Frozen Cities, Frozen Crimes? Crimes changes against mobility changes following lockdowns: case studies of London and Sydney
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Abstract
Governments around the world have deployed social distancing and lockdowns to restrict citizens’ movement to help contain the COVID-19 pandemic. A large body of evidence has emerged, showing that such dramatic changes in people’s daily mobility have triggered similarly changes in criminality and delinquency at both city and community levels. Drawing on crime data of London and Sydney in 2020, this study attempts the first one-year “look back” on the impact of massive lockdowns on crime trends with the assistance of two classic criminological theories, routine activity and general strain; and cutting-edge machine learning techniques on relating the community-level geodemographics and socio-economic profiles to crime changes. The research findings suggest a general crime reduction upon mobility change during lockdowns, but some prominent crime types experienced eye-catching increases during the period featured by city; the data-driven evidence could be further utilised for crime prediction and prevention strategies throughout post-pandemic recovery.

Keywords: crime patterns, lockdown, routine activity, general strain, mobility change

Introduction
Since its outbreak, the COVID-19 pandemic has been wreaking havoc on human wellbeing, government administration, economics, crime, and social interactions all over the world, making an irreversible impact throughout 2020 and will continue to do so into the foreseeable future (Clemens, 2020; Liu et al., 2021; Stickle and Felson, 2020). In response to the pandemic - and to contain the rapid spread of the virus - governments around the world began to impose several non-pharmaceutical interventions (NPI), i.e., lockdown, social distancing, and stay-at-home mechanisms to demobilise people’s activities. The nature of these dramatic
changes to mobility simultaneously affects the daily routines and the social interactions of millions of people, hereafter defining the calendar year 2020 as the largest experiment of criminological changes in human history (Liu et al., 2021; Stickle and Felson, 2020). This is evidenced by: the decrease in residential burglary and theft due to guardianship strengthened by stay-at-home directives (Ashby, 2020; Campedelli et al., 2020; Halford et al., 2020); the substantial decline in violent crimes against persons immediately following the COVID-19 containment measures (Abrams, 2021; Langton et al., 2021; Payne et al., 2020); the exceptional surge of domestic violence after the deployment of lockdowns (Dai et al., 2021; Mohler et al., 2020; Boserup et al., 2020; Krishnakumar and Verma, 2021; Piquero et al., 2020, 2021; Zhang, 2020); the significant increase of illegal drug abuse during the COVID-19 lockdowns (Balmori de la Miyar et al., 2020; Rashid, 2021; Niles et al., 2021; Zaami et al., 2020); and the increase in reports of cyber victimisation during the lockdowns with internet as the main sources for social interactions among millions of people (Chang et al., 2021; Buil-Gil et al., 2020; Buil-Gil and Zeng, 2021).

Drawing on crime data from two international metropolises, London and Sydney, this article explores how the widespread lockdowns have impacted major types of crime and which areas were the main hotspot regions, to advance our understanding of the unprecedented crime situations imposed by COVID-19. Most of the research we can find only focuses on one city or one country (e.g. Hodgkinson and Andresen, 2020; Mccarthy et al., 2021; Rashid, 2021); or most studies have only observed crime trends over a short period, ranging from several weeks (see, e.g. Balmori de la Miyar et al., 2020; Felson et al., 2020; Kim and Phillips, 2021), to three months (see, e.g. Mccarthy et al., 2021; Mohler et al., 2020), up to a maximum of six months (see, e.g. Langton et al., 2021; Nivette et al., 2021; Rashid, 2021).

This study aims to contribute to the field in three different aspects:

1) to deliver more comparative insights and solid evidence to the existing literature, by observing crime patterns in two cities, over a one-year period;

2) to apply classic criminological theories - routine activity and general strain - onto different cities, to identify whether some urban areas have been disproportionately affected by mobility change during lockdowns;

3) to explore how the trends and patterns in urban crimes will develop in the future, assisted by machine learning techniques and spatial predictive models. And, as a result, to provide references for efficient crime prevention and policing strategies.
Background: COVID-19 - the largest criminological experiment in human history

