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Investigating the impact of the COVID-19 pandemic on crime incidents number in different cities

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ABSTRACT

The COVID-19 pandemic is strongly affecting many aspects of human life and society around the world. To investigate whether this pandemic also influences crime, the differences in crime incidents numbers before and during the pandemic in four large cities (namely Washington DC, Chicago, New York City and Los Angeles) are investigated. Moreover, the Granger causal relationships between crime incident numbers and new cases of COVID-19 are also examined. Based on that, new cases of COVID-19 with significant Granger causal correlations are used to improve the crime prediction performance. The results show that crime is generally impacted by the COVID-19 pandemic, but it varies in different cities and with different crime types. Most types of crimes have seen fewer incidents numbers during the pandemic than before. Several Granger causal correlations are found between the COVID-19 cases and crime incidents in these cities. More specifically, crime incidents numbers of theft in Washington DC, Chicago and New York City, fraud in Washington DC and Los Angeles, assault in Chicago and New York City, and robbery in Los Angeles and New York City, are significantly Granger caused by the new case of COVID-19. These results may be partially explained by the Routine Activity theory and Opportunity theory that people may prefer to stay at home to avoid being infected with COVID-19 during the pandemic, giving fewer chances for crimes. In addition, involving new cases of COVID-19 as a variable can slightly improve the performance of crime prediction in terms of some specific types of crime. This study is expected to obtain deeper insights into the relationships between the pandemic and crime in different cities, and to provide new attempts for crime prediction during the pandemic.

1. Introduction

The COVID-19 pandemic is one of the most serious global public health events in recent years. The onset and spread of COVID-19 have affected nearly every continent. People’s daily lives and the whole society have been drastically influenced around the world [1–3]. For example, in many cities, traffic is completely restricted [4,5]; non-essential businesses have closed for a very long time; travel has become more and more difficult; and social gatherings are limited [6,7]. Moreover, the COVID-19 pandemic is a huge challenge to education activities [8,9], and many courses are moved online. At the same time, unemployment among many groups of workers increased sharply [10,11]. What’s more serious is that the pandemic has led to a dramatic loss of human life, economic losses and social disruption worldwide, presenting an unprecedented challenge to public health, food systems, and public safety [12]. This also raises attention to other questions related to our lives and security. Does the COVID-19 pandemic have an impact on crime? If so, is this impact strong or weak? If the COVID-19 pandemic has a strong impact on crime, will the pandemic be a factor for analyzing and predicting crimes? These questions motivated this study.

During the COVID-19 pandemic, a few studies have investigated the impact of the pandemic on crime in different regions. For instance, Shayegh and Malpade [13] identified an overall drop of about 40% across crime types in San Francisco and Oakland from March 16, 2020 to March 28, 2020. Campedelli et al. [14] conducted Bayesian structural time-series and focused on nine crime categories, identifying that overall crime has significantly decreased in Los Angeles, as well as robbery, shoplifting, theft, and battery. Felson et al. [15] examined burglary in Detroit during three periods which are related to government recommendations, their findings indicated an overall 32% decline in burglary, with the most substantial change in the third period. De la Mijar et al. [16] used an event study for the intertemporal variation across the 16 districts’ eight common crimes in Mexico City for 2019 and 2020, and indicated a decline in conventional crime during the COVID-19 pandemic, while organized crime remains steady. Ashby [17] found that burglary only declined in Austin, Los Angeles, Memphis, and Scan Fran-

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cisco, serious assaults declined in Austin, Los Angeles, and Louisville, but not in other cities.

In these previous studies, the investigation of the impact on fraud was not reported. Furthermore, in terms of the time series of the daily crime incidents and COVID-19 cases, are there significant correlations in different cities? This is still an open question.

As is known to all, crimes are affected by many factors, such as economic variables [18–21], spatial and temporal autocorrelation factors [22–31], environmental conditions [32–37], and current politics [38,39]. These variables are often used to predict crimes [22,26,40], providing support for crime risk prevention and control. Thus, another noteworthy question is whether COVID-19 pandemic could be considered as a new factor to predict crime? Previous studies gave few ideas about that.

In this paper, we first investigate the differences in four common crime incident numbers (theft, fraud, assault, robbery and burglary) in four large cities (namely Washington DC, Chicago, New York City and Los Angeles) before and during the pandemic. Then the Granger causal relationships between crime incident numbers and new cases of COVID-19 are studied. Finally, based on the results of Granger causality test between crime and COVID-19 pandemic, new cases of COVID-19 with significant Granger causal correlations are conducted to crime prediction to examine whether the new cases can improve the prediction performance of the daily crime incidents numbers.

