JCER Working Paper
AEPR series
No. 2020-2-4

This is the pre-peer reviewed version of the following article: "COVID-19's Lockdown and Crime Victimization: The State of Emergency under the Abe Administration", *Asian Economic Policy Review*, vol. 16, issue 2, which has been published in final form at http://onlinelibrary.wiley.com/doi/10.1111/aepr.12339/abstract and DOI: 10.1111/aepr.12339.

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This paper was prepared for the Thirty-second Asian Economic Policy Review (AEPR) Conference "The Post-Abenomics Japanese Economy," held on October 2 and 3, 2020 via Zoom.

July 2021

Asian Economic Policy Review
Japan Center for Economic Research

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Abstract:

We investigate the effect of COVID-19 on crime proxied by crime victimizations. Using a difference-in-differences approach and 2018–2020 Crime Monitoring Statistics, we find that the COVID -19 is negative associated with both violent and property crime victimization. That is, our estimates suggest that there are 31.9 and 31.6 reductions in violent and property crime victimizations after April, 2020 compared to months prior, respectively. This suggest that the COVID-19 has an unexpected negative effect on crimes.

Keywords: Pandemic, COVID-19, Crimes, Difference-In-Differences, Japan

1. Introduction and Background

1.1. Introduction

In 2020, COVID-19 spreads from Wuhan, China, to the rest of world, killing approximately 771000 people by August. In addition to health consequence, COVID-19 also has many adverse effects on society including, but not limit to joblessness, eviction, and social unrest. Indeed, most literatures show that COVID-19 significantly increases unemployment (Cobion et al., 2020; Lemieux et al., 2020; Campello et al., 2020) and inequality (Alon et al., 2020; Blundell et al., 2020; Campello et al., 2020). Despite these research, we know little of how COVID-19 affect other outcomes, such as criminal behavior.

The existing literature show that the pandemic significantly reduces crimes (Mohler et al., 2020; Hodgkinson & Andreson, 2020). Mohler et al. (2020) show that the number of calls for crimes, such as robbery and assault, decrease after March, 2020 when the stay-at-home order was put in place in Los Angeles and Indianapolis in the United States. In a similar strand of research, Hodgkinson and Andreson (2020) show that the crime rates decrease after the implementation of lockdowns in Vancouver City in Canada, and the effect of lockdowns seems to vary by the type of crimes.

Our study offers several advantages over the existing literatures. Most previous studies leverage time-series estimation, which render it difficult to adjust for the unobserved seasonal differences of crimes between the years. Our difference-in-differences model allows to provide a casual estimation of the effect of the Coivd-19 by controlling for the unobserved differences between the years. Moreover, most studies use data from a few cities (or a single city), making it difficult to generalize the trend of declining criminal behavior to other places or populations. Finally, we add to the existing by providing the heterogeneous age effect of COVID-19 on violent and property crime.

In our study, we examine the effect of COVID-19 on crime. Specifically, we proxy crime prevalence by crime victimizations, extracting from Crime Monitoring Statistics in Japan. Using 2018–2020 and a difference-in-differences approach, we find that the COVID-19 reduces both violent and property crime victimizations after April, 2020 compared to months prior. Moreover, we assess the plausibility of the common trend assumption using an event study model and find that the assumption is plausible. Finally, we also examine the heterogeneous effect of the COVID-19 on crime victimizations by age groups. We show that those between 30–59 are most affected by the COVID-19. This has important implications for the relationship between the COVID-19 and crime behavior.

