

Measuring the Impact of the COVID-19 Lockdown on Crime in a Medium-Sized City in China

Abstract: Measures intended to reduce the risk of contagion were implemented around the globe in the wake of public health concerns about COVID-19. Among the numerous methods put in place to reduce the spread of the novel coronavirus, none were more restrictive than the lockdown strategy that deeply reshaped people's lives and associated routine activities. Understanding the potential impacts of such a fundamental change on reshaping crime patterns can provide insight into how to better allocate police resources during and after similar natural or manmade disasters. In this regard, the current study examines variation in the daily incidence of eight acquisitive crimes: automobile theft, electromobile theft, motorcycle theft, bicycle theft, theft from automobiles, pickpocketing, residential burglary, and cyber-fraud before the lockdown and the duration of the lockdown for a medium-sized city in China. Regression discontinuity in time (RDiT) models are used to test the effect of the lockdown measures on crime. Results indicate that in contrast to numerous violent crime categories such as domestic violence where findings have repeatedly found increases during the COVID-19 pandemic, acquisitive crimes in this city were reduced during the lockdown period for all categories. The findings provide further support to opportunity theories of crime that are contingent upon the need for a motivated offender to identify a suitable target in physical space. 'Cyber-fraud' was found more resilient in the sense that its decrease was not as salient as for most other crime types, possibly due to people's use of the internet during the lockdown period. Recommendations for future research and practice are provided.

Keywords: COVID-19; crime; regression discontinuity in time; natural experiment; routine activities

Introduction

The COVID-19 pandemic and restrictions put in place to control the spread of the disease have deeply affected human society. Many governments around the world have invoked stay-at-home/shelter-in-place or lockdown orders that have disrupted typical individual-level routine activities that shape the rhythm of society. Public activities have been cancelled, schools and companies closed, and only those businesses deemed essential to maintaining basic human needs such as supermarkets remained opened. Though the spread of the virus has not yet ceased as vaccinations race against variants, the loosening of restrictions, and people's general feeling of being 'done' with the pandemic, there is a need to assess the impact of the pandemic and associated restrictions in order to more readily allocate public safety resources and to also better understand the underlying mechanisms responsible for influencing crime patterns and to prepare for future events (Piquero and Kurland, 2021).

The pandemic provided a historic chance to test environmental criminology. Since changes in crime patterns were observed globally (Boman and Mowen, 2021; Nivette et al., 2021), criminologists became interested in better understanding these trends and their potential causes. Theories that were focused on the patterning of crime events, especially routine activity theory (Cohen and Felson, 1979), received extensive attention. Extant research shows that the introduction of pandemic-related restrictions (e.g., social distancing, stay-at-home orders, and lockdowns) was followed by reduction in property crime, assault, drug, organized crime, and cybercrime in various countries including the United States, Mexico, Sweden, United Kingdom, Australia, New Zealand, and Indonesia (Mohler et al., 2020; Abrams, 2021; Campedelli et al., 2020; McDonald and Balkin, 2020; Estévez, 2021; Miyar et al., 2021; Gerell et al., 2020; Kirchmaier and Villa, 2020; Kim and Leung, 2020; Payne and Morgan, 2020; Payne et al., 2021; Syamsuddin et al., 2021). Borrion et al. (2020) proposed a resilience assessment tool to measure the impact of COVID-19 on crime and demonstrated it using data on commercial theft in one Chinese city. Besides this, there has been limited research on this topic in China, the country that had first experienced the outbreak. Broadening this investigation to other crime is, however, critical since China was the first country to implement drastic measures to control the spread of the disease. Doing so, would offer the field an important comparison and complement to the growing knowledge base in this space.

The current paper seeks to take advantage of the known, drastic nature of the lockdown in China to evaluate how crime levels were impacted. In what follows, we review extant work that has applied crime pattern/routine activity theory to crime during COVID-19-related lockdowns and then extend this work to the Chinese context. Following, we highlight the data and methodological framework that extend prior research in important ways, and provide analyses focused on describing changes in crime between the period prior to, and during the lockdown. Results from the study are discussed along with their relevance to theory, the practice of policing during the pandemic, and policy. We conclude with an acknowledgement of some of the limitations associated with the study and some ideas for similar studies

that should be undertaken in the future to better understand the effect, if any, of COVID-19, related lockdowns, and crime.

Initial Studies of Crime during the COVID-19 Era

As hypothesized by routine activity theory, the risk of crime increases with the convergence of suitable targets, motivated offenders, and the absence of capable guardians (Cohen and Felson, 1979). The pandemic and governmental restrictions aimed at slowing the spread of the virus, however, reshaped people's daily lives and disrupted people's routine behaviors, which caused the crime opportunity structures to change by crime types, time, and place (Stickle and Felson, 2020). Across crime types, it was believed that theft would be impacted the most in the wake of the pandemic because many stores, restaurants, and shopping centres were closed during initial lockdowns, but that there may still exist variability in crime changes within the larger theft category. For example, shoplifting might decline to a moderate level as many retail stores closed and opportunities were subsequently concentrated in the more 'essential' stores like grocers and convenience stores. Pickpocketing would experience a great curtail as compulsory stay-at-home orders required people not leave their accommodations, thus reducing the opportunities available to crowd-dependent offenders.

The second impact of the pandemic and related lockdowns on crime from a routine activity perspective lies on the temporal shift. The restrictions forcing people to stay at home disrupted their routines, meaning that traditional temporal patterns (e.g., differences between workdays and weekdays) were less noticeable in people's activities. As a result, crime was no longer expected to follow the same temporal patterns as before the pandemic. More importantly, as public activities were cancelled and people were forced to stay at home, the overall offending opportunity in time diminished and a drop in crime would likely occur after the restrictions were implemented.

The third potential change generated by the pandemic and the restrictions concerns the location of crime opportunities. The restrictions limiting people's daily activities are believed to have greatly affected the flow of potential offenders, victims, targets and guardians, and their convergence in physical space. Conversely, greater concentration may have taken place in 'cyber places'. During the pandemic period, people are believed to have spent more time on the internet than before (Buil et al., 2021)—especially during the lockdown periods, which could certainly increase the probability of cybercrime, especially as this might involve visiting new (and potentially hacked) websites, interacting with strangers on fora, making online payments, etc.

The predictions made on the basis of routine activity theory have been supported by a number of empirical studies. Table 1 provides a summary of studies focusing on a quantitative description of crime variation by the type of crime, temporal period, and place. Among the available studies, findings show

that many crimes including property offenses, vandalism, violence, and cyber victimizations occurring in the US, UK, Australia, Canada, and Sweden were indeed significantly impacted when compared with the historic or the expected crime levels (Hodgkinson and Andresen, 2020; Ashby, 2020; Halford et al., 2020; Felson et al., 2020; Mohler et al., 2020; Gerell et al., 2020; Boman and Gallupe, 2020; Buchanan et al., 2020; Piquero et al., 2020; Payne et al., 2021; Jennings and Perez, 2020; Langton et al., 2021).

Table 1 about here

As inferred from the table, property crime, the one crime type believed to be greatly impacted by pandemic-related policies, demonstrates significant reductions compared with pre-pandemic periods. As indicated by routine activity theory, lockdown, stay-at-home, and social distancing strategies serve to limit the public activities and so the opportunity of potential offenders interacting with victims or targets are significantly curtailed, which results in less property crime during the pandemic lockdown period. For example, residential burglary and robbery was observed to significantly decline in the US (Mohler et al., 2020), Sweden (Gerell et al., 2020), Mexico (Estévez, 2021), New Zealand (Cheung and Hunby, 2021), and Australia (Kim and Leung, 2020), while for vehicle theft, more reductions were observed for the US (Campedelli et al., 2020), Mexico (Miyar et al., 2021) and Australia (Kim and Leung, 2020; Payne and Morgan, 2020) except Canada (Hodgkinson and Andresen, 2020) from which the crime slightly decreased. Pickpocketing, though was only reported in a few countries, but a moderate highly reduction was reported in Sweden (Gerell et al., 2020). The one exception to this pattern of results was the increase in theft during the pandemic in Makassar, Indonesia (Syamsuddin et al., 2021). Similarly to property crimes, some types of violence and assault also experienced a decline in the US (Ashby, 2020; Boman and Gallupe, 2020; Bullinger et al., 2020), Sweden (Gerell et al., 2020), Mexico (Miyar et al., 2021; Estévez, 2021) and Australia (Kim and Leung, 2020; Payne et al., 2021). An increase in vandalism was, however, observed in the US (Mohler et al., 2020), Sweden (Gerell et al., 2020), and England and Wales (Kirchmaier and Villa, 2020), which shows that anti-social behaviors were more likely to increase during restrictions. Drug crimes, however, varied across different countries. It has been found that drug-related crime dropped in the US (Abrams, 2021), but increases were observed in Sweden (Gerell, 2020), Australia (Kim and Leung, 2020), and England and Wales (Kirchmaier and Villa, 2020).¹

