity by age groups between COVID-19’s lockdown and crime victimization rates.

Table 4 reports the estimated effect of lockdown on suicide rates. Each column reports the results for a different dependent variable. Column (1) reports the estimate for total suicide rates, and columns (2)–(4) report the estimated effect on suicide rates by three major reasons related to family, health, and economic/living conditions. Based on the estimates, we observe that the lockdown significantly reduces the total suicide rates by 2.8% after the lockdown. Stratifying by the reasons for suicide, we find that the lockdown significantly reduces suicide due to physical health and economic/living conditions, but has no effect on suicide due to family reasons. That said, the magnitude of effect is trivial for physical health which is approximately 0.6%.13

5.3 Robustness checks
Table 5 reports the results of robustness checks of our estimates with various specifications. Though our event study shows that the violation of the common trend assumption is minimal, we can further improve the confidence of our results by including age-specific linear and quadratic trends to absorb any group-specific trends in the model. Models A and B report the estimates including these trends. Overall, we do not detect significant changes in the magnitudes, signs, and significances between these estimates and our main results. We further test the robustness of our results by
estimating them using a Poisson model, and report the results in Model C. The relationship is consistent with the main results. We also examine the robustness to an alternative transformation of the dependent variable, the inverse hyperbolic sine transformation, that has the advantage of generating nonzeroes when the original rates were zero. Model D reports the estimates using this transformation. We do not find a significant difference between these estimates and the main results. Finally, recent work by Solon et al. (2015) show that it is not clear what we are weighing for in a weighted regression. Ideally, one should test the robustness of the estimates to unweighted regression. Model E reports the unweighted estimates which are similar to the weighted estimates.

6. Discussion

Applying a DD approach to the 2018–2020 Crime Statistics, we estimate the effect of the 2020 COVID-19 lockdown on crime victimization rates in Japan. Specifically, we investigate the effect of lockdown on violent and property crime victimizations, and the important subcategories of these crime victimizations. Based on the event study,
Figure 2 Event study model.
Source: 2018–2020 Crime Statistics.
Notes: Each panel presents the estimates for a separate regression that also controls for time- and age-fixed effects. All regressions are regressed using OLS and weighted using population by age levels. The standard errors are clustered at age group levels and wild-bootstrapped with 1000 replication and Webb’s weights.
we show that our estimates are unlikely to be driven by strong the pre-existing declining trends of crime victimization rates for most of the crimes, suggesting that the common trend assumption is plausible.
Table 3 Heterogeneity by age group

|                      | Violent crime          | Property crime          |
|----------------------|------------------------|-------------------------|
|                      | (1) Overall (2) Homicide (3) Sexual assault | (4) Overall (5) Break-and-enter (6) Motor vehicle theft |
| Post × Year 2020     | −0.038**                | −0.000                  | −0.001                  | −0.157**                | −0.130**                | −0.054*                  |
|                      | [0.055]                 | [0.972]                 | [0.871]                 | [0.025]                 | [0.031]                 | [0.036]                  |
| Post × Age 0–29      | −0.086***               | −0.005                  | −0.146**                | −0.001                  | 0.047                   | −0.035                   |
|                      | [0.033]                 | [0.782]                 | [0.029]                 | [0.977]                 | [0.112]                 | [0.454]                  |
| Post × Age 30–59     | −0.132**                | −0.019                  | −0.204*                 | −0.015                  | 0.037                   | −0.039                   |
|                      | [0.082]                 | [0.594]                 | [0.066]                 | [0.806]                 | [0.493]                 | [0.331]                  |
| Year 2020 × Age 0–29| −0.081*                 | −0.001                  | 0.036                   | −0.074                  | −0.108                  | −0.045                   |
|                      | [0.098]                 | [0.972]                 | [0.388]                 | [0.543]                 | [0.270]                 | [0.447]                  |
| Year 2020 × Age 30–59| −0.160*                | −0.023                  | 0.070                   | −0.045                  | −0.108                  | −0.017                   |
|                      | [0.085]                 | [0.341]                 | [0.311]                 | [0.865]                 | [0.533]                 | [0.869]                  |
| Post × Year 2020 × Age 0–29 | −0.198***        | 0.004                   | −0.250***               | −0.037                  | 0.037                   | 0.033                    |
|                      | [0.003]                 | [0.838]                 | [0.002]                 | [0.706]                 | [0.584]                 | [0.294]                  |
| Post × Year 2020 × Age 30–59 | −0.095**          | −0.020                  | −0.065**                | −0.119**                | −0.116**                | −0.029                   |
|                      | [0.017]                 | [0.155]                 | [0.022]                 | [0.021]                 | [0.041]                 | [0.384]                  |

Age Fixed Effects: Yes
Month Fixed Effects: Yes
Year Fixed Effects: Yes
Month Fixed Effects × Age Trends: Yes
Year Fixed Effects × Age Trends: Yes
N: 150

Note: See Table 2.
Although the Abe administration’s delayed lockdown policy was voluntary, we find the COVID-19 lockdown is significantly associated with 12.7% and 20.9% reductions in violent and property crime victimization rates per 100,000 people in Japan, respectively. This is consistent with previous studies in the USA and Canada where mandatory lockdowns were imposed (Hodgkinson & Andresen, 2020; Abrams, 2021).