The paper is organized as follows: In Section 1, the research background is introduced. Section 2 describes the data sets used in this study including the new cases of COVID-19 and crime incident number in different cities, and focuses on the theory and steps of the Granger causality test and crime prediction. The results are presented and discussed in Section 3. Finally, Section 4 draws a conclusion and points to future research.

2. Data and methods

2.1. Data description

Four large cities, namely Washington DC, Chicago, New York City and Los Angeles are selected as the research areas. These cities are typical large cities in the United States with adequate crime and COVID-19 data, and they have similar economic, cultural and social backgrounds. Thus, it is reasonable to compare the impacts of COVID-19 cases (as well as people’s activities influenced by them) on crime patterns among the above four cities. As for crime types, theft, fraud, assault, robbery and burglary are all the most common kinds of crimes throughout the world, specifically, theft, fraud and burglary are property crimes, while robbery and assault are violent crimes. The daily crime records of the US cities are taken from the Open Data DC in the Office of the Chief Technology Officer (https://opendata.dc.gov), the Chicago open data portal (https://data.cityofchicago.org), NYC Open Data (https://opendata.cityofnewyork.us) and Los Angeles Open Data (https://data.lacity.org), that contain the pandemic information collected by government organizations, and free download service. The new COVID-19 cases of the US cities are collected from the Bing COVID-19 Data GitHub repo (https://www.bing.com/covid).

From the datasets, we found that turning points existed, which can divide periods into those before and during the COVID-19 pandemic. Fig. 1 shows the daily new COVID-19 cases in the above cities in which the turning points of the pandemic are marked. For these cities, the turning points are assumed at the days which are related to government prevention and control recommendations of the COVID-19 pandemic. More specifically, the turning point of Washington DC is April 1, 2020 [41], Chicago’s turning point is March 21, 2020 [42], New York City’s turning point is March 20, 2020 [43] and Los Angeles’s turning point is March 15, 2020 [44]. As the daily crime incidents numbers in New York City were updated untimely, the research period of New York City during the pandemic only lasted until September 30, 2020. And the research periods lasted until November 30, 2020, in other cities. As shown in Fig. 1, the number of new COVID-19 cases in Washington DC is low and with less fluctuation. While in Chicago, the first COVID-19 pandemic wave is in April and May, and the second wave is in November. The number of new cases in New York City increases firstly, and then slowly decreases to a stable level. And the statistic is quite different in Los Angeles. The number of new cases increases to the first plateau in July, then slowly decreases, and finally breaks out rapidly in November.

Daily crime incidences numbers in different cities are shown in Fig. 2. Daily crime incidents in Washington DC are fewer than those in the other cities. It is shown that almost all types of crimes witnessed a significant decreasing trend from 2020 to 2021. Also, seasonality and relatively steady daily variations of theft, assault, robbery and burglary can be observed in all four cities. However, for fraud, the daily incidents numbers fluctuate greatly and its seasonal cycle is not very clear as shown in the second panel. The descriptive statistics of crime inci-

![Fig. 1. The daily new cases of COVID-19 in different cities. Green line, blue line, brown line and red line represent new confirmed cases of COVID-19 in Chicago, New York City and Los Angeles respectively. Green dotted line, blue dotted line, brown dotted line and red dotted line represent turning points of COVID-19 pandemic in Washington DC, Chicago, New York City and Los Angeles respectively.](image-url)
Fig. 2. Daily crime incidences numbers in different cities. Green, blue, brown and red line represent the daily crime incidents numbers in Washington DC, Chicago, New York City and Los Angeles, respectively.
Table 1
The descriptive statistics of crime incidents numbers before and during the pandemic in different cities.