In addition to these trends, researchers have also investigated the potential variability of changes in crime across space. For example, Campedelli et al. (2020) investigated how pandemic-related interventions affected criminal activity at the community level in Chicago and found that there was significant crime variation across communities and crime types. Among the 77 investigated communities, only 10 (13%) experienced a statistically significant reduction in burglary and robbery during the post-intervention

¹Although our focus in this paper lies with property crime, it is worth noting that both homicides (Rosenfeld and Lopez, 2020) and domestic violence (Piquero et al., 2021) have been found to increase since the onset of the pandemic and during lockdown periods, respectively.

follow-up period, while 18 communities (23%) experienced a significant reduction in assault, and 35 communities (46%) experienced a statistical reduction in drug offenses. These results suggest that the decline of crime that started with the pandemic was not homogeneously distributed in space. In attempting to interpret the various crime reductions in heterogenous community environments, these authors found that the number of inhabitants was the only factor positively associated with all crime types, which indicated that more people staying at home likely increase capable guardianship and served to lower the opportunities for crime. Similar effects were reported by Syamsuddin et al. (2021), in which theft was found to be higher in malls, restaurants, and shops because the places were unguarded. Using block group data from Detroit, Felson et al. (2020), examined burglary during the transition days of routine activity change and found that burglaries kept increasing in the block groups with mixed land use rather than the ones being dominated by residential land use.

Besides the physical space, cybercrime, an offense occurring in virtual space was also observed to change. Using monthly data on fraud and cybercrime known to the police in the UK, Buil et al. (2021) analyzed the changes in crime from pre to during the pandemic days. As indicated in Table 1, online cybercrime increased by 43%, with online fraud (online shopping) increasing by 51% compared with historic trends. This suggests that the lockdown orders led to more people spending more time in online entertaining, shopping², conferencing and served to enhance the offending opportunity described by routine activity theory on the internet.

Undoubtedly, these studies have served as an important foundation to what criminologists have been able to document with respect to crime in the COVID-19 era. Yet, there are some limitations to this body of work and some unique opportunities for extension that await the field. The first surrounds the measurement standard, i.e., daily, weekly, or monthly counts of crime was used as the major index to measure changes in crime by type, time, and space (Campedelli et al., 2020; Gerell et al., 2020; Kim and Leung, 2020; Syamsuddin et al., 2021), but the assumption that population size remained constant during the pandemic was not always stable. That is, lockdowns and stay-at-home orders are most relevant to individuals who permanently reside in the city, but for non-inhabitants like travellers, flow-in workers, commuters, etc., they would leave the city and lower the total population level during the pandemic period, such that the crime risk would be distributed on fewer people. Hence, an alternative solution to avoiding an over-estimated crime risk is to use a more dynamic crime rate rather than crime count to precisely compute crime levels.

Another limitation to the current work is the sampling frequency of crime. Some of the studies that have been conducted have taken advantage of weekly or monthly time series data for estimating the effect, if

²Retail Sales, Great Britain: May 2020, Office for National Statistics. Available from: <https://www.ons.gov.uk/businessindustryandtrade/retailindustry/bulletins/retailsales/latest#stores-sellingonline>.

any, of the COVID-19 pandemic and associated restrictions thus smoothing the periodicity often found in crime data when analyzed at the daily-level (e.g., Hodgkinson and Andresen, 2020; Ashby, 2020).³ Of course, researchers are often limited by the data that is made available to them, but one of the disadvantages of using less granular daily data is that it makes it more difficult to account for the drastic nature of a change to a system (Borrion et al., 2020). For example, lockdown measures that were put in place occurred on a single day and in many cases persisted for several weeks or months. In the event that both the start and end of the lockdown occurred in a temporally discrete manner, for example a Wednesday, then the true nature of the changes would be, at least partly, ‘washed out’.

The other limitation surrounds the methodology. A number of studies, including some of our own, have taken advantage of time series forecasting methods, namely intervention analyses that utilize Autoregressive Integrated Moving Average models (ARIMA) or other statistical, Bayesian, or machine learning forecasting techniques, to generate a predicted or expected crime levels. These studies have endeavoured to generate a counterfactual of the expected mean count of crime events had the pandemic not occurred (e.g., Ashby, 2020; Borrion et al., 2020; Campedelli et al., 2020; Halford et al., 2020; Piquero et al., 2020; Hodgkinson and Andresen, 2020; Kurland et al., 2021). All of these studies have endeavoured to control for stationarity (an assumption required for time-series forecasting) in the respective series of interest because crime by its nature tends to be non-stationary. Indeed, relationships between crime and meteorological conditions as well as the routine activity of a society have been repeatedly found in the extant literature and ultimately shape the opportunity structure for crime to occur. For example, holidays, extreme weather conditions, and exceptional events have all been shown to influence crime patterns (e.g., Chen et al., 2011; Cohn and Rotton, 2003; Decker et al., 2007; Kurland et al., 2014; Kurland and Johnson, 2021), and not taking account of these in one’s model may lead to less reliable forecasts.⁴

The Case of China

The fight against the COVID-19 pandemic is still ongoing and more work aiming to test pandemic restrictions on crime continues to emerge. Many of the studies that have been conducted hitherto did so for cities, counties, or regions that continued to have some form of restrictions in place. This makes quantifying the magnitude of the effect on crime stemming from the pandemic and the multitude of measures put in place by governments to curb the spread difficult, and also means that the full effect of what may have transpired may not have been fully captured by the associated models. One of the few places on earth that have not only experienced the pandemic, but also associated restrictions, and

³We recognize, of course, that some decisions to model crime data in weekly or monthly units may have more to do with the sample size, i.e., few daily cases.

⁴We noted that some of our own prior work is also limited in this regard. However, we obviously recognize the ‘ask’ made here as many of these data, including weather conditions, are simply unavailable or difficult to combine with crime data. We simply are pointing this out as another potential influence on crime changes during pandemic lockdowns, especially since these weather-related events occur in different ways throughout the world given how winters/summers operate around the globe.

reopened with a return to normal routines is China, making it a particularly interesting region for criminological studies that seek to tease apart the effect of COVID-19 and the lockdown in particular on the pattern of crime that emerged.

China was the first nation to discover and officially report a COVID-19 case and also the first to implement lockdown and stay-at-home strategy to control the spread of the virus. As early as January 23rd 2020, three provinces of China (Zhejiang, Hunan and Guangdong) started the First level Public Health Emergency Response⁵ and pandemic lockdown order⁶, and in the following week, the other 28 provinces of China began the strategy. After combating the virus for several months, all 31 provinces announced that the COVID-19 virus had been successfully controlled, and consequently, the Emergency Response level and lockdown orders in every province were lifted.⁷ Today, despite the persistence of reports in some cities and towns across China, there is a general consensus that the risk of the virus spreading across the country has ceased (although reports of the Delta variant emerging in the country may negate this statement). Given these factors, and the gradual return to normalcy that has taken place across China, a case study that tests the patterns of crime from routine activity theoretical perspective during the initial onslaught of the virus and mitigation efforts put into place is therefore not only possible, but also highly valuable.

In China the measures aimed at reducing the spread of the virus included:

- All public transport (including subway lines, shuttle bus and taxi) stopped.
- All business, entertainments, sport activities, production, and schools were closed.
- People were all required to stay at home until the lockdown was over.
- Only the necessary life suppliers (e.g., supermarket, food shops, restaurants, etc.) remained open but little customers were present at the places.
- Food, water, vegetables, fruits, etc. were delivered directly to people's accommodations by neighbourhood staff, police, and community volunteers.

Following the introduction of the above policies, public spaces were empty, crowds had disappeared, and regular properties, for example, empty residential houses, automobiles, motor cycles, bicycles become more available than before. Meanwhile, offenders were less likely to be outside due to strict stay-at-home orders. On the other hand, as people spent more time at home, much of their business

⁵According to the nature, severity and scope of impact, public health emergencies in China are classified into four levels (I, II, III and IV), with severity decreasing from Level I to Level IV. In level I, the transportation, civil aviation, railway, and other public departments were urged to formulate emergency response plans.

⁶The Pandemic lockdown refers to the strict policy meant to prevent the COVID-19 virus from spreading. During the lockdown days all public transport, including buses, railways, flights, and ferry services were suspended, the airport, railway station and metro lines were all closed, and all residents were also not allowed to leave the city without permission from the authorities.

