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(分担)研究報告書

COVID-19 のロックダウンが犯罪被害者数に与える影響について
ー安倍政権下の非常事態を一事例としてー

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研究要旨

COVID-19の世界的感染拡大により，ウイルスの蔓延を抑制する目的で、数多くの政府がロックダウン政策をとった。その影響の1つが、犯罪被害者数の減少である。本研究では、都道府県ごとのロックダウンの導入時期の違いを「自然実験(外生ショック)」と見做し，2018-2020年における都道府県ごとに集計された犯罪統計をパネル化し，当該データに差の差推定(difference-in-differences: 以下，DID)を応用することで、2020年の安倍政権下でのロックダウン政策が，日本の犯罪被害者数に及ぼす影響を検証する.

推定の結果、当該ロックダウン政策は、人口10万人あたりの暴力犯罪被害率、経済犯罪被害率をそれぞれ12.7%、20.9%減少させることがわかった。更に、侵入窃盗や性的暴行などの計画犯罪は、殺人などの非計画犯罪よりも減少することが確認された。また、年齢層別では，0-29歳では性的暴行の被害が有意に減少し、30-59歳では暴力犯罪と経済犯罪の被害者数が有意に減少していることが確認された。最後に、当該時期における短期的な自殺率が改善したことから、ロックダウンと犯罪被害の関係を部分的に媒介するメカニズムがメンタルヘルスの改善である可能性が示唆された。

A. 研究目的

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 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 (DID) 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.

B. 研究方法

To examine the effect of COVID-19's lockdown on crime victimization rates, we implement a specification similar to Leslie's and Wilson's (2020) model. We regress the following difference-in-differences (DD) model:

$$Y_{amt} = \beta_0 + \beta_1 Post_m + \beta_2 2020_t + \beta_3 Post_m \times 2020_t + \lambda_a + \gamma_m + \omega_t + u_{amt}, \qquad (1)$$

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 2020_t, which is a binary variable that equals to one if the year of observations is 2020, and zero otherwise. For the treatment period variable, $Post_m$ is a binary variable that equals to one if the month of observations is between April and June, and zero otherwise. $Post_m \times 2020_t$ is the interaction term between $Post_m$ and 2020_t, and β_3 is the main coefficient of interest, measuring the effect of the COVID-19's lockdown on crime victimizations. λ_a is a vector of age binary variables corresponding to the respective age groups. γ_m and ω_t are vectors of the month and year binary variables corresponding to respective month and year. u_{amt} is the error term.

Our DD model relies on the common trend assumption. That is, the systematic differences between treated and control groups do not differ in the absence of a policy or a shock. The crime victimization rates between January to March cohort in 2020 and the same cohort in 2018 and 2019 should be constant or parallel. To show that our DD estimates are not driven by declining trends in crime victimization rates before the lockdown, we implement the following event study model:

$$Y_{amt} = \beta_0 + \sum_{m=5}^{1} \delta_m Month_m \times 2020_t + \lambda_a + \gamma_m + \omega_t + u_{amt}, \qquad (2)$$

where all dependent variables and fixed effects are identical to equation (1), except for the interaction terms. Our interest lies in the interaction term, $Month_m \times 2020_t$, and the associated parameter, δ_m. The baseline category is March that is one month prior to the lockdown began. Compared to the baseline, if the magnitudes, directions, and significances on 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 dataset 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:

$$\begin{aligned} Y_{amt} = \alpha + \beta_1 Post_m \times 2020_t \times Age0-29_a \\ + \beta_2 Post_m \\ \times 2020_t \times Age30-59_a \\ + \lambda_a + \gamma_m + \omega_t + \gamma_m\lambda_a \\ + \omega_t\lambda_a + u_{amt}, \qquad (3) \end{aligned}$$

where $Age0-29_a$ is a binary variable that equals to one if the age group is between 0 and 29, and zero otherwise. $Age30-59_a$ is a binary variable that equals to one if the age group is between 30 and 59, and zero otherwise. 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 retire and widowed (or divorced). Thus, they would not be as severely affected by labor market shocks or family shocks of the COVID-19 as those who are below 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 lockdown and crime victimization is mental health. Literature shows that COVID-19 has a direct effect on mental health (Tanaka & Okamoto, 2020; Ueda et al., 2020). Moreover, COVID-19 can also have indirect effects on mental health through labor market, family, and stress. To examine the effect of the lockdown on mental health, we proxy mental health with suicide rates. We estimate the following model:

$$\begin{aligned} S_{amt} = \beta_0 + \beta_1 Post_m + \beta_2 2020_t + \beta_3 Post_m \\ \times 2020_t + \lambda_a + \gamma_m + \omega_t \\ + u_{amt} \qquad (4) \end{aligned}$$

where all independent variables are the same as equation (1). S_{amt} is the natural logarithm of suicide rates per 100,000 people for age group *a* in month *m* and year *t*. We also estimate the effect on the suicide rates by three different reasons—family, health, or economic/living condition—to further explore the mechanisms.