| City          | The research period                          | Data category | Mean  | Standard deviation |
|---------------|-----------------------------------------------|---------------|-------|--------------------|
| Washington DC | Before the pandemic (From April 1, 2019 to   | Theft         | 44.828| 7.894              |
|               | November 30, 2019)                            | Fraud         | 28.955| 8.532              |
|               |                                                | Assault       | 4.631 | 2.258              |
|               |                                                | Robbery       | 6.643 | 2.906              |
|               |                                                | Burglary      | 3.398 | 1.963              |
|               | During the pandemic (From April 1, 2020 to    | Theft         | 27.020| 6.866              |
|               | November 30, 2020)                            | Fraud         | 20.320| 6.982              |
|               |                                                | Assault       | 4.775 | 2.385              |
|               |                                                | Robbery       | 5.857 | 3.184              |
|               |                                                | Burglary      | 3.381 | 2.626              |
| Chicago       | Before the pandemic (From March 21, 2019 to   | Theft         | 202.388| 27.107            |
|               | November 30, 2019)                            | Fraud         | 51.380| 13.658             |
|               |                                                | Assault       | 63.886| 10.560             |
|               |                                                | Robbery       | 22.592| 5.888              |
|               | During the pandemic (From March 21, 2020 to   | Theft         | 132.792| 24.017            |
|               | November 30, 2020)                            | Fraud         | 40.576| 16.910             |
|               |                                                | Assault       | 53.925| 11.785             |
|               |                                                | Robbery       | 21.933| 7.757              |
|               |                                                | Burglary      | 21.164| 8.862              |
| New York City | Before the pandemic (From March 20, 2019 to   | Theft         | 386.210| 45.522            |
|               | September 30, 2019)                           | Fraud         | 17.005| 6.163              |
|               |                                                | Assault       | 215.523| 33.840           |
|               |                                                | Robbery       | 37.287| 8.316              |
|               |                                                | Burglary      | 29.400| 6.953              |
|               | During the pandemic (From March 20, 2020 to   | Theft         | 309.907| 60.942            |
|               | September 30, 2020)                           | Fraud         | 8.538 | 4.213              |
|               |                                                | Assault       | 170.256| 36.746           |
|               |                                                | Robbery       | 32.656| 10.195             |
|               |                                                | Burglary      | 39.579| 9.390              |
| Los Angeles   | Before the pandemic (From March 15, 2019 to   | Theft         | 136.602| 17.411            |
|               | November 30, 2019)                            | Fraud         | 28.068| 13.287             |
|               |                                                | Assault       | 133.602| 21.040           |
|               |                                                | Robbery       | 26.368| 5.829              |
|               |                                                | Burglary      | 82.330| 12.541             |
|               | During the pandemic (From March 15, 2020 to   | Theft         | 94.85 | 14.218             |
|               | November 30, 2020)                            | Fraud         | 17.70 | 7.570              |
|               |                                                | Assault       | 120.64| 20.594             |
|               |                                                | Robbery       | 21.23 | 5.206              |
|               |                                                | Burglary      | 68.52 | 15.351             |

...dents numbers before and during the pandemic in different cities are shown in Table 1. In these cities, theft and fraud incidents numbers are large and spread out over a wider range than the other types of crime incidents numbers in most of the cases. For example, the number of theft incidents \((M=44.828, SD=7.894)\) is larger than that of fraud incidents \((M=28.955, SD=8.532)\), assault incidents \((M = 4.631, SD=2.258)\), robbery incidents \((M=6.643, SD=2.906)\) and burglary incidents \((M =3.398, SD=1.963)\) in Washington DC before the pandemic. Here, \(M\) is the mean value of the crime incidents number and SD indicates the standard deviation. In addition, some crime incidents numbers during the pandemic are much fewer than those before the pandemic in these cities, such as theft.

2.2. The Granger causality test between COVID-19 pandemic and crime

To know whether the COVID-19 pandemic influences crimes, Granger causality test is applied [45]. First, time series stationarity is examined with the Augmented Dickey-Fuller (ADF) unit root test to avoid spurious regression [46]. If the calculated ADF statistic is lower than 1% and the p-value of the significance level are lower than 0.05, the null hypothesis that assumes the presence of unit root is rejected, inferring that the time series is stationary. In contrast, if the null hypothesis is not rejected, the time series should be non-stationary. In this study, the first-order difference is applied to non-stationary time series to make all the time series stationary. Then, the Granger causality test is performed, and the optimal lags of the Granger causality test are obtained by the vector autoregressive models through the minimum Akaike information criterion (AIC) value [47].