1.2. Background

The first Japanese Covid-19 case was detected in Hokkaido on January 28th, 2020. The state of emergency was declared in that region to reduce the spread of the COVID-19. However, the virus was eventually spread to other prefectures through both internal and external travels. On February 5th, the Diamond Princess cruise ship was quarantined in Yokohama Port, causing a political debate on the emergency measures that can be taken by Japanese government. Under the Japanese constitutions, the governments cannot impose any kind of lockdowns. Given the unprecedented crisis, the laws were amended by the Digest to allow the government to declare a "state of emergency" in order to combat the virus. The "state of emergency" gives governments power to 1) request people from going-out for unnecessary services, unless they are workers of essential services such as healthcare; 2) request to restrict the use of public spaces, such as school and business, temporarily; 3) expropriate private spaces, such as hotels, to be used for emergency medical area; and 4) request the sales and the seizure of medical or other goods. On March 13th, the measures were amended. On April 7th, Prime Minister Abe Shinzo issued a one-month state of emergency for seven prefectures: Tokyo, Saitama, Chiba, Osaka, Hyogo, Fukoka, and Hokkaido. The state of emergency was eventually extended to all prefectures of Japan on April 16th. On May 4th, the state of emergency was further extended to the end of May. Near the end of May, multiple prefectures have lifted the state of emergency, but the state of emergency is still in place for the seven prefectures declared on April 7th.

Given we investigating the effect of the Covid-19 on crime, we may use the state of emergency as a signal for the severity of the crisis. Generally, it is difficult for average people to understand the severity of the crisis based on numbers given by government. However, a declaration of the state of emergency would effectively notify everyone in the area that the crisis is severe to warrant social distancing and other measures. Since the declaration of the state of emergency would be a good signal to the indication of severity of the crisis, we may use it as our treatment variable. Specifically, the period between April and June may serve as a treatment, while the period between January and June can serve as a control. We elaborate the control and treatment in Section 2.2.

2. Data Source and Empirical Strategy

2.1. Data Source:

Our primary data source of crime victimization data, the dependent variables, comes from the publicly available crime monitoring statistics, *Hanzai Tokei*. The statistics covers all prefectures of Japan and collects monthly information on all types of crimes and victimization, ranging from violent crimes to property crimes, reported by police stations located across each respective prefecture annually. We extract the confirmed violent and property crime victimization cases by age groups from the database. In total, we collect January to June of 2018, 2019, and 2020 crime victimization counts by 10 age groups: 0–12, 13–19, 20–29, 30–39, 40–49, 50–59, 60–69, 70–79, and ≥ 80. We use only 2018 to 2020 as the economic conditions or other unobserved factors influencing crimes may be similar when the timeframe is short. Also, we extract only January to June of each year in order to control for the seasonality effect of crime. Moreover, we aggregate at age levels since there may be a significant heterogeneity across age groups in terms of how the Covid affect their labor market outcomes and various outcomes (See Section 4.4). We have a total of 180 observations. The unit of observation is age-month-year cell.

2.2. Empirical Strategy

To investigate the effect of COVID-19 on crime behavior, we follow a model similar Leslie's and Wilson's (2020) specification. We regress the following difference-in-differences (DD) model:

$$Y_{amt} = \beta_0 + \beta_1 Post_m + \beta_2 2020_t + \beta_3 Post \times 2020_{mt} + \lambda_a + \gamma_m + \omega_t + u_{amt} \quad (1)$$

where Y_{amt} is the inverse hyperbolic sine of numbers of violent or property crime victimizations reported by age group a on month m and year t, or the numbers of violent or property crime victimizations reported by age group a on month m and year t. We use the inverse hyperbolic sine transformation, instead of the logarithm transformation. This is because we have a lot of zeroes that would lead to sever missing-ness problem when these cells are log-transformed. The inverse hyperbolic sine transformation has the advantage of not generating missing observations when transforming zero, but the interpretations are relatively similar to that of logarithm transformation. $Post_m$ is a binary variable equals to one if the month is between April and June and zero otherwise. 2020_t is a binary variable equals to one if the year is in 2020 and zero otherwise. β_3 is the main coefficient of interest, measuring the effect of COVID-19 on violent and property crime victimizations. λ_a is a vector of age binary variables corresponding to each of ten age groups. γ_m and ω_t are vectors of month and year binary variables corresponding to each month and year. u_{pmt} is the error terms.

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 overrejection of the null hypothesis. Given our age level is only 10, our inferences may suffer from the issue of too “few” cluster. One strategy is to utilize wild bootstrapping. This method has been shown to work reasonably well (Cameron et al., 2015). We wild bootstrap our cluster inferences with 1000 replications. The p-values are reported, instead of the standard errors (Roodman et al., 2019). We also test the sensitivity of our inferences to cluster by the age and month levels with wild bootstrapping over 1000 replications. The results are reported in Column (2) of Tables 2 and 3.