⁷The lockdown order was implemented instantly when the first level of Emergency Response was started up, thus, the sign of lockdown lifting is defined as the Emergency Response being adjusted from level I to level II.

activities switched from offline to online, and they also spent more time shopping online, using e-commerce, engaging in entertainment, etc. which exposed them to cybercrime (Buil et al., 2021). In this paper, we assess the following hypotheses:

H1: Traditional property crime incidence would experience significant reductions during the pandemic because stay-at-home orders reduced many opportunities for crimes such as burglary and theft.

H2: Cybercrime, specifically online fraud, would not decrease as much as property crimes and even increase during the pandemic period as people spend more time using the internet to conduct activities related to business, school, e-commerce, and entertainment.

Data and methods

The data utilized for this study are the daily counts of calls for police service that were reported to the local Police Bureau and kept in the Computer Aid Dispatch system (CAD) from an anonymous medium-sized city⁸ (M1-city hereafter) located in south China. Although the calls to police data is a subset of all recorded crimes in the city, it does provide a good measure of crime during the pandemic period, one that has been used in other COVID-19/crime-related studies (Dai et al., 2021; Bullinger et al., 2020). The data includes eight typical property offenses: automobile theft, electromobile (also referred to as electric scooters) theft, motorcycle theft, bicycle theft, theft from automobiles, residential burglary, cyber-fraud, and pickpocketing.⁹ Given the offense types included in the analysis, and the conditions required to carry out these different crimes, the pandemic provides a more direct opportunity to assess the utility of routine activity theory (Hawdon et al., 2020; Machimbarrena et al., 2018). The data are for the period between 1 March, 2017 through 31 March, 2020. According to an official report, the First Level Public Health Emergency Response to COVID-19 and the lockdown strategy in the city commenced on 24 January 2020 and was lifted on 31 March 2020 by the local municipal government, providing a lockdown period that lasted a total 68 days. Figure 1 provides the standardized cumulative distribution of COVID-19 cases that occurred in M1-city across both the lockdown period and the period immediately after the restriction was lifted. Considerable growth in COVID-19 cases occurred in M1-city during the first roughly 30 days, but this leveled off with relatively limited additional growth resulting in the flattening of the curve thereafter. Indeed, not a single additional case was found during the entire month of March and so it was determined that the spread of the virus had been successfully stopped leading to a lifting of the lockdown order on 31 March, 2020.

Insert Figure 1 Here

⁸The city has a population of around 11 million, is roughly 8,000 km², and is largely urbanized. Prior to the pandemic the city had some of the country's lowest unemployment rates of around 3% and among the China's top ranked GDPs.

⁹The crime types were assigned to the call for police service manually in two steps. Firstly, the operator will assign an initial crime type to the call according to the victim's oral or text description, and then the crime type would be confirmed or corrected after officers' on-site investigation.

Much of the research on COVID and crime published thus far has utilized raw crime counts with several also attempting to control for the underlying population at risk (see e.g., Mohler et al., 2020; Campedelli et al., 2020). Herein we make use of the raw counts of these crime types of interest, but also consider the underlying population. More specifically, given the intersection of the start of the COVID-19 pandemic and the Chinese Spring Festival (24th to 31st January 2020) we needed to try and account for this known change in the availability of potential offenders and targets. Approximately one third of the population of M1-City departed at the onset of the Chinese Spring Festival. They left the city and returned to their home cities/towns prior to the lockdown commencing, and also not returning to M1-City until after the lockdown order was lifted (on 31 March 2020), that is 60 days after the end of the festival.¹⁰ Given the above, we attempt to control for this by generating daily offense rates for the period before and during the COVID-19 lockdown by calculating an offense rate per 100,000 population by day.

A regression discontinuity in time (RDiT) design, also sometimes referred to as an interrupted time series analysis with segmented regression, is employed to analyze the potential impact of the COVID-19 pandemic lockdown on crime in M1-city. However, prior to the RDiT a stepwise multi-stage de-seasonalization process has to be undertaken to better isolate the overall change that can be confidently attributed to the lockdown treatment. The entire time series $\{y_1, \dots, y_N\}$, is partitioned into two segments, the pre-lockdown period given by $\{y_1, \dots, y_M\}$ and the lockdown period given by $\{y_{M+1}, \dots, y_N\}$, with $N = 1127$ ¹¹ and $M = 68$. Figure 2 below provides a visualization of each of the respective categories of crime of interest in this study with a Loess smoother (blue) applied at a yearly-bin as well two vertical green lines that demarcate the first and final day of the lockdown period, $\{y_{M+1}, \dots, y_N\}$, and the lockdown segment.

Insert Figure 2 Here

Each respective segment is decomposed using Seasonal-Trend-Loess (additive) decomposition, as per equation 1:

$$y_t^i = S_t^i + T_t^i + R_t^i \quad (1)$$

¹⁰Traditionally, the floating population would return to their home cities/towns during the Spring Festival days. As the outbreak time was coinciding with the Spring Festival in 2020, we assumed M1 city's entire floating population left before January 23rd and did not return until the lockdown order was lifted. To more accurately capture the city's population, the rates were calculated using the total population for the non-lockdown periods (11 million population according to the city's Annual Statistic Yearbook in 2019). While the reduced population count, 8 million, was utilized for the lockdown period rate calculation (approximately 3 million people belonged to the floating population according to the Statistic Yearbook in 2019, roughly one-third of the whole population in the city).

¹¹The time length of historic days before lockdown period (1 March, 2017 through 23 January, 2020)

Where y_t^i is the number of daily cases (or rate) for call for service type i on day t , S_t^i is the season component, T_t^i is the trend component, and R_t^i is the remainder component, all for call for service type i at day t .

A four-stage stepwise approach is taken herein to illustrate how trend, seasonality, and other covariates that are major contributors to the total variance in each series (pre- and lockdown), but are criminologically (at least herein) unimportant, are removed to ensure they do not obscure the potential lockdown effect, that is of greater significance (Lovell, 1963; Granger, 1978; Zellner, 1978). First the trend component is estimated as per equation 2:

$$y_t^i = \beta_0^i + \beta_1 T_t^i + u_t^i \quad (2)$$

where, u_t^i is white noise.

Next, a series of harmonic terms are identified to account for seasonality that occurs faster than the primary seasonality of the series is estimated as per equation 3:

$$y_t^i = \beta_0^i + \beta_1 T_t^i + \sum_{\langle k \rangle} \beta_{2,k}^i \cos(2\pi\omega_k^i t) + \beta_{3,k}^i \sin(2\pi\omega_k^i t) + u_t^i \quad (3)$$

where the set of K harmonics, $\cos(2\pi\omega_k^i t)$ and $\sin(2\pi\omega_k^i t)$, is determined for each segment using the small sample corrected Akaike Information Criterion (AICc)¹², and where ω_k^i is a multiple of $1/365.25$ for daily data.

The third step included the addition of fixed-effects meant to control for the various cyclicities that occur over different periods of time that were not fully captured using harmonics as per equation 4:

$$y_t^i = \beta_0^i + \beta_1 T_t^i + \sum_{\langle k \rangle} \beta_{2,k}^i \cos(2\pi\omega_k^i t) + \beta_{3,k}^i \sin(2\pi\omega_k^i t) + \beta_4 DW_t^i + \beta_5 WM_t^i + \beta_6 M_t^i + \beta_7 Y_t^i + u_t^i \quad (4)$$

where DW_t^i , WM_t^i , M_t^i , Y_t^i , are fixed-effect indicator variables for the day of the week, week of the month, month, and year¹³ respectively for call for service type i at day t .

¹² Fourier order did vary by the segment being modeled and was optimized through the identification of the order that minimized AICc (De Livera et al., 2011).

¹³ This term was not included for the lockdown period as the entirety of this segment occurred in 2020.

The penultimate step in the de-seasonalization process incorporates numerous time varying covariates that have been shown to have a relationship to crime patterns in the extant criminological literature. This is done as per equation 5:

$$\begin{aligned}
y_t^i = & \beta_0^i + \beta_1 T_t^i + \sum_{\langle k \rangle} \beta_{2,k}^i \cos(2\pi\omega_k^i t) + \beta_{3,k}^i \sin(2\pi\omega_k^i t) + \\
& \beta_4 DW_t^i + \beta_5 WM_t^i + \beta_6 M_t^i + \beta_7 Y_t^i + \\
& \beta_8 H_t^i + \beta_9 P_t^i + \beta_{10} W_t^i + \beta_{11} TMP_t^i + \beta_{12} AQ_t^i + u_t^i
\end{aligned} \tag{5}$$

where H_t^i is a time varying covariate for holidays where 1 if a holiday, 0 otherwise, while P_t^i , W_t^i , TMP_t^i , and AQ_t^i , are time varying covariates for precipitation, wind, temperature and air quality for call for service type i at day t .