We cluster the standard errors at the age levels. Recent works by Cameron et al. (2008) and MacKinnon and Webb (2017) show that the cluster inferences with less than 50 would lead to an overrejection of the null hypothesis. Given our age level is only 10, our inferences may suffer from the issue of too "few" clusters. One strategy is to utilize wild bootstrapping. This method has been shown to work reasonably well (Cameron et al., 2008; Cameron et al., 2015). We wild bootstrap our cluster inferences with 1000 replications with Webb's weights. The p-values are reported, instead of the standard errors (Roodman et al., 2019).

C. 研究結果

C-1. Summary Statistics

Table 1 reports the means and standard deviations of the dependent variables by treatment groups and treatment periods. Column (1) report all years; Columns (2) and (3) report 2018 and 2019; and Columns (4) and (5) report 2020. First, property crime victimization rates are overall higher than violent crime victimization rates. For instance, the logarithm of property crime victimization rates per 100,000 people is 1.397, whereas the logarithm of violent crime victimization rates per 100,000 people is 0.393. Second, the means of the logarithm of violent and property crime victimization rates increase between Jan–Mar cohort and April–May in 2018 and 2019, whereas the means decrease between the two cohorts in 2020. Finally, there are significant heterogeneity across the subtypes of crimes. For example, homicide victimization rates between the two cohorts decline less than (1.6% in 2018 and 2019 versus -15.9% in 2020) sexual obscenity victimization rates do (21.8% in 2018 and 2019 versus -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.

C-2. Main Results

Table 2 reports the estimated effect of the lockdown on crime victimization rates from equation (1). Columns (1)–(3) report the estimates for violent crimes, and Columns (4)–(6) report the estimates for property crimes. Each column reports 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 sexual obscenity victimization rate by 9%. For the subtypes of property crimes, we find that break-and-enter reduced by 16.4% and motor vehicle theft reduced by 6.1%.

Figure 2 shows the event study model for violent, property crime victimizations, and their respective subtypes from equation (2). As a reminder, the baseline category is March, one month prior to the lockdown. Panels A–C report the estimates of the event study model for violent crime victimization rates and its subtypes. Panels D–F report the estimates of the event study model for property crime victimization rates and its subtypes. We observe that the estimates on January (Month 1) and February (Month 2) are statistically insignificant for violent 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 on January (Month 1) and February (Month 2) are positive but statistically significant. The statistically significant estimates before March seem to suggest a 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 decomposed the property into subtypes: break-and-enter and motor vehicle theft. The trends only appear in break-and-enter 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 likely to hold 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 above. Each column reports the estimates using a different dependent variable. Overall, our estimates suggest that different age group is affected differently between violent and property crime by the lockdown. Based on Columns (1)–(3), we find that lockdown significantly reduces the 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, but we find that sexual obscenity is significantly affected. 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 break-and-enter and motor vehicle theft suggest that only break-and-enter are more affected by 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. In particular, there is a consistent negative effect for those between the ages of 30 and 59 for both violent and property crime victimizations.

Table 4 reports the estimated effect of lockdown on mental health proxying with suicide rates. Each column reports 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 family, health, and economic/living condition reasons. Based on the estimates, we observe that the lockdown significantly reduces the total suicide rates per 100,000 people by 2.8%. 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 reason. That said, the magnitude of effect is trivial for physical health which is approximately 0.6%. All in all, our estimates suggest that a decline in suicide may partially explain the decline in crime and victimization during a lockdown, and the decline in suicide due to economic and living conditions that may be an important mediator of the relationship. This finding is somewhat contradict our expectation that the suicide due to economic and/or living conditions would increase (or 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 lagged behind the lockdown. Therefore, the remote work channel is more dominant during the lockdown, leading to a significant decline in suicide due to economic and/or living conditions, as work stress in corporate environment declines when people stay in their home environment.