The magnitude of the COVID-19 pandemic has manifested in the dramatic changes of social orders and controls, making it the largest criminological experiment in human history (Liu et al., 2021; Stickle and Felson, 2020). During the pandemic, a variety of evidence began to emerge to indicate dramatic changes in crime, the clearest manifestations of which are in property crime. With the introduction of COVID-19 containment measures, people have had to stay at home. This has strengthened guardianship over personal property and space, resulting in a significant decrease in residential burglary and theft (Ashby, 2020; Campedelli et al., 2020; Halford et al., 2020). Whereas, for violent crimes and crimes against persons, most researchers (Abrams, 2021; Langton et al., 2021; Payne et al., 2020) have found a substantial level of decline immediately following COVID-19 containment measures, except for domestic violence. Calls-for-service (Dai et al., 2021; Mohler et al., 2020) and reported cases (Boserup et al., 2020; Krishnakumar and Verma, 2021; Piquero et al., 2020, 2021; Zhang, 2020) of domestic violence both surged upon the deployment of lockdown measures.

In addition to conventional crimes, the COVID-19 pandemic has also given rise to other types of crime and delinquencies. For example, drug-lords in Mexico City still maintained active businesses despite the stay-at-home order (Balmori de la Miyar et al., 2020); the total number of arrests for illegal drug trafficking in Dhaka, Bangladesh, steeply increased by 75% (Rashid, 2021); in parallel to these specific examples, illegal drug abuse significantly increased during the COVID-19 outbreak (Niles et al., 2021; Zaami et al., 2020). Hate crimes towards different ethnicities or religions skyrocketed during the lockdowns as well: for example, during the research period, Chinese and other Asian Americans have suffered discrimination and hate crimes due to social stigmas such as the fear of the virus, mask culture, and political ideology (Gover et al., 2020; Xu et al., 2021). Meanwhile, as the internet has become a primary source of social interaction during lockdown, reports of cyber victimisation (e.g., online romance fraud) have experienced an eye-catching increase (Buil-Gil et al., 2020; Buil-Gil and Zeng, 2021).

Literature: Explanations from classic criminological theory for lockdowns’ impact on crimes

With the hope of containing the outbreak of the contagion, governments around the world have deployed NPI strategies of social distancing and mandatory lockdowns to restrict citizens’ activities during the ongoing pandemic, including stay-at-home orders, social distancing, contact tracing, and border closures. The changing organisation of individuals’
routine activities (Cohen and Felson, 1979) is best situated to account for inclinations, patterns, distributions, and trends in criminal activities amid lockdowns. Meanwhile, the intensified social isolation, the worsening financial conditions, and the uncertainty and anxiety caused by a lockdown can impose general strain (Agnew, 1992) on people, which may lead them to commit a crime. A combination of routine activity theory and general strain theory seems to be a useful theoretical integration for understanding crime changes in the context of a pandemic.

Cohen and Felson’s (1979) routine activity theory (RAT) sets up a key foundation to the situation and opportunity perspective that facilitates criminal acts, when there is a temporal-spatial convergence of a motivated offender with a suitable target, in the absence of a capable guardian (Cohen and Felson, 1979). RAT, as one of the most prominent criminological explanations for crime and risk of victimisation, focuses on how a situation or social context influences people’s vulnerability to crime (Dugan and Apel, 2005; Xu, 2009). For example, Hayes (2018) applied RAT to understand domestic violence and found that, with the presence of the victim’s friends/family as guardians, re-victimisation was reduced by 60%. Conversely, by applying RAT in the absence of guardians to the growth of domestic violence cases during the pandemic (Boman and Gallupe, 2020; Mohler et al., 2020; Piquero et al., 2021) it could be hypothesised that stay-at-home measures have extended the periods of contact between the most vulnerable victims and potential motivated abusers.