To help readers visualize the approach to de-seasonalizing the data we have taken the fitted values from each of the eight models (Figure 3), four for the pre-lockdown period given by $\{\hat{y}_1, \dots, \hat{y}_M\}$ and four for the lockdown period given by $\{\hat{y}_{M+1}, \dots, \hat{y}_N\}$ and joined them to have the fitted values for the entire series, $\{\hat{y}_1, \dots, \hat{y}_N\}$ as a single segment. As an example of our approach, each facet of Figure 3 shows how the fitted (red) improves relative to the observed (black), starting from the first simple trend model to the fourth most complex model that included a trend term, harmonics components, fixed effects and time varying covariates thus capturing more of the variance that might be explained by factors other than the lockdown. Such an approach is critical to isolating any time-based intervention/treatment effect for a regression discontinuity study design or interrupted time series design.

Insert Figure 3 Here

The seasonal component of the model is calculated by subtracting the trend and residuals from our final pre- and lockdown models (equation 5) as per equation 6:

$$S_t^i = y_t^i - T_t^i - u_t^i \tag{6}$$

where S_t^i is the seasonal for call for service type i at day t .

De-seasoning was completed by subtracting the seasonal component, S_t^i , from the observed series, y_t^i .

$$DS_t^i = y_t^i - S_t^i \tag{7}$$

where DS^i is the de-seasoned series. A new time-series, C_t^i , is then created by joining the values from the final de-seasonalized models for the pre- and lockdown periods. A simple RDiT model is then used to test (1) whether a difference exists between pre- and lockdown periods, and, if so, (2) how large and in what direction, and (3) what this amounts to across the entirety of the lockdown period as per equation 8:

$$C_t^i = \gamma_0^i + \gamma_1^i time_t^i + \gamma_2^i lockdown_t^i + \gamma_3^i timeafterlockdown_t^i + e_t^i \quad (8)$$

Where C_t^i is the observed crime trend value in day t , $(1, \dots, 1127)$, for i th crime type, $time_t^i$ $(1, \dots, 1127)$, is a continuous variable indicating time in days at day t from the start of the observation period, $lockdown_t^i$ is an indicator for day t occurring before (lockdown = 0) or after (intervention = 1), $timeafterlockdown_t^i$ is a continuous variable counting the number of days after the lockdown began on day t , coded 0 before the lockdown and $(1, \dots, 68)$ after the lockdown, and e_t is random error.

The same method is used across all eight crime types for the crime counts and rates (per 100,000 population) for the period between 1 March 2017 and 31 March 2020 to estimate the immediate effect of the lockdown on the count (or rate) of the different categories. However, it is possible to further compare estimates for the time after lockdown values of the lockdown outcome to values estimated at that time but based on baseline level and trend only, as if the lockdown (counterfactual value) had not occurred. We can express the lockdown effect as the absolute difference between the predicted outcome based on the intervention and the counterfactual value. To estimate the lockdown effect in M1-City, we express the expected results from the RDiT equation (6) at day 1127 (23 January 2020), which is 68 (31 March 2020) days after the lockdown was implemented as per equation 7:

$$\widehat{C}_{1127(\text{with lockdown})}^i = \widehat{\gamma}_0^i + 1127\widehat{\gamma}_1^i + \widehat{\gamma}_2^i + 68\widehat{\gamma}_3^i \quad (9)$$

Next we considered RDiT equation (6) at 1127 days, had the lockdown policy not been implemented. Put differently, without any lockdown effects in the model as per equation 8:

$$\widehat{C}_{1127(\text{without lockdown})}^i = \widehat{\gamma}_0^i + 1127\widehat{\gamma}_1^i \quad (10)$$

The difference between equations 7 and 8, $\widehat{C}_{1127(\text{lockdown})}^i - \widehat{C}_{1127(\text{no lockdown})}^i = \widehat{\gamma}_2^i + 68\widehat{\gamma}_3^i$, is the estimate of the absolute lockdown effect or the total difference in the number (or rate) of calls for service for each respective category of crime for the entirety of the lockdown period.

Results

The results from the RDiT suggest an immediate, drastic impact of the lockdown on the counts and rates for all eight crime categories for M1-City. Figure 4 provides a clear illustration of the difference between the period before and after the lockdown and the fitted values and trends for each of the series.

Insert Figure 4 Here

There was an immediate reduction in daily auto theft of ~ 3 (-3.09, 95% CI: [-4.38, -1.81]). Similarly sized decreases were found in daily motorcycle (-3.15, 95% CI: [-4.18, -2.13]), bicycle (-1.98, 95% CI: [-2.84, -1.12]), and theft from auto (-4.33, 95% CI: [-5.54, -3.16]) calls for service events. More sizeable reductions were found in the daily count of pickpocketing (-14.49, 95% CI: [-18.72, -10.26]), residential burglary (-23.71, 95% CI: [-27.18, -20.23]), and electromobile theft (-35.61, 95% CI: [-39.83, -31.37]). The largest overall daily reduction of call for service counts was for the cyber-fraud category (-82.62, 95% CI: [-89.73, -75.52]). Of importance to note here is that cyber-fraud was the only category of crime prior to the lockdown to have a positive trend and was the most prevalent form of daily crime examined for M-1 City. This combination of factors makes the drop in cyber-fraud, in Figure 4, quite large. Notably, the trend for cyber-fraud during the lockdown period is also steep and positive, nearly approaching pre-lockdown levels by the end of the period suggesting a kind of criminogenic resiliency not seen in the other crime categories included in the study and in the majority of the research conducted on COVID-19 lockdowns and criminal activity.

The main advantage of the RDiT approach to other similar techniques, is the ability to estimate the counterfactual period as opposed to providing a simple estimate of a change in the mean count (or rate). Here the results of the RDiT illuminate just how profound the effect of the lockdown really was on changes in the crime patterns for M1-City. When taken together, the reduction among these categories of crime results in $\sim 9,939$ fewer calls for police service during the lockdown than what would have been expected had the lockdown not occurred. Bicycle theft (-148.66 (95% CI: [-269.18, -28.14]), motorcycle theft (-157.55, 95% CI: [-301.06, -14.03]), auto theft (-205.88, 95% CI: [-386.05, -25.71]), and theft from auto (-276.69, 95% CI: [-443.48, -109.90]) all experienced a hundred to several hundred fewer calls. While pickpocketing (-1068.56, 95% CI: [-1660.01, -477.11]), residential burglary (-1240.09, 95% CI: [-1726.36, -753.82]), electromobile theft (-2833.04, 95% CI: [-2833.04, -1650.09]) and cyber-fraud (-4007.44, 95% CI: [-5000.91, -3013.97]) experienced thousands of fewer calls for service. Figure 5 below provides a visualization of the magnitude of both the immediate impact identified using the RDiT model, as well as the impact of the lockdown for the entire lockdown period.

Insert Figure 5 Here

The same analysis applied to crime rates, that is taking into account the approximately 30% drop in population during the lockdown, yields very similar results. Significant reduction in crime rates were found for almost all studied crime categories, both immediately and across the lockdown period. The one exception is motorcycle theft, which was not statistically significant in the longer term: -1.23 (95% CI: [-2.54, 0.07]). The greatest change concerns cyber-fraud, with an immediate reduction in rates of -0.7 (95% CI: [-0.7662, -0.63683]) and -27.7 (95% CI: [-36.75, -18.75]) over the entire lockdown period. Comparison between other crime types shows the *immediate* and *longer-term* effects follow a similar order as that found with crime counts: theft of electromobiles (-0.3; -18.3) followed by burglary (-0.2; -9.47) and pickpocketing (-0.12; -1.31). Other categories showed the least decline, with a smaller reduction in crime rates: theft from automobiles (-0.03; -2.29), automobile theft (-0.02; -1.74), motorcycles (-0.02; -1.23). Theft of bicycles (-0.01; -1.31) comes last.

Insert Figures 6 and 7 Here

Discussion

China was the first country to experience the novel coronavirus and the public health and safety consequences of COVID-19 and its related policies initiated to thwart its spread have been studied around the world. A great majority of those studies have examined the effect of pandemic lockdown strategies on changes in criminal activity, as there are reasons to suspect that some crimes would increase, such as aggravated assault and domestic violence—the reality which has been borne out (see e.g., Rosenfeld and Lopez, 2020; Piquero et al., 2021), while other types of crime, such as acquisitive property-oriented offenses would be expected to decrease because of changes in routine activities thwarted many crime opportunities from occurring.