We further implement a DDD approach to investigate the heterogeneous age effect of the lockdown on both types of crime victimizations. During the lockdown periods, while those who are between the ages of 30 and 59 become less likely to be victimized by sexual assault, a category of violent crime, and breaking-and-entering, a category of property crime, those between the ages of 0 and 29 tend to be less victimized only by sexual assault, and the magnitude of the effect is large. These results would reflect people’s behavioral change in accordance to their education and labor status at their respective age. For those between the ages of 0 and 29, these individuals are the most sexually active and have least amount of obligations to work (and other commitments) (Ueda et al., 2020b). Because of this, they would normally be more likely to have a large geographic area of activity and to spend extended periods of time outside the home without the COVID-19 pandemic. For them, the lockdown could be a signal that there is an increase in the risk of infection when contacting with other people and raising the cost of being sexually active. Consequently, the lockdown would restrict the behavior for both offenders and victims between the ages of 0 and 29, reducing the victimization rates of sexual assault for this age group. In contrast, for those in prime working age (30–59), the lockdown promotes remote work, which may largely decrease the cost of staying home and increase its benefits. Therefore, the crime victimization rates are decreased, particularly for property crimes, like breaking-and-entering, for the prime working age group (Angelucci et al., 2020; Brynjolfsson et al., 2020). In other words, from the offender’s perspective, people staying home all the time due to the lockdown would increase the cost of breaking-and-entering.

Finally, we explore the mental health mechanisms mediating the relationship by using suicide rates as a proxy variable and find that suicide rates decline by 2.8% during the lockdown. In particular, the effect seems to be driven by a decline in suicides due to economic and living conditions. Our findings from the analysis of suicide rates suggest that an improvement in mental health during the lockdown maybe an important mediator in the relationship between the lockdown and crime victimization, since mental health is one of the determinants of crime and victimization (Choe et al., 2008). This finding somewhat contradicts our expectations that suicides due to economic and/or living conditions would increase (or their change would be statistically insignificant) due to the lockdown, as literature points to a significant increase in unemployment. One potential explanation of this phenomenon is that labor market effect is not immediate, rather the labor market effect lags behind the lockdown. Therefore, the remote work channel is more dominant during the lockdown, leading to a significant short-term decline in suicides due to economic and/or living conditions, such as declines in work stress in the corporate environment when people stay in their home environment.
Our study has several implications. First, we would like to regard the allocation of scarce socioeconomic resources under the lockdown policy. We find that the lockdown reduces both the violent and property crime victimization rates. This would suggest that limited resources can be reallocated from some public sectors, such as police and criminal justice, to health care sectors in order to alleviate the added stresses on the health care sector during a pandemic. Also, even within police sector, the lockdown does not affect all types of crimes uniformly. That is, some crimes are more affected than others. For those crimes that are not affected by the lockdown, the police may need to devote more resources to policing these crimes during a lockdown.

Second, although the media and public have criticized the delayed and lenient lockdown policy implemented by the Abe administration, it seems to have been effective in at least reducing crime victimization rates. Needless to say; however, this does not indicate a high level of crisis management capability by the administration. Rather, it would be an incidental effect of the lockdown policies, shown by previous research for the USA and Canada (Hodgkinson & Andresen, 2020; Mohler et al., 2020). Any public policy would not necessarily have spillover effects that are beneficial to the society all the time; for instance, the short-term reduction of crime victimization rates during the lockdown. Therefore, the role of government is to prepare measures corresponding to the multiple scenarios that could occur in a crisis, and conduct simulations including the beneficial and detrimental spillover effects, based on scientific methodology (Hubbard, 2020). For example, if the government had been able to foresee that the lockdown policy would reduce crime victimization rates, the emergency reallocation of socioeconomic resources we have proposed might have made it easier to get people on board with the said policy.