Beyond the three igniting factors of RAT, general strain theory (GST) explains that people engage in criminal behaviours because they undergo certain strains or stressors (Agnew, 1992, 2002, 2010, 2015), which, in turn, necessitates criminal conduct as one of those individuals’ coping strategies to alleviate or escape from strains and relieve negative emotions (Agnew, 2002; Broidy, 2001). Strains are most likely to become criminogenic for people when there are a high-level of constraints to non-delinquent coping mechanisms like exercise or negotiation (Agnew, 2010), but the constraints to delinquent coping strategies are low (Agnew & White, 1992). Agnew (1992) specifically identifies three sources of strain that produce criminal or delinquent conducts: (1) the failure to achieve positively valued goals, which frustrate people who may end up adopting inappropriate approaches to achieve those goals (e.g. robbing to get money); (2) the removal of positively valued stimuli, which may be manifested as a breakup in a romantic relationship; and (3) the presentation of negative stimuli, such as physical abuse of parents or emotional sufferings from an unexpected incident.
The COVID-19 pandemic could be regarded as a historic disaster in human history, triggering structural changes to routine activity patterns, such as fewer motivated offenders, targets who have already evacuated, and an increase in capable guardians, inducing to a decline of criminal activity in those hardest hit regions by disasters (Leitner et al., 2011). The rollout of massive containment measures has changed people’s routine activities dramatically. As a result, both people’s movement and time spent in public areas have dramatically decreased, whilst time spent in residential areas has increased. As a result, crime rates have plummeted. On the other hand, similar as other disasters, the pandemic also provide an overwhelming source of strain as people have to cope with traumatic reactions to it, the loss of material possessions and valued family memorabilia, and financial pressure due to soaring unemployment (Frailling and Harper, 2017; Zahran et al., 2009).

Robertson et al.’s (2010) research found that greater exposure to Hurricane Katrina resulted in serious delinquency in adolescent girls, alongside maladaptive coping strategies such as escapist substance use. Once again, the COVID-19 pandemic is another such disaster; extensive lockdowns significantly boosted the number of unemployed people, as well as the number of unemployment benefit claims (Goolsbee and Syverson, 2021; Lemieux et al., 2020). For example, throughout March of 2020, Australia witnessed a 7.5% decrease in the job market and an 8.2% reduction in payments to employees (Australian Bureau of Statistics, 2020). The impact of financial stress due to unemployment and inequality can be substantial, as violence and property crimes are found concentrated in socio-economically disadvantaged regions (Hipp and Yates, 2011; Hooghe et al., 2011; Hulme et al., 2019; Payne et al., 2020). Beyond the financial impact of lockdowns, the constrained freedom of movement is also likely to be compounded by a range of negative psychological impacts. Young people have suffered greatly with loneliness during the pandemic because they would usually engage in gregarious social activity in their normal lives (Bu et al., 2020). It is predicted that the pandemic led to an increase in suicides of about 9570, which can also be associated with the rising worldwide unemployment rate due to the pandemic (Kawohl and Nordt, 2020).

A survey of 2567 police officers across five European countries shows that risk of infection and deficient communication emerged as main stressors for police officers who are playing a crucial role in the effort to contain the virus, maintain public order, and promote safer communities (Frenkel et al., 2021). According to the general strain theory, if these negative emotions are left unchecked, commission of crimes may be the ultimate coping strategy (Agnew, 1992). In line with GST, we can understand why drug abuse/possession has become
more prevalent during the pandemic, as stress change, intaking illicit drugs to make the strained person feel better, and loneliness and depression can all be triggers for a delinquent coping mechanism (Niles et al., 2021). Meanwhile, the stress and anxiety caused by coronavirus and lockdown orders may lead to escalating anger and potential violence in the home (Piquero et al., 2021). Viewing these potential outcomes in tandem, we can see how the risk of domestic violence may have been magnified further in conjunction with the abuse of alcohol and drugs during the isolation periods (Piquero et al., 2020).

Research Design and Data

Lockdown Timelines
To reduce the transmission rates and impacts of COVID-19 in target cities in 2020, several non-pharmaceutical intervention (NPI) strategies had been set in place in line with respective national public health policies and guidelines. Examples of NPIs include, most prevalently, the national lockdowns. Haug et al. (2020) assessed the effectiveness of lockdowns depending on cities’ local context, with an emphasis on the corresponding impacts on local mobility. Halford et al. (2020) further theorised that such mobility changes were the primary causes to crime rate changes in UK cities during the pandemic. In view of these insights, this study will take the lockdown milestone events as the temporal benchmarks to compare mobility and crime changes. The COVID-19 lockdown timelines in London and Sydney are depicted in Fig.1, demonstrating the first lockdown from late March until mid-to-late May 2020, and the second lockdown in November and December 2020.
**Research design**

Considering RAT and GST theories, this study utilises city-wide land use functioning data derived from Open Street Map on six land use categories - recreation, grocery, work, transit, residential and parks - this data is used to calculate both monthly and daily average mobility change in space (see detailed animation visualised on the project website http://www.comparecitycome.com) further relating to inner-city crime changes, either on monthly or daily basis basis (Equation 1).