This article investigated the impact of the lockdown strategy in responding to COVID-19 on crime levels before and during the lockdown period in a middle-sized Chinese city. By introducing the strict lockdown strategies aiming to control the virus spreading, it is believed that pandemic-related policies seriously disrupted people's routine activities there, and so the crimes are expected to be significantly influenced (Borrion et al., 2020). Two theoretical assumptions following the principles of routine activity theory were proposed to assess the potential impact of lockdown on crime, then 8 acquisitive crimes, pickpocketing, residential burglary, electromobile theft, automobile theft, motorcycle theft, bicycle theft, theft from automobiles, cyber-fraud were analyzed in raw daily counts and the daily rate. By controlling the long-term trend, seasonality, metrological, and harmonic factors, a regression discontinuity in time (RDiT) model was applied to measure the crime variation before and during the lockdown days. Findings show that all acquisitive crimes in the studied city were reduced during the lockdown period, which

largely coincides with the theoretical expectations for routine activities theory and meanwhile findings contrary to the hypothesis were also observed.

The first is that the traditional property crimes, including automobile theft, electromobile theft, motorcycle theft, bicycle theft, theft from automobiles, pickpocketing, residential burglary, largely followed what would have been expected from the theoretical assumptions underlying routine activity theory in that significant reductions occurred at the beginning of the lockdown days, and then the crimes maintained at relative low levels until the end of lockdown period. In line with previous findings (Borrion et al., 2020), it can be noticed that property crimes significantly changed during the pandemic period in China. We found that some crime types (pickpocketing, residential burglary and electromobile theft) experienced more reductions than others (automobile theft, motorcycle theft, bicycle theft, theft from automobiles). From this, it can be inferred that lockdown and stay-at-home orders have had a different impact on target distribution during the pandemic period. Indeed, the lockdown orders forced people to stay at home for curtailing the spread of the virus, thus all outdoor activities including urban traffic stopped and the vehicles and bicycles parked on the street or the other public spaces became easy access targets for offenders. At the same time, with people forced to remain at home, guardianship increased thereby enhancing protection for these places (and against crime victimization). Moreover, for electromobile theft, as people living in China were used to disassembling the battery and keeping it at home for safe keeping when they do not use them (Chen and Lu, 2018), the value of the mobile was lowered and few offenders would likely to steal it. Hence, the enhanced empty houses, lower value of the electromobile and disappearing outdoor crowds may have reduced offending opportunities.

The exception to this pattern of findings, however, lies with cyber-fraud, the crime type that had among the largest number of cases just prior to the lockdown being instituted. Contrary to previous findings that cyber-victimization increased during the lockdown days, the results from this study showed that cyber-fraud in the city decreased like property crimes, which is somewhat contrary to the expectations in the second hypothesis and observations in other works (Buil et al., 2021). However, it is interesting to see the cyber-fraud experienced some resilience. More specifically, at the beginning of the lockdown, cyber-fraud, like other property crimes, experienced significant reductions, but unlike previous research that has had short follow-up periods, our results showed an eventual return to pre-lockdown levels. As a matter of fact, the occurrence of cyber-fraud differs from the property crimes strongly depending on the convergence of potential offenders and suitable targets in physical space and time, it is more determined by the encounter of offenders and victims in online space¹⁴ as opposed to people living in the ‘normal rhythm’ life. At the beginning of lockdown period, the strict stay-at-home discomfited people and the panic facing the horrible virus and unknown lockdown period led them to focus on their own survival.

¹⁴To be sure, the effect of COVID-19 lockdowns on different types of cyber-fraud, while not as extensively studied as more traditional street crimes, has been mixed with some studies finding no changes in cyber victimization (Hawdon et al., 2020) and other studies reporting increases in cyber-fraud victimization more generally (Payne, 2020).

In that sense, people had to adjust their daily lives from the ‘normal’ to stay-at-home state, switch work/study from offline to online, change their previous freely entertainment/shopping activities to limited styles, etc. Therefore, as people gradually adapted to the new stay-at-home life their routine activity rhythm were adjusted to a new ‘normal’ state and the time they spent online become more than before, more contacts and opportunities for cyber-fraud were generated.

We believe that our study, among the first to examine crime during the COVID-19 era in China is an important addition to the knowledge base, especially with respect to the methodological approach using RDiT alongside the crime data and environmental factors considered, afforded us the opportunity to estimate the variation process during the counterfactual period as opposed to providing a simple estimate of a change in the mean count (or rate). In so doing, we are able to estimate the net effect of restrictions on crime, from the vantage point of both counts and rates, for M1-City in south China. Some limitations to our study are worth noting. First, our data are based on official records which, while commonplace in research on COVID-19 and crime, still does not capture undetected and unreported crime—which is quite common with respect to cybercrime (and may be why our data show an almost return to pre-lockdown levels by the end of our lockdown observation window). Second, we explored only acquisitive crimes in one city, other crime types such as assault, violence, and drugs, await more analysis. Thus, expanding our work in China to other crime types or in more cities for cross comparison would be of interest. Third, our work was unable to perform an in-depth investigation of crime variation across space. The occurrence of crime in place is an attractive phenomenon since the lockdown restrictions required people to stay at home and led to the disruption of routine activities. Given evidence that crime may have space-related variability (Campedelli et al., 2021; Felson et al., 2020), it is important to continue work in this area. Lastly, as China goes through openings and lockdowns over time, it is important to continue tracking changes in different types of criminal activity, especially those crimes that often go undetected, such as identity theft and various types of fraud.

Several implications for crime prevention in practice could be inferred from our investigation. The first concerns the observation that most property crimes declined during lockdowns in large part without any police influence. Yet, though not investigated here, some specific types of violence, such as homicide and domestic violence, increased. This suggests that police should consider some differential enforcement or differential allocation during lockdown periods. A second suggestion from our work surrounds cyber-fraud. As our analysis showed that cyber-fraud shows a strong return to pre-lockdown levels, it is incumbent on local, state, and federal agencies to pay significant attention to this crime type and for citizens to take extra precautions when online.

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1 **Tables**

2 **Table 1 Quantitative measurement of pandemic related restriction strategies on crime in different countries**

Crime category	Context	Data	Mechanism	Outcome
Drug crimes	25 large US cities	Daily and weekly crime incidents rate per 100000 residents	Comparison with historic recordings with DID model, but 12 cities provided data	65% drop relative with same period in old years
	Community level in Chicago	Daily counts	Structural Bayesian Time-Series model	Statistically significant reduction was observed for 35 of 77 communities
	Sweden	Weekly count	Standard Swedish police procedure	1.4% increase relative with prior pandemic
	NSW, Australia	Weekly count	Seasonally adjusted forecast model	Cocaine possession incidents were 40 per cent lower than expected while amphetamine possession incidents were 30 per cent higher than expected
	England and Wales	Monthly count	General regression	17% increase
Residential burglary	25 large US cities	Daily and weekly crime incidents rate per 100000 residents	Comparison with historic recordings with DID model	23.5% drop relative with same period in old years
	Community level in Chicago	Daily counts	Structural Bayesian Time-Series model	Statistically significant reduction was observed for 10 of 77 communities
	Sweden	Weekly count	Standard Swedish police procedure	45.6% drop relative with prior pandemic
	New Zealand	Crime rate per 1000 people	Simple regression	30% declined for property crime
	Mexico city, Mexico	Weekly crime rate per 100000 inhabitants	Comparison with historic recordings with DID model	69% drop relative with pre-pandemic days
	NSW, Australia	Weekly count	Seasonally adjusted forecast model	Residential break-ins (down 29 per cent)
Violent crimes (domestic violence, sexual violence)	25 large US cities	Daily and weekly crime incidents rate per 100000 residents	Comparison with historic recordings with DID model	Rapes dropped by 39% relative with same period in old years
	NSW, Australia	Weekly count	seasonally adjusted forecast model	Non-domestic violence related assaults were 39 per cent lower than expected, Sexual offences were 32 per cent lower
	Queensland, Australia	Offence rate	Comparison with ARIMA predicted level	The decline of serious assault and sexual assault were beyond statistical expectations
	Mexico city, Mexico	Daily count	Comparison with ARIMA predicted level	Sexual violence declined by 53.3% and 66.5% in post pandemic and post lockdown days
	Sweden	Weekly count	Standard Swedish police procedure	Indoor violence declined 10.6% increase relative with prior pandemic
Vehicle theft	25 large US cities	Daily and weekly crime incidents rate per 100000 residents	Comparison with historic recordings with DID model	20.3% drop relative with same period in old years