The essence of the Granger causality test is to test whether the lagged values of a time series can be introduced into the equation of other time series. If a time series is influenced by the lagged values of other time series, both series have Granger causality. For crime time series \(Y_t\) and new COVID-19 cases time series \(X_t\), the regression equation is represented as follows:

\[
Y_t = \sum_{j=1}^{k} a_j Y_{t-j} + \sum_{i=1}^{k} \beta_i X_{t-i} + \epsilon_t
\]

(1)

where \(k\) represents the number of lags included in the regression, \(a_i\) and \(\beta_i\) represent the weights of \(Y_{t-j}\) and \(X_{t-i}\), and \(\epsilon_t\) represents random white noise. The null hypothesis of time series \(Y_t\) and new COVID-19 cases time series \(X_t\) is COVID-19 pandemic does not Granger cause crime, namely, \(H_{0}) \beta_i = 0 (i = 1, 2, ..., k)\), the test statistic for the null hypothesis is computed as follows:

\[
F = \frac{(RSS_R - RSS_{R_0})/k}{RSS_{R_0}/(T - 2k - 1)} \sim F(k, T - 2k - 1)
\]

(2)

where \(T\) is the sample size, \(RSS_R\) represents the residual sum of squares of Eq [40]. When \(\beta_i = 1 (i = 1, 2, ..., k)\), and \(RSS_{R_0}\) represents the residual sum of squares of equation [40] when \(\beta_i \neq 1 (i = 1, 2, ..., k)\). The test statistic follows an \(F\) distribution with \(k\) and \(T - 2k - 1\) degrees of freedom. If the p-value of F-Statistic is lower than 0.05, we can reject the null hypothesis which means that new confirmed cases of COVID-19 Granger cause the crime incidents numbers. In contrast, we accept
Finally, day_avg, time, and causal crime are used to improve the performance of the daily crime incidents numbers. Two indices are used to quantitatively evaluate and compare the prediction results with and without conducting the new COVID-19 cases: root mean square error (RMSE) [31], and percentage root mean square error (PRMSE) [50], which are defined as follows:

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (O_i - P_i)^2} \times 100\% 
\]

\[
\text{PRMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (O_i - P_i)^2} \times \frac{1}{\frac{1}{2} \sum_{i=1}^{n} O_i} \times 100\% 
\]

where \(O_i\) represents the observed value and \(P_i\) represents the predicted value. \(n\) is the total number of predicted days, and the value of \(n\) in this study is 14.

3. Results and discussion

3.1. The difference of crime incidents numbers before and during the COVID-19 pandemic

To examine the impact of COVID-19 on crime incidents numbers in large cities, the differences in crime incidents numbers before and during the COVID-19 pandemic are investigated. Fig. 3, shows the distributions of daily theft incidents numbers before and during the pandemic in four large cities of the U.S (Washington DC, Chicago, New York City, and Los Angeles). As shown in Fig. 3, the theft incidents numbers during the pandemic are much fewer than those before the pandemic in all four cities. The stories of fraud, assault and robbery are quite like that of theft which means that all the four selected cities in the US witness significant decreases in crime incidents number (as shown in Fig. A1, Fig. A2 and Fig. A3, respectively).

The Mobility Trends Reports of Apple (see https://covid19.apple.com/mobility) provides the relative volume of route requests for each country/region, subregion, or city compared to the baseline volume on January 13, 2020. The data of Apple Mobility Trends Reports is based on the direction requested by the users in Apple Maps, which are classified into three categories: walking, driving, and public transit. The average of the three categories’ relative volume is selected to represent mobile trends in different cities. Fig. 4 shows the mobile trends before and during the COVID-19 pandemic in different cities of the U.S. As shown in Fig. 4, the mobile trends of these four cities decreased significantly in March. Specifically, the mobile trend of New York City on March 29, 2020 decreased by 78.97% compared to the baseline. This indicates that people’s activities may have greatly reduced since the COVID-19 pandemic. Because the local authorities of these cities imposed a range of strategies during the COVID-19 pandemic, such as stay-at-home orders, travel bans, closures of schools and so on [51]. These strategies are aimed at limiting interaction to avoid being infected by COVID-19 during the pandemic. According to Routine Activity (RA) theory, less person-to-person contact means less opportunity for crimes, which may explain why the incidents number of crimes decreased during the pandemic.