\[
M_{ob_{ik}} = \sum_{j=1}^{6} M_{ob_{jk}} \times \left( \frac{Area_{ij}}{Area_{i}} \right) 
\]  

\[ ...... \quad (1) \]

where i is the index for fine geographical unit (i.e., i=1,2,3, ..., 4835 LSOA in London, i =1,2,3, ..., 312 SA2 in Sydney), j is the land use category (j =1,2,3,4,5,6), and k is the index for consecutive dates (15th February 2020 - 31st December 2020) or months (February to December 2020).

The comparative studies to identify the correlation between these mobility change and crime change maps, in the context of each city, incorporated: (1) time series analyses on both crime rate change and mobility change in each city, at the finest available scale, alongside inter-city comparisons; (2) exploratory data analysis within each city, to locate the most significantly affected crime type during featured periods; and (3) spatial regression analysis considering spatial influence monthly across target cities, to address the starting question.
**Data Sources and Methodologies**

To realise the research design, the mobility change data at inter-city level was collected through Apple Mobility Data (https://covid19.apple.com/mobility). This data reflects Apple users’ map service requests through 3 means: by driving, by taking public transport and by walking, measuring its relative volume change against the baseline volume dated on 13th January 2020. The inner-city level mobility data was collected from Google Mobility Reports, upon aggregating locational data shared by users of Android smartphones onto London boroughs. This data was used to compare the time and duration of visits to the six categorised place types (retail and recreation, groceries and pharmacies, parks, residential, workplaces and transit stations) to the baseline day before social distancing measures were introduced.

Crime data in target cities was compiled from respective official statistics (London from https://data.london.gov.uk/dataset/recorded_crime_summary, and Sydney from https://www.bocsar.nsw.gov.au/Pages/bocsar_datasets/Datasets.aspx), dated from January 2008 to December 2020 consecutively at monthly intervals. This data was also aggregated by year for time-series trend comparison among them. Detailed individual crime incidents data for 2019 and 2020 was also collected and aggregated to corresponding geographical units at either monthly or daily frequency.
Fig. 3 Annual Crime Rate Comparison in London and Sydney (2008-2020)

Fig.3 visualises the trajectory of crime rates (cases per 100,000 residents) in each target city from 2008 to 2020. A consistent decrease in crime rate can be seen from 2008 to 2014 for both cities, followed by diverted strands from 2015 onwards. Taking 2020, as the focused time point for this study, both London and Sydney experienced significant drops in crime rate compared to 2019 during the national pandemic incurred changes. In acknowledgement of the different crime classifications between the two cities, major crime types will be analysed in this study, as listed in Table 1.

Table 1 Crime Classifications in Target Cities

<table>
<thead>
<tr>
<th>City</th>
<th>Crime Categories and Types</th>
</tr>
</thead>
<tbody>
<tr>
<td>London</td>
<td>● Property Crimes: Burglary, Robbery, Theft, Vehicle Offences</td>
</tr>
<tr>
<td></td>
<td>● Violent Crimes: Arson and Criminal Damage, Miscellaneous Crimes Against Society, Possession of Weapons, Public Order Offences, Sexual Offences, Violence Against the Person</td>
</tr>
<tr>
<td></td>
<td>● Drug Offences</td>
</tr>
<tr>
<td>Sydney</td>
<td>● Property Crimes: Betting and gaming offences, Blackmail and extortion, Robbery, Theft</td>
</tr>
<tr>
<td></td>
<td>● Violent Crimes: Abduction and kidnapping, Against justice procedures, Arson, Assault, Disorderly conduct, Homicide, Intimidation, stalking and harassment, Prohibited and regulated weapons, Sexual offences, Other offences against the person</td>
</tr>
<tr>
<td></td>
<td>● Drug offences</td>
</tr>
<tr>
<td></td>
<td>● Other offences</td>
</tr>
</tbody>
</table>