Finally, our DD relies the common trend assumption. That is, the systematic differences across treated and control cohorts do not differ in the absence of treatment (or pre-treatment period). In other words, before the pandemic occurs, the crime victimization of treated cohort (April to June) should not be decreasing. To show that our DD estimates are not driven by a declining trend in crime victimization, we implement an event study model:

$$Y_{amt} = \beta_0 + \beta_1 2020_t + Month \times 2020'_{mt}\delta + \lambda_a + \gamma_m + \omega_t + u_{amt} \quad (2)$$

where all variables are identical to the ones identified in equation (1). Our interest lies in δ, a vector of parameters indicating the interaction terms between a vector of month binary variables and 2020_t. The omitted category is one month prior to the "beginning" of the pandemic, March. If the magnitudes of estimates on January and February are small and statistically insignificant, we may conclude that the common trend assumption is plausible for our study.

Finally, given our dataset contain age group, there may exist a significant heterogeneity across age groups when they are exposed to the COVID-19. We estimate a triple-differences model by interacting our DD interaction term with three categories of age group. Specifically, we estimate the following equation:

$$\begin{gathered} Y_{amt} = \alpha + \beta_1 Post \times 2020 \times Age0-29_{amt} + \beta_1 Post \times 2020 \times Age30-59_{amt} \\ + \lambda_a + \gamma_m + \omega_t + \gamma\lambda_{ma} + \omega\lambda_{ta} + u_{amt} \quad (3) \end{gathered}$$

where $Age0-29_a$ is a binary equals to one if the age group is between 0 to 29 and zero otherwise. $Age30-59_a$ is a binary equals to one if the age group is between 30 to 59 and zero otherwise. The baseline level is those age above and equal to 60. We use these cutoffs as those above 60 are more likely to be retire and lives alone; hence, they would not be as severely affected by labor market shocks and family shocks of the Covid-19 as those between 0 and 60 years-old. Moreover, we divide those below 60 into two groups: 0–29 and 30–59, since we expect those between 30 and 59 years-old to be most affected by labor market given they are in the prime working age groups. α is a vector of binary variables for $Post_m$, 2020_t, and the interaction terms between them and the three-category age group.

4. Results

4.1. Summary Statistics

Table 1 reports the summary statistics of the inverse hyperbolic sine of dependent variables by years and cohorts. IHS(VCV) stands for the inverse hyperbolic sine of the number of violent crime victimizations, IHS(PCV) stands for the inverse hyperbolic sine of the number of property crime victimizations. Columns (1)–(2) report the means and standard deviations of IHS(VCV) and IHS(PCV) for 2018; columns (3)–(4) the means and standard deviations of IHS(VCV) and IHS(PCV) for 2019; and ; columns (5)–(6) the means and standard deviations of IHS(VCV) and IHS(PCV) for 2020. Overall, we observe that in both 2018 and 2019 the means of both IHS(VCV) and IHS(PCV) are increasing from January and March cohort to April and June cohort. This suggests that it is unlikely our estimates are a product of random decline in crime victimizations, given the years before 2020 are increasing. As expected, we can see that in 2020 the means of victimizations decrease between the two cohorts in 2020. It would suggest that the pandemic has a negative effect on crime victimizations, but a more detail analysis is required.

[Table 1]

4.2. Graphical Trends

Before we present the main results, we first show the graphical trends of crime victimizations between January 2019 and June 2020. The dotted dark red line represents March 2020, one-month before the COVID-19 cases dramatically increases in the following months and a state of emergency is announced. Overall, we may observe that the trends before March 2020 are relatively stable and do not seem to increase or decrease over time. There does not seem to exhibit any pattern before March 2020. Moreover, we can see that after March 2020 there were a significant decline in the both types of crime victimizations, suggesting that the pandemic has a negative effect. Overall, the figure suggests that the common trend assumption is likely to hold for our study. We will further address the concern in later result sections (See Section 4.3.2).