C-3. Robustness Checks

Tables 5 reports the robustness checks of our estimates with various specifications. Though our event study shows that the violation of 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. Panels A and B report the estimates including these trends. Overall, we do not detect significant changes in magnitudes, signs, and significances between these estimates and the main results. We further test the robustness of our results to alternative model by estimating them with Poisson. We use non-log transformed rates as our dependent variables. Panel C reports the estimates using Poisson. The relationship is consistent with the main results. In addition to an alternative model, we also examine the robustness to alternative transformation, inverse hyperbolic sine transformation, that has the advantage of generating non-zeroes when the original rates were zeroes. Panel 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. Panel D reports the unweighted estimates. Similar to the weighted estimates, no significant differences were found.

D. 考察／E. 結論

Using 2018–2020 Crime Statistics and a DD approach, we estimate the effect of the COVID-19's lockdown on crime victimization rates. Specifically, we investigate the effect of lockdown on violent, property, and their respective subtypes of crime victimization rates in Japan. We find that the COVID-19's lockdown is significantly associated with 12.7% and 20.9% reductions in violent and property crime victimization rates per 100,000 people, respectively. We also implement an event study to investigate whether the common trend assumption is plausible. We find that our estimates are unlikely to be driven by the pre-existing declining trends of crime victimization rates for most of the crimes. We further implement a DDD approach to investigate the heterogeneous age effect of the lockdown on both types of crime victimizations. We find that those who are between 30 and 59 are most affected by the lockdown. Finally, we explore the mental health mechanisms mediating the relationship by proxying with suicide rates and find that suicide rates decline by 2.8% during the lockdown. Moreover, the effect seems to be driven by suicide due to economic and living conditions. Overall, the lockdown has a consistent negative effect on crime victimization rates in Japan.

Our study has several implications. First, we find that the lockdown reduces both the violent and property crime victimizations. In other words, there may be less crime being committed during the lockdown. It would suggest that additional resources can be re-allocated from some public sectors, such as police and criminal justice, to healthcare sectors in order to alleviate the added stresses on the healthcare sector during a pandemic. Second, the lockdown does not affect different subtypes of crimes uniformly. That is, some crimes are more affected than others. For the crimes not affected, the police may need to devote more resources to policing these crimes during a lockdown. Third, individuals who are in the prime working-age are consistently affected by the lockdown. These individuals are more likely to travel during peak hour and different area. It would suggest that frequent contact between offenders and victims is an important mechanism mediating the relationship between lockdown and crime. Finally, our mental health mechanisms show that lockdown significantly reduces suicide rates, and it was driven largely by the decline in suicide to economic and living conditions. This implies that policymakers wishing to reduce victimization should focus on not just reducing the contact between offenders and victims but also improving the overall mental health conditions of the population.

Our study has limitations. First, our data is aggregated, not micro-level data. This limits our ability to track a single individual. Having access to micro-level data would allow one to understand how the lockdown affects one’s criminal behavior in long term and would allow us to do additional heterogeneous analyses. Second, the crime victimization rates used in this study may be underreported. If this is the case, our estimates may be biased upward, given the “true” rates may be higher. Finally, given the limited data, we cannot further detangle the mechanisms behind the relationship between a lockdown and crime. Our current study cannot fully explain all the potential channels mediating the relationship.

F. 健康危険情報

特に無し.

G. 研究発表

1. 論文発表

Shen, Y., Fu, R., Noguchi, H. (2021) “Covid-19's lockdown and crime victimization: The state of emergency under the Abe administration”. *Asian Economic Policy Review,* 16(2): 327-348.

2. 学会発表

October/2020: Asian Economic Policy Review 16th Conference. “Pandemic and crimes: The effect of covid-19 on criminal behavior in Japan”. Online

H. 知的財産権の出願・登録状況(予定を含む)

1. 特許取得

特に無し.

2. 実用新案登録

特に無し.

3. その他

特に無し.

参考文献

Alon, T. M., Doepke, M., Olmstead-Rumsey, J., & Tertilt, M. (2020). *The impact of COVID-19 on gender equality* (No. w26947). National Bureau of Economic Research.

Angelucci, M., Angrisani, M., Bennett, D. M., Kapteyn, A., & Schaner, S. G. (2020). *Remote work and the heterogeneous impact of covid-19 on employment and health* (No. w27749). National Bureau of Economic Research.