Alongside the data, the socio-economic status (SES) data for each city was derived from the latest census sources for target cities, including measures on 13 dimensions: 'age', 'deprivation', 'education', 'employment', 'ethnicity', 'household_composition', 'household_language', 'income', 'marital_status', 'mode_of_travel', 'place_of_birth', 'sex' and 'tenure_type', which made the comprehensive dataset for London as 4835 (number of LSOAs)*93 (sub-indicators), and 11171 (number of the census units)*109 (sub-indicators)
for Sydney. After data cleaning and pre-processing, like dropping indicators with missing values or those highly-skewed, removing those variables with too many strong correlations, and data transformation operation on normalisation. The final retained variables are listed in Table 2:

Table 2 SES Variables for Clustering

<table>
<thead>
<tr>
<th>City</th>
<th>Retained Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>London</strong></td>
<td>• Age 10 to 14, Age 16 to 17, Age 30 to 44, Age 20 to 24, Age 0 to 4, Age 25 to 29, Age 45 to 59, Age 8 to 9, Age 90 and over, Age 5 to 7, Age 85 to 89</td>
</tr>
<tr>
<td></td>
<td>• Household is not deprived in any dimension, Household is deprived in 4 dimensions, Household is deprived in 1 dimension</td>
</tr>
<tr>
<td></td>
<td>• Level 3 qualifications, Apprenticeship, No qualifications, Other qualifications</td>
</tr>
<tr>
<td></td>
<td>• Economically active: Self-employed with employees, Economically inactive: Looking after home or family, Economically inactive: Student (including full-time students), Economically active: Full-time student, Economically active: Self-employed without employees</td>
</tr>
<tr>
<td></td>
<td>• Other ethnic group: Arab, Other ethnic group: Any other ethnic group, Mixed/multiple ethnic groups, Asian/Asian British</td>
</tr>
<tr>
<td></td>
<td>• One person household, Divorced or formerly in a same-sex civil partnership which is now legally dissolved, In a registered same-sex civil partnership</td>
</tr>
<tr>
<td></td>
<td>• Taxi, Motorcycle, scooter or moped, On foot, Underground, metro, light rail, tram, Bicycle, Train, Europe</td>
</tr>
<tr>
<td></td>
<td>• United Kingdom: Northern Ireland, Europe: Ireland, Europe: Jersey, Europe: Guernsey, Europe: Isle of Man, Europe: United Kingdom not otherwise specified</td>
</tr>
<tr>
<td></td>
<td>• Females, Males</td>
</tr>
<tr>
<td></td>
<td>• Shared ownership (part owned and part rented), Living rent free</td>
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<tr>
<td><strong>Sydney</strong></td>
<td>• 30-34 years, 10-14 years, 40-44 years, 25-29 years, 15-19 years, 45-49 years, 0-4 years, 5-9 years, 75-79 years</td>
</tr>
<tr>
<td></td>
<td>• Quartile 1, Quartile 2, Quartile 3, Quartile 4</td>
</tr>
<tr>
<td></td>
<td>• Advanced Diploma and Diploma Level, Postgraduate Degree Level, Secondary Education - Years 9 and below, Graduate Diploma and Graduate Certificate Level, Bachelor Degree Level, Certificate III &amp; IV Level, Secondary Education - Years 10 and above</td>
</tr>
<tr>
<td></td>
<td>• Unemployed, looking for full-time work, Unemployed, looking for part-time work, Employed, worked part-time, Not in the labour force, Employed, worked full-time, Employed, away from work</td>
</tr>
<tr>
<td></td>
<td>• North-West European, North-East Asian, Southern and Central Asian, North African and Middle Eastern, Peoples of the Americas, South-East Asian, Oceanian, Southern and Eastern European</td>
</tr>
<tr>
<td></td>
<td>• Multiple family household, Non-family household, One family household</td>
</tr>
<tr>
<td></td>
<td>• Eastern Asian Languages, Northern European Languages, Southwest and Central Asian Languages, Southern Asian Languages, Other Languages, Southern European Languages, Southeast Asian Languages</td>
</tr>
<tr>
<td></td>
<td>• $400-$499 ($20,800-$25,999), $800-$999 ($41,600-$51,999), $1,750-$1,999 ($91,000-$103,999), Negative income, $3,000 or more ($156,000 or more), $1,500-$1,749 ($78,000-$90,999), $150-$299 ($7,800-$15,599)</td>
</tr>
<tr>
<td></td>
<td>• Widowed, Never married, Divorced, Married</td>
</tr>
<tr>
<td></td>
<td>• Motorbike/scooter, Car, as driver, Taxi, Bicycle, Car, as passenger, Train, Bus, Truck</td>
</tr>
<tr>
<td></td>
<td>• Americas, Oceania and Antarctica, North-West Europe, South-East Asia</td>
</tr>
<tr>
<td></td>
<td>• Male, Female</td>
</tr>
<tr>
<td></td>
<td>• Rented, Owned with a mortgage, Owned outright</td>
</tr>
</tbody>
</table>
This data was clustered by machine learning KMeans algorithm (provided in Scikit-learn package) to provide contextual clusters. This is in order to separate the target dataset, say by of N samples, into K disjoint clusters C by equal variance and minimised inertia (also known as within-cluster sum-of-squares, WCSS) as described in equation 2.