	Mexico city, Mexico	Weekly crime rate per 100000 inhabitants	Comparison with historic recordings with DID model	58% drop relative with pre-pandemic days
	Vancouver, Canada	Weekly count	Interrupted time series	Slight decrease compared with previous years
	NSW, Australia	Weekly count	Seasonally adjusted forecast model	24% drop
Assault	Community level in Chicago	Daily counts	Structural Bayesian Time-Series model	Statistically significant reduction was observed for 18 of 77 communities
	Sweden	Weekly count	Standard Swedish police procedure	9.7% increase relative with prior pandemic
	25 large US cities	Daily and weekly crime incidents rate per 100000 residents	Comparison with historic recordings with DID model	Aggravated assault declined 15.9%, simple assault declined 33.3% relative with same period in old years
Robbery	Community level in Chicago	Daily counts	Structural Bayesian Time-Series model	Statistically significant reduction was observed for 10 of 77 communities
	Sweden	Weekly count	Standard Swedish police procedure	14% drop relative with prior pandemic
	Mexico city, Mexico	Daily count	Comparison with ARIMA predicted level	Robbery against residence declined by 45.6% and 58.6% in post pandemic and post lockdown days
	NSW, Australia	Weekly count	Seasonally adjusted forecast model	42% lower than expected
	25 large US cities	Daily and weekly crime incidents rate per 100000 residents	Comparison with historic recordings with DID model	20.2% drop relative with same period in old years
Pickpocketing	Sweden	Weekly count	Standard Swedish police procedure	59% drop relative with prior pandemic
Vandalism	Sweden	Weekly count	Standard Swedish police procedure	34% increase relative with prior pandemic
	England and Wales	Monthly count	General regression	35% increase
Theft	Indonesia, Makassar City	Monthly count	Simple descriptive analysis	Increase by 42.65% compared with pre pandemic days
	25 large US cities	Daily and weekly crime incidents rate per 100000 residents	Comparison with historic recordings with DID model	28.2% drop relative with same period in old years
	Vancouver, Canada	Weekly count	Interrupted time series	Slight decrease compared with previous years
Homicide & shootings	Mexico city, Mexico	Weekly crime rate per 100000 inhabitants	Comparison with historic recordings with DID model	No impact
	25 large US cities	Daily and weekly crime incidents rate per 100000 residents	Comparison with historic recordings with DID model	Unaffected by the pandemic
Cybercrime	UK	Monthly count of fraud and cybercrime	Quantitative statistic	Online fraud increase 50.95% compared with same period in old year, all cybercrime increase 43.24%

Figures

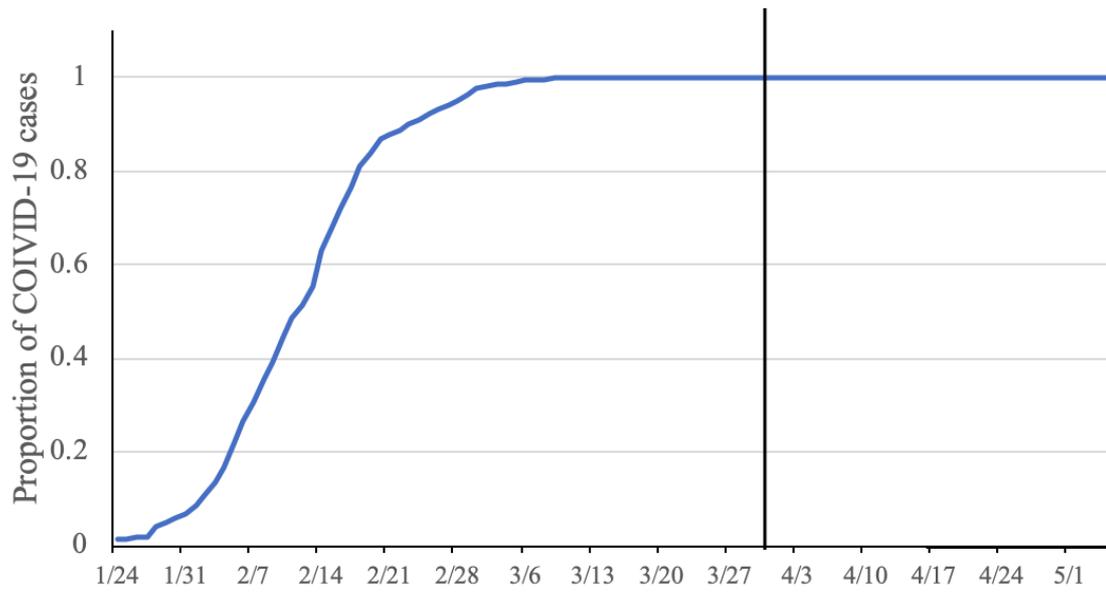


Figure. 1 Standardized cumulative distribution of confirmed COVID-19 cases over time in M1-city, China. The black line is the day when lockdown order was lifted by the government. The data was accessed via: <https://github.com/BlankerL/DXY-COVID-19-Data> (accessed 1 May 2021).

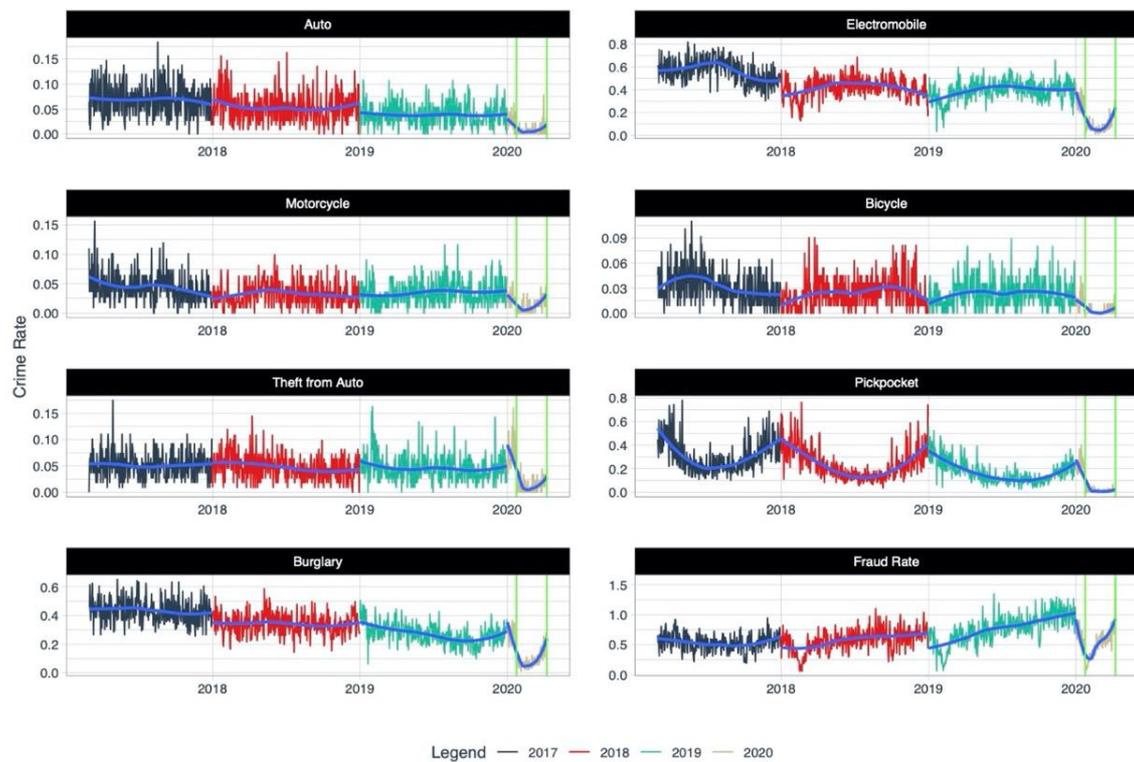


Figure 2. The observed series of auto theft, electromobile theft, motorcycle theft, bicycle theft, theft from auto, pickpocketing, residential burglary, and cyber-fraud calls for service rates from 1 March 2017 to 31 March 2020 by year with a Loess smoother (blue) to help visualize the overall yearly trend of the rates (per 100,000 persons), and green vertical lines demarcating the full temporal extent of the lockdown period in M1-City.