Bargain, O., & Ulugbek, A. (2020). Poverty and Covid-19 in Developing Countries. *Bordeaux University*.

Becker, G. S. (1968). Crime and punishment: An economic approach. In *The Economic Dimensions of Crime* (pp. 13-68). Palgrave Macmillan, London.

Blundell, R., Costa Dias, M., Joyce, R., & Xu, X. (2020). COVID-19 and Inequalities. *Fiscal Studies*, *41*(2), 291-319.

Brynjolfsson, E., Horton, J. J., Ozimek, A., Rock, D., Sharma, G., & TuYe, H. Y. (2020). *COVID-19 and remote work: an early look at US data* (No. w27344). National Bureau of Economic Research.

Burbidge, J. B., Magee, L., & Robb, A. L. (1988). Alternative transformations to handle extreme values of the dependent variable. *Journal of the American Statistical Association*, *83*(401), 123-127.

Cameron, A. C., & Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources*, *50*(2), 317-372.

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics*, *90*(3), 414-427.

Campello, M., Kankanhalli, G., & Muthukrishnan, P. (2020). *Corporate hiring under covid-19: Labor market concentration, downskilling, and income inequality* (No. w27208). National Bureau of Economic Research.

Coibion, O., Gorodnichenko, Y., & Weber, M. (2020). *Labor markets during the covid-19 crisis: A preliminary view* (No. w27017). National Bureau of Economic Research.

Ehrlich, I. (1996). Crime, punishment, and the market for offenses. *Journal of Economic Perspectives*, *10*(1), 43-67.

Griffith, A. K. (2020). Parental burnout and child maltreatment during the COVID-

19 pandemic. *Journal of Family Violence*, 1-7.
Han, J., Meyer, B., & Sullivan, J. X. (2020). Income and Poverty in the COVID-19 Pandemic. *NBER working paper*, (w27729).
Hodgkinson, T., & Andresen, M. A. (2020). Show me a man or a woman alone and I'll show you a saint: Changes in the frequency of criminal incidents during the COVID-19 pandemic. *Journal of Criminal Justice*, *69*, 101706.
Lemieux, T., Milligan, K., Schirle, T., & Skuterud, M. (2020). Initial impacts of the COVID-19 pandemic on the Canadian labour market. *Canadian Public Policy*, *46*(S1), S55-S65.
Leslie, E., & Wilson, R. (2020). Sheltering in place and domestic violence: Evidence from calls for service during COVID-19. *Available at SSRN 3600646*.
MacKinnon, J. G., & Webb, M. D. (2017). Wild bootstrap inference for wildly different cluster sizes. *Journal of Applied Econometrics*, *32*(2), 233-254.
Mohler, G., Bertozzi, A. L., Carter, J., Short, M. B., Sledge, D., Tita, G. E., ... & Brantingham, P. J. (2020). Impact of social distancing during COVID-19 pandemic on crime in Los Angeles and Indianapolis. *Journal of Criminal Justice*, 101692.
Piquero, A. R., Riddell, J. R., Bishopp, S. A., Narvey, C., Reid, J. A., & Piquero, N. L. (2020). Staying Home, Staying Safe? A Short-Term Analysis of COVID-19 on Dallas Domestic Violence. *American Journal of Criminal Justice*, 1-35.
Prime Minister's Office of Japan. (2020). News. https://www.kantei.go.jp/jp/news/index.html
Roodman, D., Nielsen, M. Ø., MacKinnon, J. G., & Webb, M. D. (2019). Fast and wild: Bootstrap inference in Stata using boottest. *The Stata Journal*, *19*(1), 4-60.
Solon, G., Haider, S. J., & Wooldridge, J. M. (2015). What are we weighting for? *Journal of Human Resources*, *50*(2), 301-316.
Tanaka, T., & Okamoto, S. (2020). Suicide during the COVID-19 pandemic in Japan. *medRxiv*.
Ueda, M., Nordström, R., & Matsubayashi, T. (2020). Suicide and mental health during the COVID-19 pandemic in Japan. *medRxiv*.