$$\sum_{i=0}^{n} \min_{\mu_j \in C}(\|x_i - \mu_j\|^2)$$  \hspace{1cm} (2)

where $\mu_j$ is the mean of samples in each cluster. The WCSS criteria had been picked to choose the optimal number of clusters, by repeating the aforementioned algorithm for possible clusters in the range of interest from 3 clusters to 11 clusters and plot the average WCSS respectively. It is found that the optimal “turning” point for least WCSS is 6, which indicated an optimal cluster number at 6 and further fit into the spatial regression models, for the purpose of predicting crime and providing evidence for crime prevention priority strategies.

To account for the spatial dependence from nearby neighbours in space, this study applied the Spatial Lag Regression (SLM) model and Spatial Error Regression (SEM) model to measure the crime-influential associations. The SLM model in equation (3) captures spatial diffusion process on crime change from neighbouring units, by incorporating the spatial lag value of the spatial unit in the regression model. The SEM model in equation (4) assumes the observed spatial autocorrelation is caused by an independent variable (or variables, the matrix of $X$)

$$Y = \beta_0 + \beta X + \rho W Y + \zeta$$  \hspace{1cm} (3)

$$Y = \beta_0 + \beta X + \lambda W \varepsilon + \zeta$$  \hspace{1cm} (4)

where $Y$ is an $n*1$ matrix of the dependent variable (crime change) at $n$ spatial units (number of census units), $\beta_0$ is the interception value, $\beta$ and $X$ are both $n*k$ matrices of regression coefficients and $k$ independent variables, $\rho$ is the autoregressive parameter which indicates the extent to which spatial autocorrelation in $Y$ is explained by the neighbouring values of $Y$. $\lambda$ is the autoregressive parameter which indicates the extent to which the autocorrelation in the errors accounts for the autocorrelation observed in $Y$. $\varepsilon$ is an $n*1$ matrix of autocorrelated error terms, $W$ is an $n*n$ matrix of spatial weights, and $\zeta$ is an $n*1$ matrix of independent and identically distributed error values.
Results

**Mobility change among cities**

Apple daily Mobility Data in 2020 was utilised to present the time-series trend for city mobility in Fig.4. The yellow rectangular boxes in figure 4 highlight the lockdown milestones.

Taking the mobility index of 13th January 2020 as the benchmark for each city, it was obvious that mobility dropped significantly during each lockdown, especially during the early stages of each. This same trend is noticeable regardless of the mobility mode or the city. To get a vivid impression of the mobility change in the context of each city specifically, spatial exploration of at the finest geographical scale could be realised in an interactive way. Both monthly and daily mobility change data among finest geographical units (LSOA and SA2) could be accessed from [http://comparecitycrime.com](http://comparecitycrime.com)

To investigate the relationship between mobility change and crime change, this study goes on to explore monthly crime changes of the main crime categories - property crime and violent crime - as presented in section 5.2.
Inter-city monthly crime change by main categories (2020 vs. 2019)

In Fig.6, monthly crime changes in 2020 can be seen alongside year-on-year crime rates in 2019. The graph visualises overall crime rate, property crime rate and violent crime rate respectively, to compare the impact of lockdowns on crime changes. Once again, yellow rectangular frames are used to highlight the lockdown periods in each city (shaded in light yellow).