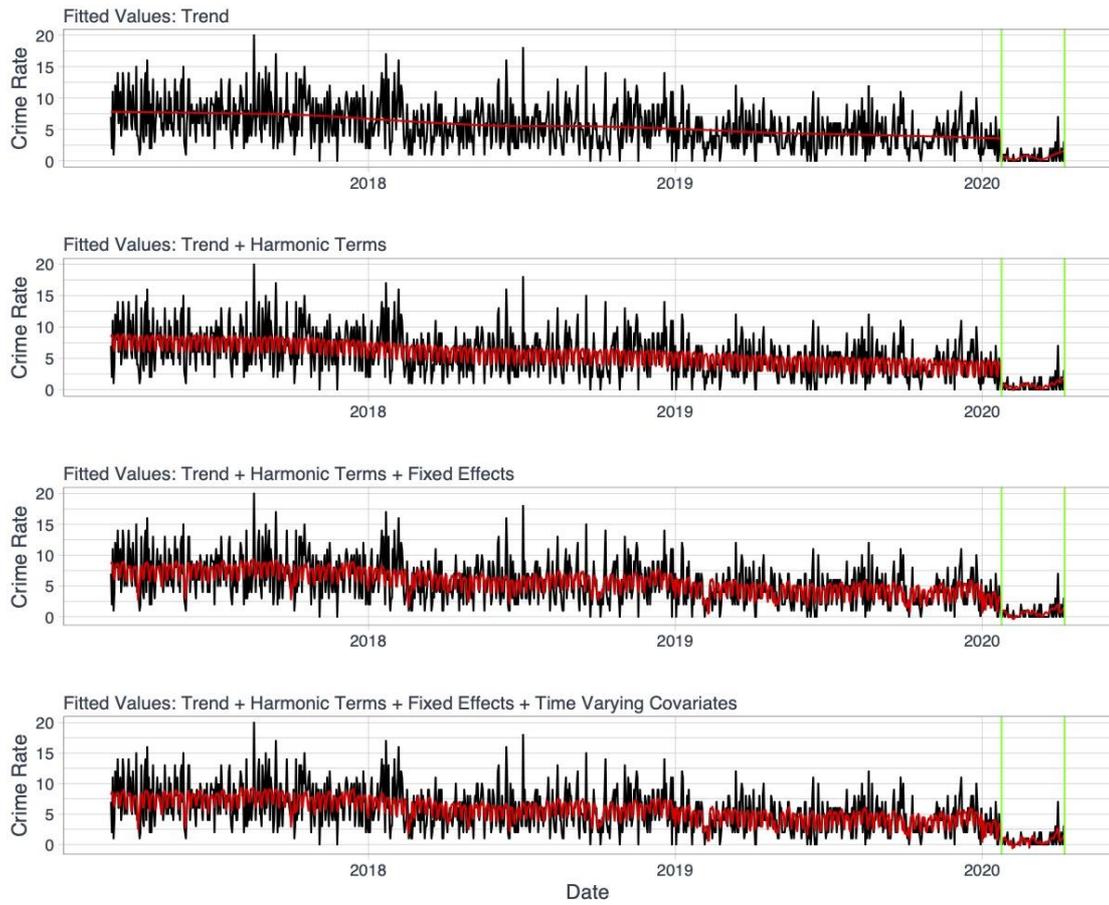


Figure 3. The observed series for cyber-fraud calls for service rates from 1 March, 2017 to 31 March 2020 (black) with the fitted values (red) for each of the step-wise models for the full temporal extent of the lockdown period in M1-City.

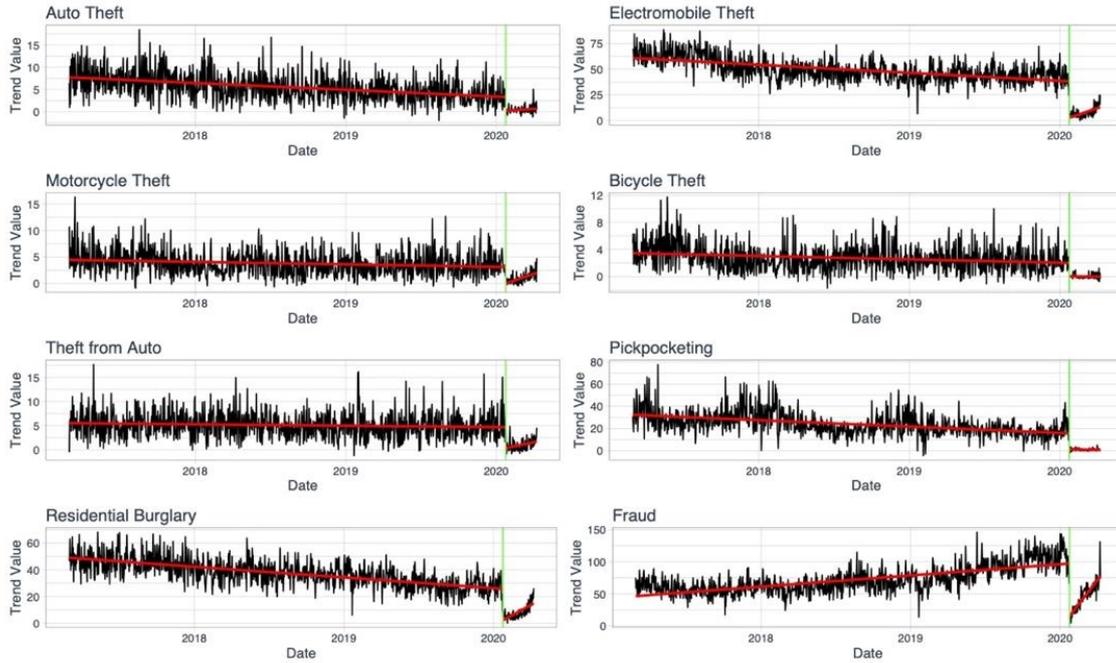


Figure 4. Regression Discontinuity in Time (RDiT) results for each of the trends (black) for the eight categories of crime from 1 March, 2017 to 31 March 2020 with associated linear fit (red) for the period prior to the lockdown and the lockdown for M1-City after controlling for trend, seasonality, and numerous time-varying covariates.

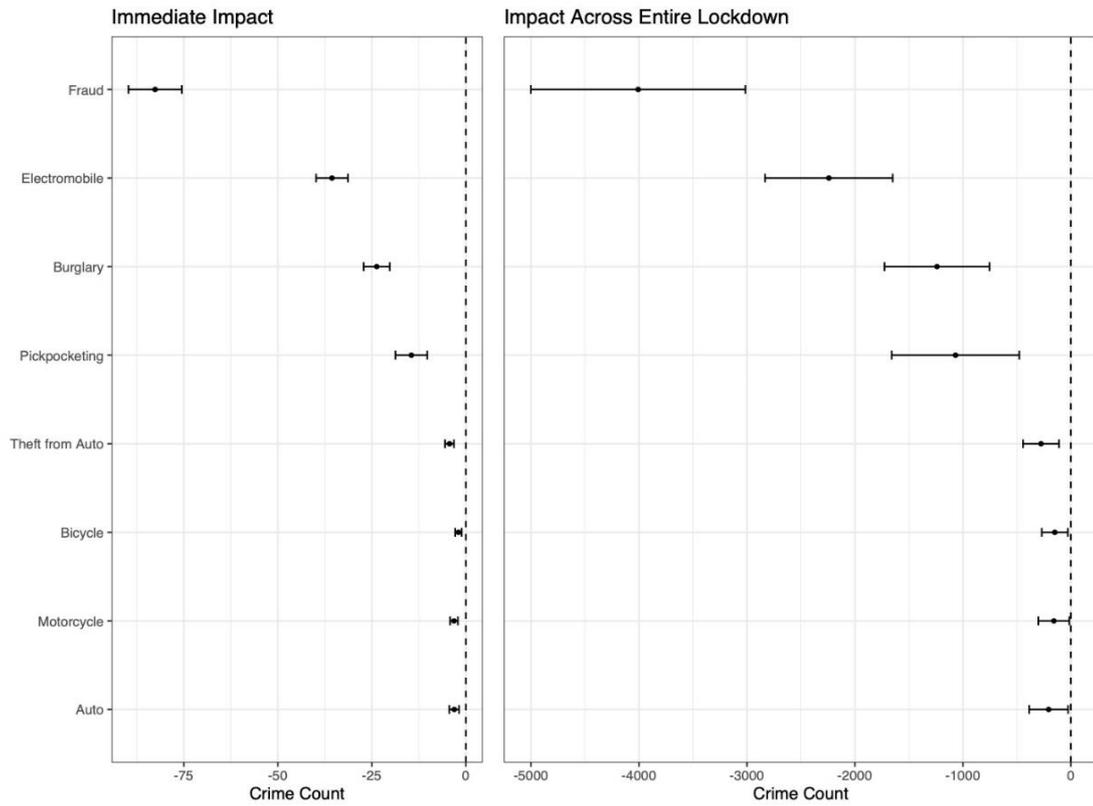


Figure 5. Regression Discontinuity in Time (RDiT) coefficients and associated 95% CIs for the immediate impact (left panel) and the impact across the entire lockdown period (right panel) for each of the eight categories of crime.