Table 4 The effect of COVID-19’s lockdown on suicides

| Reason(s)                  | (1) Total suicide | (2) Family | (3) Physical health | (4) Economic/living conditions |
|----------------------------|-------------------|------------|--------------------|-------------------------------|
| Post × Year 2020           | −0.028***         | −0.012     | −0.006**           | −0.012**                      |
| [0.002]                    | [0.108]           | [0.044]    | [0.015]            |                               |
| Age Fixed Effects          | Yes               | Yes        | Yes                | Yes                           |
| Month Fixed Effects        | Yes               | Yes        | Yes                | Yes                           |
| Year Fixed Effects         | Yes               | Yes        | Yes                | Yes                           |
| N                          | 120               | 120        | 120                | 120                           |

Notes: Columns (1)–(4) report the effect of COVID-19 lockdown on suicide rates and the suicide rates by causes. Each column reports an estimate for a different dependent variable. All regressions include age, month, and year fixed effects and are weighted by the appropriate population. We cluster at the age levels and wild bootstrap the standard errors over 1000 replications with Webb’s weights. The numbers reported in the square brackets are P-values. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.
Third, our mental health mechanisms show that the lockdown significantly reduces suicide rates, and this was driven largely by the decline in suicides due to economic and living conditions during the lockdown. This implies that policymakers wishing to reduce crime victimization should focus on not just reducing the contact between offenders and victims but also improving the overall mental health and economic and living conditions of population.

Finally, as previous studies have shown, the lockdown policy significantly increases the number of unemployed and the unemployment benefit claims (Campello et al., 2020; Coibion et al., 2020; Lemieux et al., 2020) and also it could increase inequalities, such as racial and income inequalities (Alon et al., 2020; Blundell et al., 2020; Campello et al., 2020). All of these socioeconomic phenomena could lead an increase in the crime victimization rates in the long run. Therefore, in order to consider the appropriate measures to prevent victimization rates rebounding, we need to evaluate carefully the additional potential effects of lockdown policies on the society as a whole.
Notes

1 The “Go-To-Travel” (Go To Toraberu in Japanese) program is a subsidy program which paid for 35% of the cost of a person’s travel costs (other restrictions may also apply). The program was implemented from July 2020 in an effort to boost domestic tourism to alleviate the effect of the lockdown (and COVID-19) on the hospitality and tourism industry. See https://goto.jata-net.or.jp/about/ (in Japanese).

2 We do not differentiate between voluntary and mandatory lockdowns. Though the effect of a voluntary lockdown is expected to be smaller than that of a mandatory lockdown, the general mechanisms through which both types of lockdowns affect crime or victimization should be similar.

3 We do not explicitly explain the supply side, given our data is not measuring crime directly. Of course, one could expect the supply side to also be affected by a lockdown. For the supply side, the lockdown would reduce the costs associated with crime, such as breaking-and-entering into shops, for offenders. That is, the lockdown would reduce the number of shops open for business and increase the number of empty shops, reducing the certainty of being caught. Moreover, a lockdown would also reduce the number of potential witnesses, as people are staying at home more often.

4 Although the literature from other countries is relatively scant, a paper on Peru has also shown that suicide rates decline after a lockdown (Calderon-Anyosa and Kaufman, 2020).

5 See http://www.cas.go.jp/jp/influenza/pdf/130413houritu_gaiyou.pdf (in Japanese) for all the powers available as a result of declaring a “state of emergency.”

6 A systematic review has found that poor mental health is a significant risk factor of suicide (Hawton et al., 2013).

7 The data can be accessed from the Japanese webpage https://www.e-stat.go.jp/stat-search/files?page=1&toukei=00130001. This webpage provides access to the data for all years. To access the data for any single year, you need to click on the relevant row to gain access to them.

8 We restrict our analysis to data to 2018 onward due to a concern of a downward trend in crime victimization rates prior to 2018. As Figure 1 suggests, including data from 2016 and 2017 may introduce some bias into our estimates. Thus, limiting the data to a shorter pre-2020 period may reduce the bias from the pre-existing declining trends.

9 We have translated the Japanese term Juyou Hanzai as violent crime, since most of the crimes involve some form of force. We have translated the Japanese term Juyou Setto Han as property crime, as most of the crimes involves the loss of property or items.

10 The data can be accessed from https://www.mhlw.go.jp/stf/seisakunitsuite/bunya/0000140901.html.

11 The data can be accessed from https://www.stat.go.jp/data/jinsui/index.html.

12 A concern is that the observed drop in crime and victimization is not due to an actual decline in crime, rather it is due to a decline in reporting. Our data do not contain data for victimization reporting. We do have an aggregated reporting of crime data which we can used to show that the are no declines in reporting of crimes after the lockdown. The results are reported in Figure OSM1 in the Online Supplementary Material. Overall, we do not observe declines in reporting of crimes for both violent and property crimes.

13 We also check the event study model for all the suicide outcomes. The results are reported in Figure OSM2 in the Online Supplementary Material.
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Supporting information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix S1: Supporting Information

Figure S1. Trends of crime reporting.

Figure S2. Event study model for suicide rates.