Table 1. Summary statistics

	All (N=150)	2018–2019 (N=100)		2020 (N=50)	
	All	Jan–Mar	April–May	Jan–Mar	April–May
	(1)	(2)	(3)	(4)	(5)
Ln(Violent Crime Victimization Rates)	0.393	0.384	0.436	0.400	0.326
	(0.240)	(0.229)	(0.267)	(0.242)	(0.209)
Ln(Homicide Victimization Rates)	0.061	0.061	0.062	0.063	0.053
	(0.027)	(0.025)	(0.028)	(0.031)	(0.024)
Ln(Sexual Obscenity Victimization Rates)	0.195	0.187	0.239	0.185	0.147
	(0.225)	(0.211)	(0.278)	(0.205)	(0.165)
Ln(Property Crime Victimization Rates)	1.397	1.432	1.492	1.340	1.191
	(0.608)	(0.617)	(0.634)	(0.583)	(0.550)
Ln(Break-and-Enter Victimization Rates)	1.240	1.267	1.315	1.194	1.078
	(0.562)	(0.572)	(0.593)	(0.536)	(0.506)
Ln(Motor Vehicle Theft Victimization Rates)	0.340	0.359	0.372	0.311	0.263
	(0.234)	(0.245)	(0.245)	(0.219)	(0.188)

Note: Columns (1)–(5) report the means and standard deviations of all, 2018–2019, and 2020 samples. The standard deviations are reported in round brackets. The variables are log-transformed victimization rates per 100,000 people. All statistics are weighted by populations.

Table 2. The effect of COVID-19's lockdown on crime victimization

	Violent Crime			Property Crime		
	(1) Overall	(2) Homicide	(3) Sexual Obscenity	(4) Overall	(5) Break-and-Enter	(6) Motor Vehicle Theft
Post × Year 2020	-0.127***	-0.010	-0.090**	-0.209***	-0.164***	-0.061***
	[0.000]	[0.131]	[0.015]	[0.001]	[0.002]	[0.006]
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	150	150	150	150	150	150

Note: Columns (1)–(6) report the effect of Covid-19's lockdown on crime victimization rates. Each column reports an estimate for a different dependent variable. All regression estimations control for age, month, and year fixed effects and weighted by population. We cluster at the age levels and wild bootstrap the standard errors over 1000 replications with Webb's weights. The p-values are reported in the square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Heterogeneity by age group

	Violent Crime			Property Crime		
	(1) Overall	(2) Homicide	(3) Sexual Obscenity	(4) Overall	(5) Break-and-Enter	(6) Motor Vehicle Theft
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]
Post × Year 2020 × Age ≥ 60	Baseline	Baseline	Baseline	Baseline	Baseline	Baseline
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	150	150	150	150	150	150

Note: Columns (1)–(6) report the effect of Covid-19's lockdown on crime victimization rates. Each column reports an estimate for a different dependent variable. All regression estimations control for age, month, and year fixed effects and weighted by population. We cluster by the age levels and wild bootstrap the standard errors over 1000 replications with Webb's weights. The p values are reported in the square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	120	120	120	120

Note: Columns (1)–(4) report the effect of Covid-19's lockdown on suicide rates and its causes. Each column reports an estimate for a different dependent variable. All regression estimations control for age, month, and year fixed effects and weighted by population. We cluster by the age levels and wild bootstrap the standard errors over 1000 replications with Webb's weights. The p values are reported in the square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

.01

Table 5. Robustness check

	Violent Crime			Property Crime		
	(2) Overall	(3) Homicide	(4) Sexual Obscenity	(5) Overall	(6) Break-and-Enter	(7) Motor Vehicle Theft
Panel A: Age-specific linear trends						
Post × Year 2020	-0.127***	-0.010	-0.090**	-0.209***	-0.164***	-0.061***
	[0.000]	[0.131]	[0.015]	[0.001]	[0.002]	[0.006]
Panel B: Age-specific quadratic trends						
Post × Year 2020	-0.127***	-0.010	-0.090**	-0.209***	-0.164***	-0.061***
	[0.000]	[0.135]	[0.013]	[0.000]	[0.002]	[0.006]
Panel C: Poisson						
Post × Year 2020	-0.438***	-0.101	-0.614**	-0.294***	-0.244***	-0.241***
	[0.002]	[0.403]	[0.021]	[0.002]	[0.000]	[0.006]
Panel D: Inverse hyperbolic sine transformed						
Post × Year 2020	-0.170***	-0.011	-0.118**	-0.258***	-0.206***	-0.080***
	[0.001]	[0.138]	[0.014]	[0.001]	[0.001]	[0.002]
Panel E: Unweighted	-0.126***	-0.005	-0.095***	-0.204***	-0.154***	-0.052***
Post × Year 2020	[0.001]	[0.432]	[0.008]	[0.002]	[0.002]	[0.002]
N	150	150	150	150	150	150