[Figure 1]

4.3. Main Results

4.3.1. DD Model

Table 2 reports the estimated effect of COVID-19 on violent crime victimizations from equation (1). Columns (1)–(5) report the estimates using a different specification. Column (1) report the baseline estimations; column (2) the estimations clustering by the age and month levels; column (3) the estimations controlling month-specific age-varying and year-specific age-varying effects; column (4) the estimations using non-IHS numbers; and column (5) the estimation using Poisson. Based on column (1), our baseline estimate suggests that there is a 31.9% decline in violent crime victimizations for all age groups after April, 2020 relative to the months prior. Similarly, our estimate is not affected by how we cluster (clustering by the age and month levels), based on the estimate shown on column (2). Controlling for month-and year-specific age varying effects, the estimate of column (3) is same as that of baseline estimate in terms of magnitudes and significances. When using non-IHS transformed variables (columns (4) and (5)), the negative association between the DD interaction term and violent crime victimization is still consistent with the baseline estimate.

[Table 2]

Table 3 reports the estimated effect of COVID-19 on property crime victimizations from equation (1). Columns (1)–(5) report the estimates using a different specification. Column (1) report the baseline estimations; column (2) the estimations clustering by the age and month levels; column (3) the estimations controlling month-specific age-varying and year-specific age-varying effects; column (4) the estimations using non-IHS numbers; and column (5) the estimation using Poisson. Similar to violent crime victimizations, our baseline estimate suggests that there is a 31.6% decline in property crime victimizations for all age groups after April, 2020 relative to the months prior. Using different specifications, our baseline estimate is robust to alternative clustering, inclusion of month-and year-specific age varying effects, alternative dependent variable, and alternative estimation method.

[Table 3]

4.3.2. Event Study Model

Figures 2 and 3 show the event study model for violent and property crime victimizations from equation (2). The omitted category is March. We observe that the estimates on January and February, corresponding to Months 2 and 3, are statistically insignificant. Moreover, the magnitudes of these estimates are small compared to the estimates after April, suggesting that our estimates are not driven by a declining trend in crime victimizations. In particular, we see that the estimates for January and February on property crime victimizations are very close to zero, indicating that the trends are stable before the pandemic. Overall, our event study model suggests that the common trend assumption is plausible for our study.

[Figure 2]

[Figure 3]

4.4. Heterogeneous Effect Across Age

Table 4 reports the estimated effect of COVID-19 on violent and property crime victimizations using a triple-differences approach. Our estimates suggest that those who are of the prime working age, between 30 and 59, are most affected by the pandemic for both violent and property crime victimizations compared to those greater and equal to 60 years-old. Specifically, our estimates suggest that there are 25.0% and 13.5% declines in violent and property crime victimizations for those between 30 and 59 after April, 2020 relative to those age over 60. This would imply that labor market is an important factor in determining the relationship between the Covid-19 and crime victimizations.

[Table 4]

5. Discussion

Using 2018–2020 Crime Monitoring Statistics and a DD approach, we estimate the effect of the COVID-19 on crime behavioral proxied by crime victimizations. Specifically, we investigate the effect of pandemic on violent and property crime victimization. We find that the COVID-19's state of emergency declaration is associated with 31.9% and 31.6% declines in both violent and property crime victimizations, respectively. Our results are robust to various specifications. We also implement an event study to investigate whether the common trend assumption is plausible. We find that our estimates are not likely to be driven the pre-existing declining trends of crime victimizations. Finally, we estimate the heterogeneous age effect of the COVID-19 on both types of crime victimizations. We find that those who are between 30 and 59 are most affected by the pandemic, suggesting the labor market may play an important role in mediating the relationship. Overall, our results suggest that the pandemic has a negative effect of crime victimizations, which translate to a negative effect in crimes.