When compared to the previous year, the monthly changes in overall crime rate witnessed a cliff-drop reduction for all target cities during their first lockdowns (i.e. March to May), and for a majority part of their second lockdowns (i.e. November to December). Since property crimes represent a large proportion of overall crimes, the property crime rate shared similar impacts as overall crimes in response to lockdown. There was a general decreasing trend in the property crime rate during lockdowns. There was an exceptional case in Sydney during the second lockdown, but with a relatively mild change to the crime rate. Violent crimes across both cities shared similar dramatic drops during the first lockdown when compared to
2019. However, unlike property crime rates, violent crime rates remained steady in the second lockdown.

**Inner-city crime change breakdowns during lockdown months**

To locate the prominent crime changes among research units (SA2 in Sydney, and LSOAs in London), it is crucial not only to describe the crime change breakdowns by category (Fig.6 and 8), but also to map the spatial patterns during each lockdown month. Doing so highlights the areas that experience the most significant crime increase and decrease (Fig.7 and 9).

**Sydney**

When compared year-on-year against data from 2019, the variance in crime rate fluctuated according to the type of crime across the lockdown months of March, April, May, and December. During the first lockdown, from March to May, (the winter season in Sydney) there were significant increases in violent crimes like homicide. The data also shows increased crime rates for several types of offences, including pornography, prostitution and owning weapons in the March. General Strain Theory hosts certain explanatory capability for these trends (Agnew, 1992). For example, offences such as pornography might be used as a mechanism to release the strain caused by lockdowns. For sex workers, lockdowns might largely cut off their legitimate income sources, and the perishing financial situation forced them to rely on the street business further. During the same period, there were obvious year-on-year decreases in gaming offences, kidnapping, liquor offences and robbery. Similar crime change impacts were reflected in April and May, and even in December, during the second lockdown. This can be well explained by RAT (Cohen & Felson’s, 1979), given that mobility of motivated offenders and suitable targets is constrained, and people are mostly staying at homes as capable guardians. Blackmail and extortion became the dominating category to experience increased crime rates, quadrupling by the end of the year. These two types of crime might have risen because mobility and direct contact between offenders and victims is not necessary, which thus had not been impacted by lockdowns. Theft, as the main crime type, didn’t experience much change during the lockdown; there was a slight decrease in the number of theft cases during the lockdown first period. This trend for theft can be seen in parallel with another type of crime: transport regulatory offences. Overall, these findings are consistent with the mobility change trends seen upon implementation of NPI measures under lockdown policy.
London witnessed the most significant crime rate drop during the first lockdown, especially for crime types like theft, burglary, and robbery. These categories saw an average decrease of more than 50% year-on-year, dropping most dramatically in April. There were comparable decreases in Violence Against the Person cases in April (down 30%), and Possession of Weapons dropped in March (by over 30%). These patterns are consistent with the findings of most researchers (e.g., Abrams, 2021; Langton et al., 2021; Payne et al., 2020), who attributed the substantial decline of violent crimes to various COVID-19 containment measures.
However, some other crimes - such as Domestic Abuse and Anti-Social Behaviour - saw large increases during the lockdown period when compared to 2019. Lockdowns largely boost the chance of encounters between offenders and victims of domestic violence (RAT is well applicable here). In addition, pressure during lockdowns could somewhat bring down the mental and emotional conditions of couples, which then enhanced the likelihood of violence and confrontation within families. Similarly to many other studies (e.g., Niles et al., 2021; Zaami et al., 2020), we also found illegal drug offences increased by over 50% in May compared to 2019 and continued increasing into the second lockdown in November. According to GST, drug abuse could be one possible strategy used by many people to alleviate or escape from strains and other mental sufferings caused by lockdowns and the pandemic.

Fig. 8 London Crime Change (%) During Lockdowns (2020 vs. 2019) by Category

Fig. 9 London Crime Change (%) During Lockdowns (2020 vs. 2019) by LSOAs
The visualisation of results identified hot spots in both cities where the crime rate had dropped significantly. These areas with the greatest reduction in crime centred around transportation hubs and city centre areas, which is consistent with the hypothesis that mobility-related crime decreases during periods of national lockdown. It also demonstrates increasing crime rates in parks and other outdoor leisure spaces, in line with the RAT hypothesis that a lack of surveillance, or guardianship, results in increased delinquency. Alongside the overarching trends, the results depict an emerging increase of certain crimes, i.e. cybercrime, and a rocketing increase in drug-dealing over the lockdown periods. These crimes were found to occur in rural areas and parks in the city outskirts, possibly related to tension as defined in the GST model.