Note: Columns (1)–(6) report the effect of Covid-19's lockdown on crime victimization rates. Each column reports an estimate for a different dependent variable. All regression estimations control for age, month, and year fixed effects and weighted by population. We cluster by the age levels and wild bootstrap the standard errors over 1000 replications with Webb's weights. The p values are reported in the square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

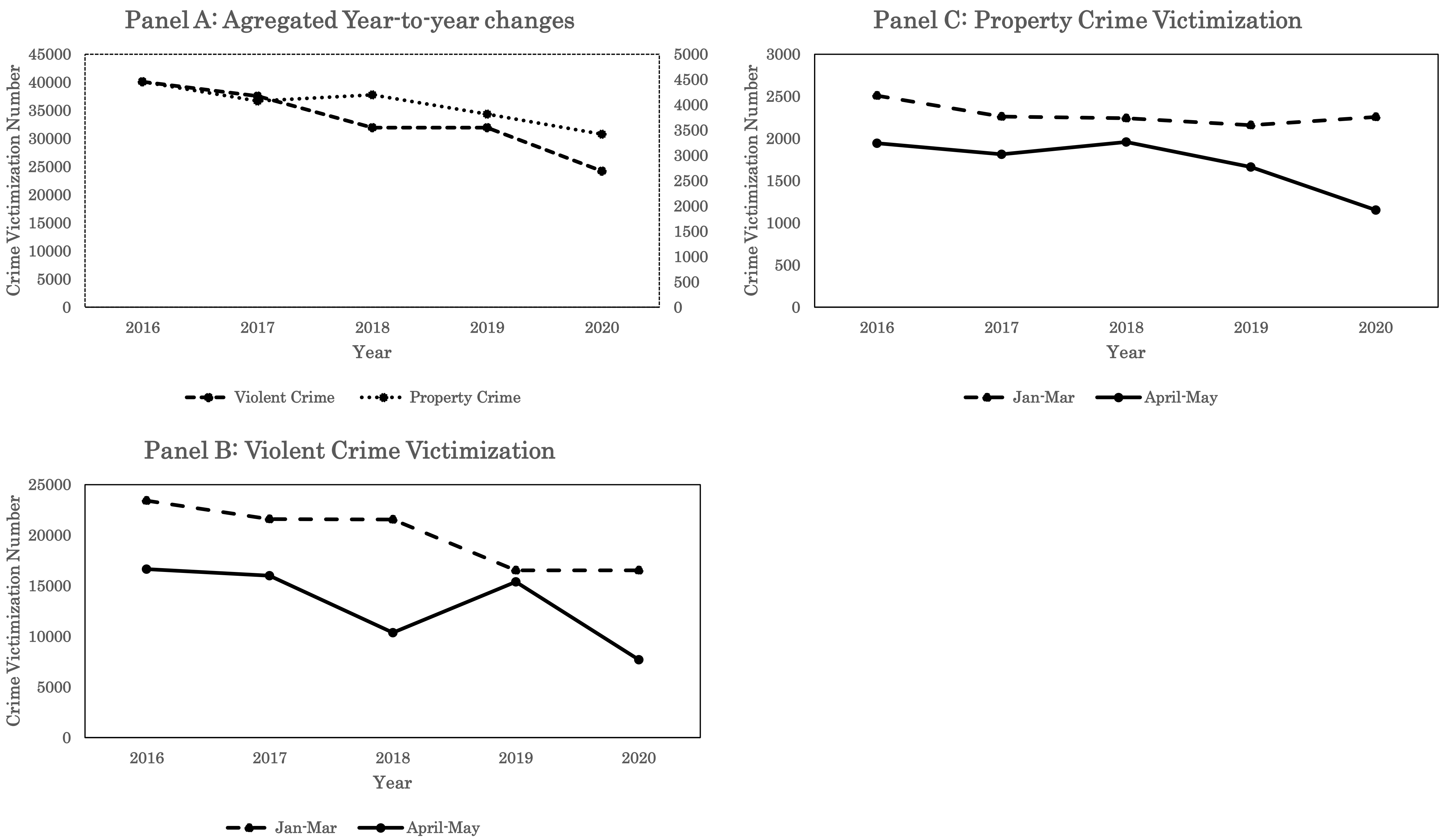

Figure 1. Crime Victimizations from 2016 to 2020. Source: 2016–2020 Crime Statistics.