There are several channels as to why the pandemic could reduce crimes and victimizations. First, social distancing would create less contact between perpetrator and victim. That means there would be less probability of crime occurring given a lower chance of meeting between the two parties. Second, the COVID-19 has been shown to severely affect the labor market, reducing the employment and wages of the employed (Cobion et al., 2020; Lemieux et al., 2020; Campello et al., 2020). This may lead to a lower income overall for all households, and lead to a lower consumption on alcohol or narcotics that inhibit the cognitive function of these individuals. Third, the pandemic may create opportunities that can increase the time spend together with families. Social support has been shown to reduce crime and crime victimizations. Through these channels, the pandemic may reduce crime and crime victimizations. However, given the limitations of our data, we are unable to precisely assess which channel is affecting the relationship between the COVID-19 and crime victimizations.

Our study has important implications. First, we find that the pandemic unexpectedly reduces the crime victimizations. In other words, there may be less crime being committed during the pandemic. It would suggest that additional resource can be re-allocated from certain public sector, police and related-sector, to healthcare sector in order to alleviate the stress on healthcare sector during the pandemic. Second, those who are in the prime working age are most affected by the pandemic. It would appear to imply that the labor market or income is an important factor in determining crime and crime victimizations. It implies that effective policing should target certain populations, such as income-low area, or populations, the low-income population, in order to reduce crimes and victimizations.

Several limitations affect our study. First, given the short-duration of our dataset, we are limited in terms of how we can examine the long-term effect of COVID-19 on crimes. Future study with longer data could further explore this point. Second, our data is aggregated, not micro-level data. It limits our ability to track a single individual. It would be interesting to understand what effect would COVID-19 has on certain population, such as low-income, over time. Finally, the crime victimizations may be underreported. In other words, the true number of victimizations may be higher than the observed data. If it is the case, our estimates may be bias downward, given the “real” counts may be higher. Our estimates should be treated as the “lower” bound estimates of the relationship between the COVID-19 and crimes.

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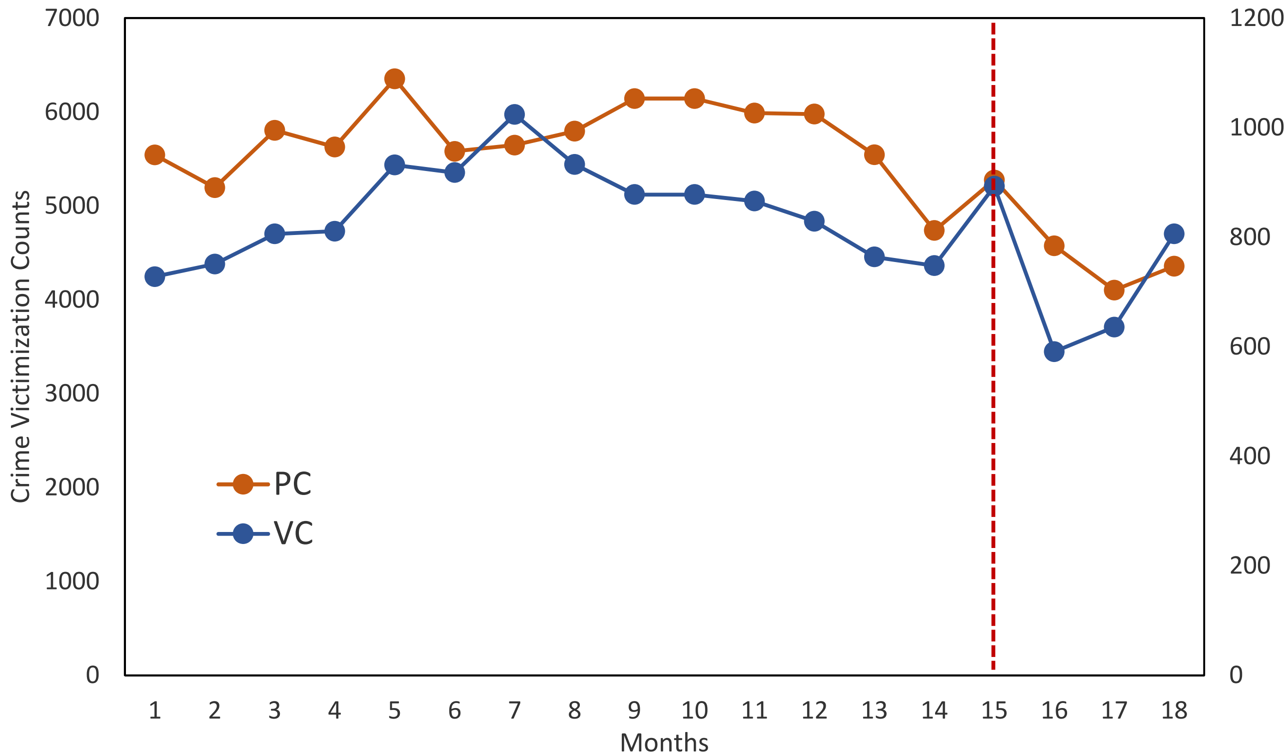