**Localised Socio-Economic-Status (SES) Clustering and Spatial Regression**

Upon applying K-Means clustering technique on selected demographical, social, and economic status (SES) variables at the finest geographical scale, an optimal 6 clusters was found in both target cities. The clustering features were included in a spatially weighted regression model on crime change and mobility change, for prediction purposes.

Taking into consideration of the neighbouring regions’ influences on crime change, the mobility change and regional SES profiling, spatial lag model (SLM) and spatial error model (SEM) had been compared to identify the most influential factors on crime change against lockdowns in Table 3. In London, mobility change and neighbouring regions’ crime change had exhibited significant positive influences on crime change; in exception with the insignificant relation between crime change and local SES features. However, Sydney’s crime change had been identified as only affected by its neighbouring areas’ crime changes, rather than the mobility change throughout lockdowns.

Table 3 Spatial Regressions between London and Sydney

<table>
<thead>
<tr>
<th></th>
<th>London</th>
<th>Sydney</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SLM</td>
<td>SEM</td>
</tr>
<tr>
<td>1st Lockdown (i.e., April)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.553</td>
<td>0.068</td>
</tr>
<tr>
<td>Mobility Change</td>
<td>0.304***</td>
<td>0.342***</td>
</tr>
<tr>
<td>SES Cluster</td>
<td>0.178</td>
<td>0.129</td>
</tr>
<tr>
<td>Neighbours’ Crime Change</td>
<td>0.127***</td>
<td>0.130***</td>
</tr>
<tr>
<td>2nd Lockdown (i.e., November/December)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.534</td>
<td>0.062</td>
</tr>
<tr>
<td>Mobility Change</td>
<td>0.375***</td>
<td>0.397***</td>
</tr>
<tr>
<td>SES Cluster</td>
<td>0.149</td>
<td>0.118</td>
</tr>
<tr>
<td>Neighbours’ Crime Change</td>
<td>0.125***</td>
<td>0.127***</td>
</tr>
</tbody>
</table>
Conclusion and discussion

The study modelled mobility change related crime changes in target cities, London and Sydney, to identify places where the crime types experienced the most significant drops during lockdowns (e.g., transit hubs, city centres, etc.), where the main types of crime jumped high due to lack of surveillance (e.g., national parks, public venues, etc.), and where the crimes bounced back due to tension resentment or strain expression, and where were the hot spots for city-featured emerging crime types (e.g., blackmail, drug offences, etc.). It also highlighted the driving effect from mobility change to crime change during lockdown periods in London, but this was not the case in Sydney. The changes in crime patterns during the pandemic provide a natural experiment for two prominent criminological theories: RAT and GST. It is safe to conclude that the impacts of the Covid-19 pandemic on the decline of most crimes greatly rest on RAT as people’s mobility is constrained by lockdowns and the crime triangle of RAT is disrupted. GST, in addition, can be used to explain the increase of particular types of crimes, such as domestic violence and drug abuse, which could be a result of people’s coping mechanisms to escape from the mental and emotional pressure caused by lockdowns and other sufferings of the pandemic. However, we could not ignore a major analysis problem of the current study that the theoretical hypotheses regarding the impact of RAT and GST cannot be warranted by the descriptive and explorative data set. In future studies, dependent variables measuring the actual strain levels people have experienced and changes of routine activities should be included for advanced logistic regression to test how the two theories can account for the changes of different crimes during the pandemic.

The work is expected not only to generate some comparative data-driven evidence for city policy makers on crime prevention strategies and efficient policing, but also to build up a replicable workflow/model based on the identified similarities among target cities, to expand further to a broader range of cities. As crime takes new forms and dynamics during the pandemic, law enforcement agencies should accordingly modify and re-allocate police resources for the emerging priorities. The temporal trends-predictive models based on past observations may not be sufficiently informative now (Campedelli et al., 2020). Therefore, alternative predictive tools, which are capable of considering disruptions of social life as the triggers of new criminal risks, are urgently needed for data-driven strategies to re-assess criminal trends and prevention strategies.
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**Yan Zhang** is a Ph.D. scholar in the School of Regulation and Global Governance (RegNet), Australian National University and Managing Editor of the Asian Journal of Criminology. Research interests: restorative justice, China study, qualitative research.

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