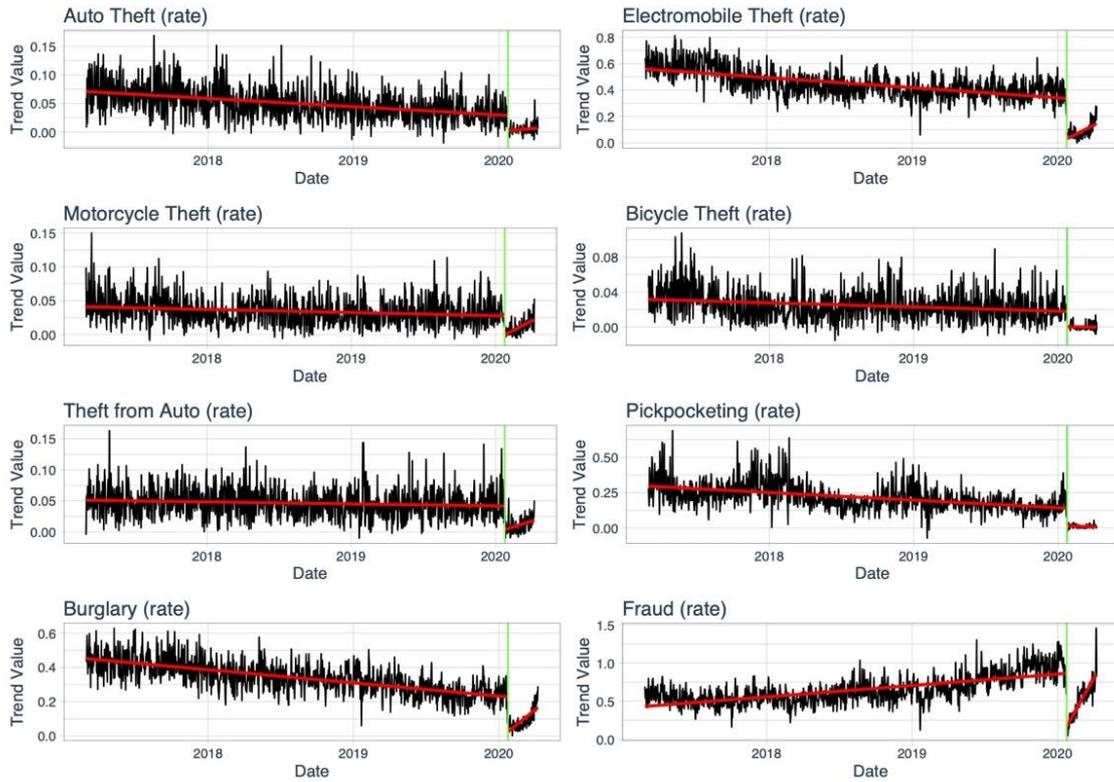


Figure 6. Regression Discontinuity in Time (RDiT) results for each of the rate trends (black) for the eight categories of crime from 1 March, 2017 to 31 March 2020 with associated linear fit (red) for the period prior to the lockdown and the lockdown for M1-City after controlling for trend, seasonality, and numerous time-varying covariates.

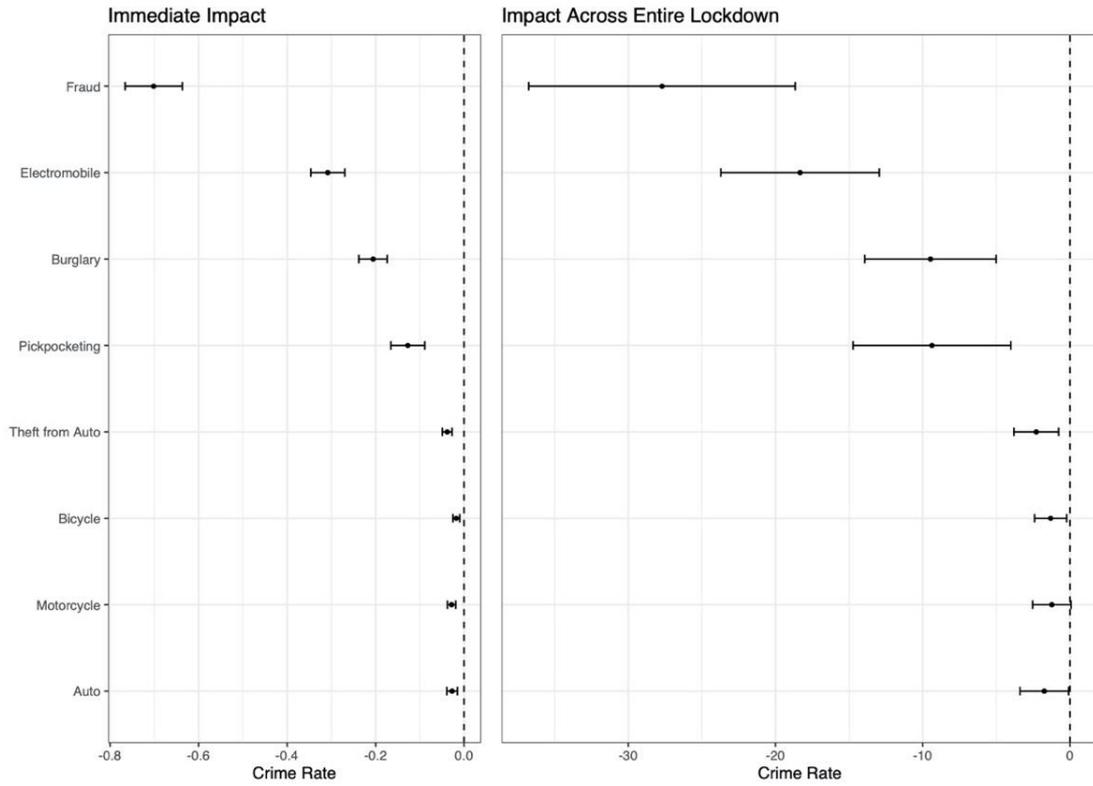


Figure 7. Regression Discontinuity in Time (RDiT) coefficients and associated 95% CIs for the immediate impact (left panel) and the impact across the entire lockdown period (right panel) for each of the eight categories of crime.

Appendix

Appendix 1: Regression-discontinuity in time models for daily calls for service crime counts in M1-City across the pre- and lockdown period controlling for trend and seasonal effects.

Crime	Intercept	Slope	Immediate Lockdown Effect	Longer-term effect of Lockdown
Auto	7.71	-0.004182	-3.09 (95% CI: [-4.38, -1.81])	-205.88 (95% CI: [-386.05, -25.71])
Electromobile	60.78	-0.021	-35.61 (95% CI: [-39.83, -31.37])	-2833.04 (95% CI: [-2833.04, -1650.09])
Motorcycle	4.45	-0.001280	-3.15 (95% CI: [-4.18, -2.13])	-157.55 (95% CI: [-301.06,-14.03])
Bicycle	3.44	-0.0013566	-1.98 (95% CI: [-2.84, -1.12])	-148.66 (95% CI: [-269.18, -28.14])
Theft from Auto	5.51	-0.0007928	-4.33 (95% CI: [-5.54, -3.16])	-276.69 (95% CI: [-443.48, -109.90])
Pickpocketing	32.35	-0.0158000	-14.49 (95% CI: [-18.72,-10.26])	-1068.56 (95% CI: [-1660.01, -477.11])
Burglary	49.02	-0.02195	-23.71 (95% CI: [-27.18,-20.23])	-1240.09 (95% CI: -1726.36, -753,82)]
Cyber-Fraud	46.44	0.047988	-82.62 [95% CI: [-89.73, -75.52])	-4007.44 (95% CI: [-5000.91, -3013.97])

*All bolded results have a p -value $<.05$

Appendix 2: Regression-discontinuity in time models for the rates of daily calls for service in M1-City across the pre- and lockdown period controlling for trend and seasonal effects.

Crime	Intercept	Slope	Immediate Lockdown Effect	Longer-term effect of Lockdown
Auto	0.07	-0.000039	-0.02 (95% CI: [-0.0388, -0.01523])	-1.74 (95% CI: [-3.39, -0.09])
Electromobile	0.55	-0.000210	-0.30 (95% CI: [-0.3465, -0.26955])	-18.32 (95% CI: [-23.71, -12.94])
Motorcycle	0.04	-0.000012	-0.02 (95% CI: [-0.0375, -0.01887])	-1.23 (95% CI: [-2.54, 0.07])
Bicycle	0.03	-0.000131	-0.01 (95% CI: [-0.0098, -0.02531])	-1.31 (95% CI: [-2.40, -0.22])
Theft from Auto	0.05	-0.000008	-0.03 (95% CI: [-0.0489, -0.02725])	-2.29 (95% CI: [-3.80, -0.77])
Pickpocketing	0.29	-0.000147	-0.12 (95% CI: [-0.0888, -0.16547])	-1.31 (95% CI: -2.40, -0.22)
Burglary	0.45	-0.000210	-0.20 (95% CI: [-0.2374, -0.17370])	-9.47 (95% CI: -13.93, -5.01)
Cyber-Fraud	0.43	-0.000408	-0.70 (95% CI: [-0.7662, -0.63683])	-27.70 (95% CI: -36.75, -18.75)

*All bolded results have a p -value $<.05$