Figure 1. Graphical Trends of Violent and Property Crime Victimization Count Between January 2019 (Month 1) and June 2020 (Month 18). Note: Month 15 is March, 2020, corresponding to one month prior to the declaration of a state of emergency in Japan.

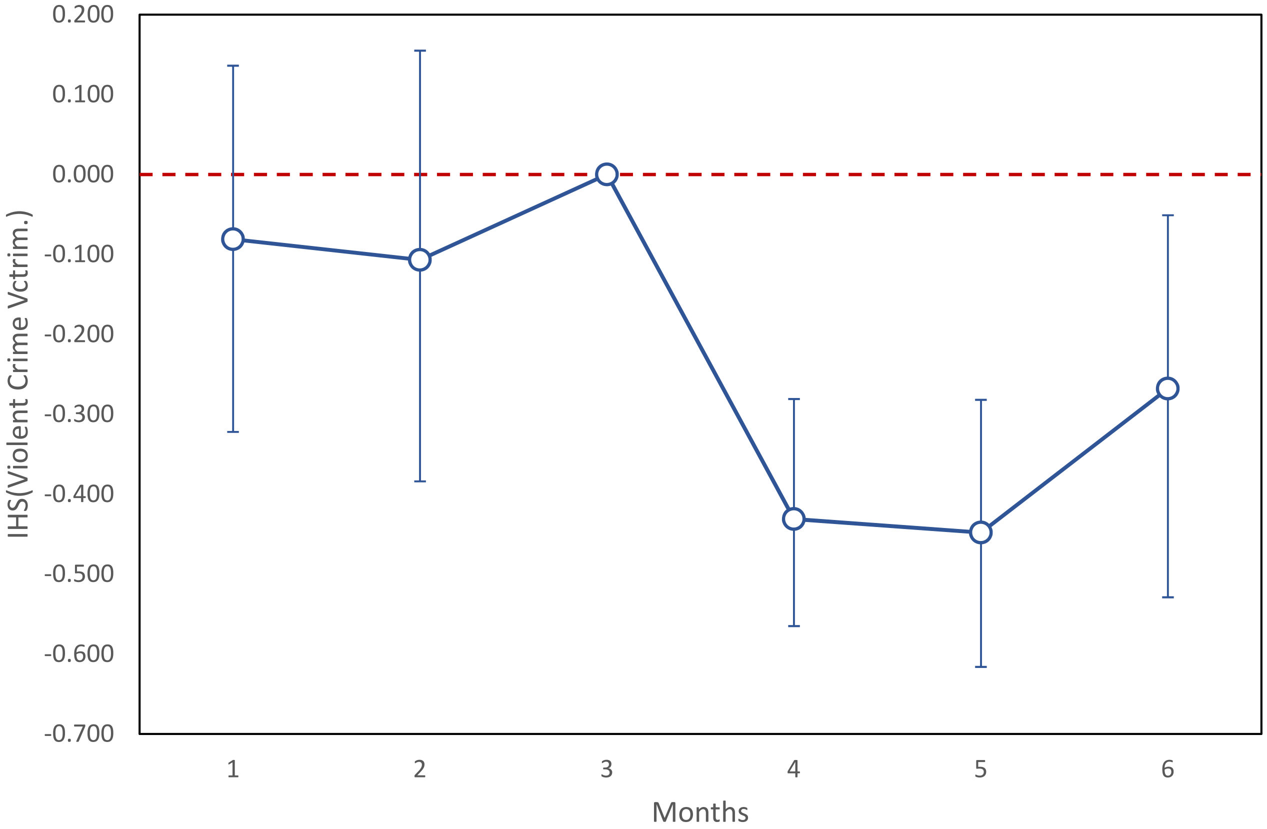

Figure 2. Event Study Model for Violent Crime Victimization. Note: The regression controls for age-, month-, and year-fixed effect. The depend variable is the inverse hyperbolic sine of numbers of violent crime victimizations. The dots are the point estimates, and the lines around it