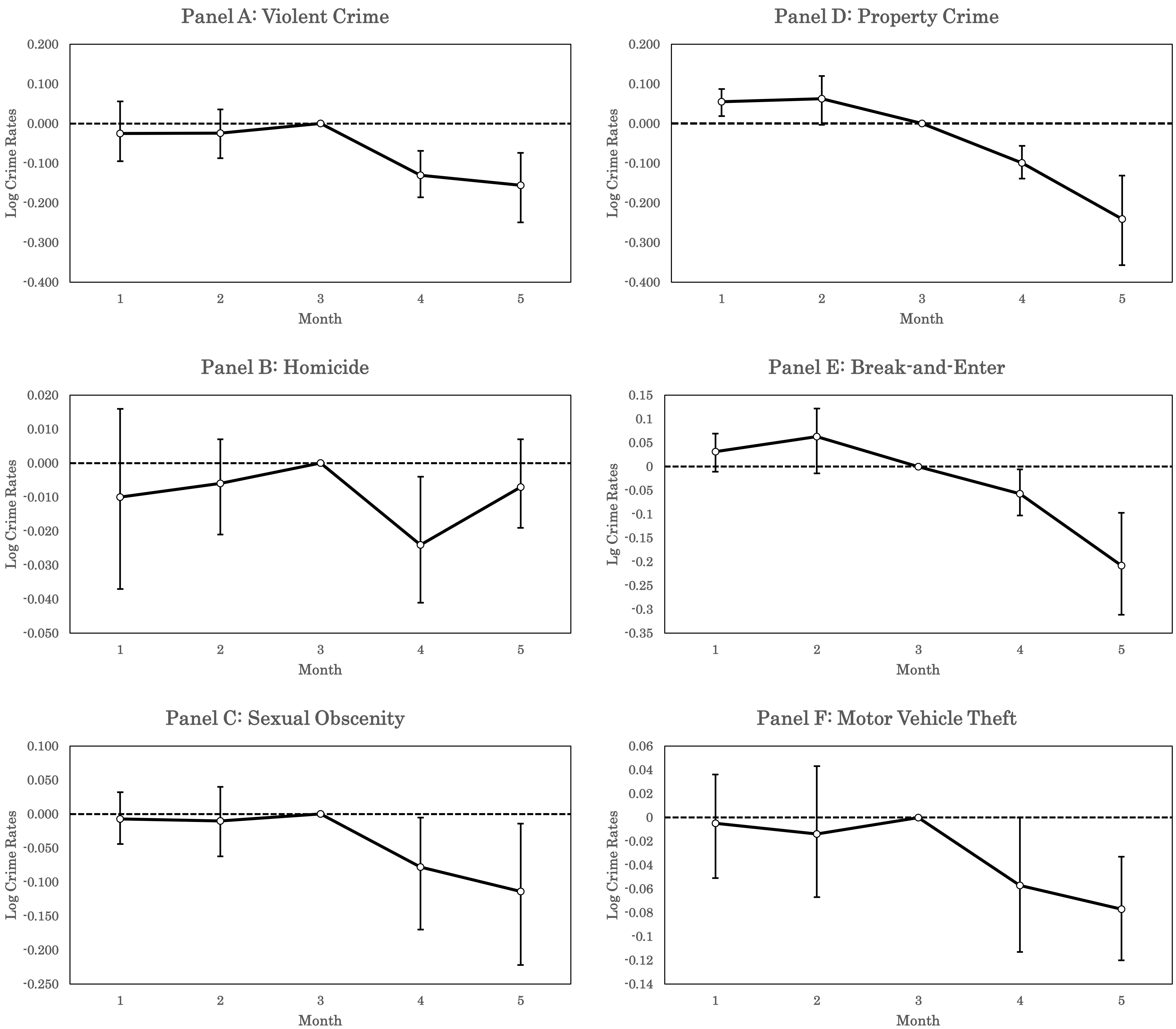

Figure 2. Event study model. Note: Each panel represents a separate regression results. Each regression controls for time-and age-fixed effects. All regressions are regressed using OLS and weighted using population by age levels. Source: 2018–2020 Crime Statistics.