are the 95% confidence intervals. The regression is clustered by the age levels and wild bootstrapped over 1000 replications.

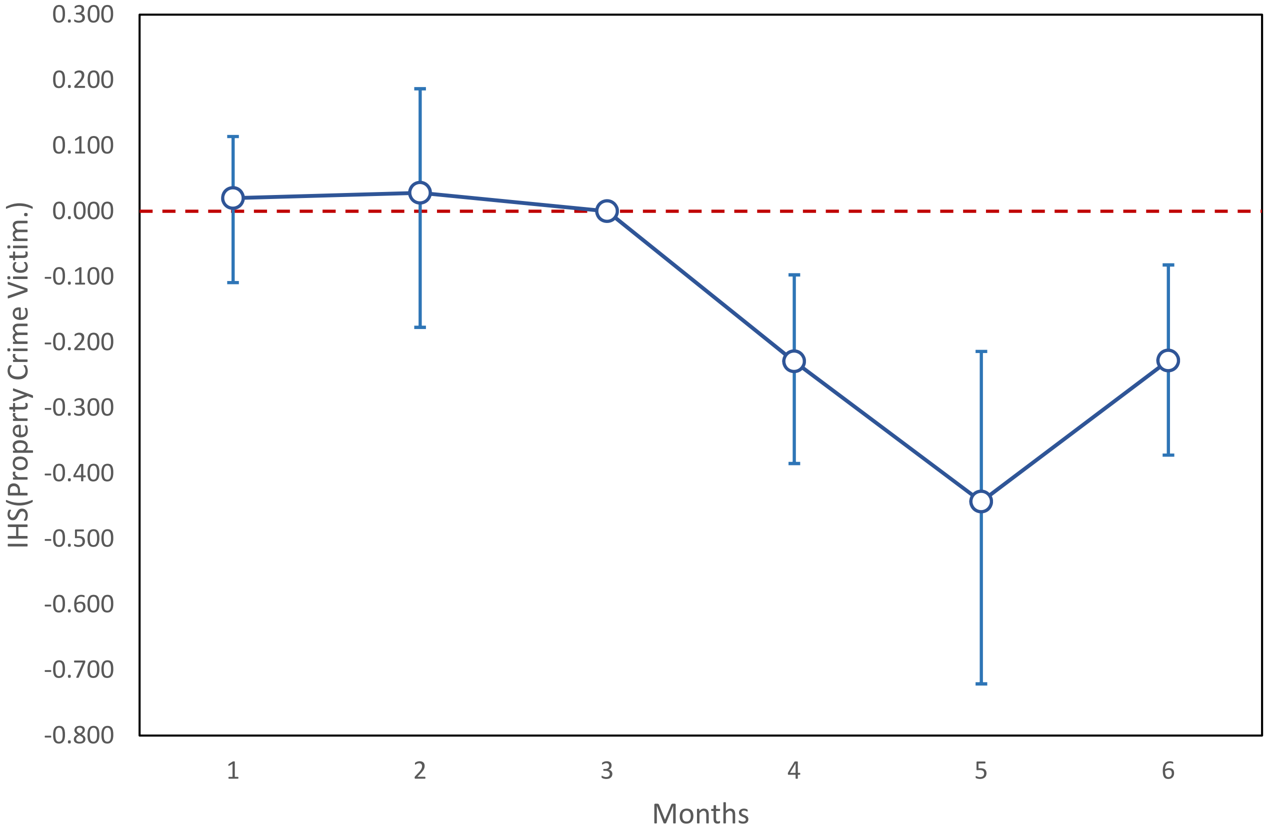

Figure 3. Event Study Model for Property Crime Victimization. Note: The regression controls for age-, month-, and year-fixed effect. The depend variable is the inverse hyperbolic sine of numbers of property crime victimizations. The dots are the point estimates, and the lines around it are the 95% confidence intervals. The regression is clustered by the age levels and wild bootstrapped over 1000 replications.

Table 1. Summary statistics (N=180)

	2018		2019		2020	
	Jan-Mar (1)	**Apr-June (2)**	**Jan-Mar (3)**	**Apr-June (4)**	**Jan-Mar (5)**	**Apr-June (6)**
IHS(VCV)	4.623	4.784	4.610	4.714	4.628	4.442
	(0.774)	(0.904)	(0.817)	(0.899)	(0.860)	(0.865)
IHS(PCV)	6.277	6.322	6.158	6.212	5.990	5.724
	(1.769)	(1.844)	(1.811)	(1.809)	(2.046)	(2.102)

Note: Columns (1)–(6) report the means and standard deviations by year and cohorts. HIS(VCV) stands for inverse hyperbolic sine violent crime victimization, and HIS(PCV) stands for inverse hyperbolic sine property crime victimization

Table 2. The effect of Covid-19 on violent crime victimization

	(1) IHS(VCV)	(2) IHS(VCV)	(3) IHS(VCV)	(4) VCV	(5) VCV
Post × Year 2020	-0.319***	-0.319***	-0.319***	-25.600***	-0.356***
	[0.005]	[0.001]	[0.002]	[0.002]	[0.005]
Age FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month × Age	No	No	Yes	No	No
Year × Age	No	No	Yes	No	No
Method	OLS	OLS	OLS	OLS	Poisson
Clustering	Age	Age and Month	Age	Age	Age
N	180	180	180	180	180

Note: Columns (1)–(5) report the effect of Covid-19 on each type of violent crime victimization. Each column reports a different specification. All regression estimations control for age, month, and year fixed effects. We cluster by the age levels (or age and month levels) and wild bootstrap the standard errors over 1000 replications. The p-values are reported in the square brackets.

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

Table 3. The effect of Covid-19 on property crime victimization

	(1) IHS(PCV)	(2) IHS(PCV)	(3) IHS(PCV)	(4) PCV	(5) PCV
Post × Year 2020	-0.316***	-0.316***	-0.316***	-103.150***	-0.270***
	[0.000]	[0.001]	[0.000]	[0.003]	[0.000]
Age FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month × Age	No	No	Yes	No	No
Year × Age	No	No	Yes	No	No
Method	OLS	OLS	OLS	OLS	Poisson
Clustering	Age	Age and Month	Age	Age	Age
N	180	180	180	180	180

Note: Columns (1)–(5) report the effect of Covid-19 on each type of property crime victimization. Each column reports a different specification. All regression estimations control for age, month, and year fixed effects. We cluster by the age levels (or age and month levels) and wild bootstrap the standard errors over 1000 replications. The p-values are reported in the square brackets.

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

Table 4. Heterogeneous effect by age groups

	(1) IHS(VCV)	(2) IHS(PCV)
Post × Year 2020 × Age 0–29	-0.200	-0.296
	[0.179]	[0.320]
Post × Year 2020 × Age 30–59	-0.250*	-0.135**
	[0.099]	[0.035]
Post × Year 2020 × Age ≥ 60	Baseline	Baseline
Age FE	Yes	Yes
Month FE	Yes	Yes
Year FE	Yes	Yes
Month × Age	Yes	Yes
Year × Age	Yes	Yes
Method	OLS	OLS
Clustering	Age	Age
N	180	180

Note: Columns (1)–(5) report the effect of Covid-19 on each type of property crime victimization. Each column reports a different specification. All regression estimations control for age, month, and year fixed effects. We cluster by the age levels and wild bootstrap the standard errors over 1000 replications. The p-values are reported in the square brackets.

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