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Table 2

| City          | Train Sets          | Test Sets         |
|---------------|---------------------|-------------------|
| Washington DC | From 1/1/2010 to 11/16/2020 | From 11/17/2020 to 11/30/2020 |
| Chicago       | From 12/01/2010 to 11/16/2020 | From 11/17/2020 to 11/30/2020 |
| New York City | From 1/1/2010 to 9/16/2020 | From 11/17/2020 to 9/30/2020 |
| Los Angeles   | From 1/1/2010 to 11/16/2020 | From 11/17/2020 to 11/30/2020 |

Table 3

| Data Features | Feature value |
|---------------|---------------|
| month         | Current month |
| weekend       | 0: weekday, 1: weekend |
| holiday       | 0: non-holiday, 1: holiday |
| weekend_avg   | Average number of crime incidents per weekday |
| month_avg     | Average number of crimes incidents per month |
| weekday_avg   | Average number of crimes incidents per weekday |

The statistical law of stationary time series data changes little over time, and can usually be used for time series prediction. Therefore, the stationarity of the time series is examined by ADF test and can apply the first-order difference to make all the time series stationary firstly. Some features including “month”, “weekend”, “holiday”, “week-day_avg”, “weekend_avg” and “month_avg” are extracted in this study (see Table 3). Next, the number of lagging observations is set to one. In other words, the crime incidents numbers at the previous moment are used to predict the crime incidents numbers at the current moment. Finally, all the time series are normalized for LSTM model training.

The LSTM models constructed in this paper are mainly composed of two layers: LSTM and Dense. The train sets that do not contain the features of daily new cases are inputted to the LSTM model. The model uses RMSE as the loss function and uses the Adaptive Moment Estimation to optimize it. The prediction results without conducting the new COVID-19 cases are obtained by input the test set into the LSTM models. Then, the train sets that contain the features of the COVID-19 pandemic are inputted to the LSTM model with the same parameters. The prediction results with conducting new cases are obtained by inputting the test set into the LSTM models. To examine whether the new cases of COVID-19 can improve the prediction performance of the daily crime incidents numbers, two indices are used to quantitatively evaluate and compare the prediction results with and without conducting the new COVID-19 cases: root mean square error (RMSE) [31], and percentage root mean square error (PRMSE) [50], which are defined as follows:

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (O_i - P_i)^2} \times 100\% 
\]

\[
\text{PRMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (O_i - P_i)^2} \times \frac{1}{\frac{1}{2} \sum_{i=1}^{n} O_i} \times 100\% 
\]

where \(O_i\) represents the observed value and \(P_i\) represents the predicted value. \(n\) is the total number of predicted days, and the value of \(n\) in this study is 14.

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Fig. 3. The distributions of daily theft incidents numbers before and during the COVID-19 pandemic in different cities of the U.S. The green boxplots represent the daily theft incidents numbers before the pandemic (2019) while the yellow ones are during the pandemic (2020).

Fig. 4. The mobile trends before and during the COVID-19 pandemic in different cities of the U.S. Green, blue, brown and red line represent the new confirmed cases of COVID-19 in Washington DC, Chicago, New York City and Los Angeles, respectively. Black dotted line represents the baseline of the mobile trends.
An exception is burglary in New York City, since obvious increase in incidents number is witnessed in Fig. A4, while in Washington DC, Chicago and Los Angeles the trend is decreasing. As reported by the New York Post (see https://nypost.com/2020/11/14/new-stats-reveal-massive-nyc-exodus-amid-coronavirus-crime/), more than 300,000 New Yorkers moved away from the city during the pandemic, so large numbers of unoccupied houses and departments may provide many chances for burglaries.

3.2. The Granger causality between COVID-19 pandemic and crime

To answer the question of whether COVID-19 pandemic influences crimes, Granger causality test is conducted. First, stationarity of the time series is examined and ensured to avoid spurious regression. Then, the optimal lags are selected by vector autoregressive models and the results are shown in Table 4. After that, the Granger causality test between crime incident numbers and new confirmed cases of COVID-19 in different cities is implemented, and the results are also shown in Table 4.

As shown in Table 4, several Granger causal relationships are found in these US cities. For example, new confirmed cases of COVID-19 Granger cause the theft incidents numbers in Washington DC since the p-value is lower than 0.05, which means that the relationship is significant. In the US cities, both the number of crime incidents and the new confirmed cases of COVID-19 changed considerably during the periods studied in this paper. So, it is relatively easier to study their statistical laws.

3.3. Crime prediction with conducting new cases of COVID-19

Based on the results of Granger causality test between crime incidents numbers and new cases of COVID-19, several Granger causal relationships are confirmed in the US cities, which motivates us to conduct the new cases of COVID-19 into crime prediction in these cities, and to examine whether the new cases of COVID-19 can improve the prediction performance of the daily crime incidents numbers. In this study, new cases of COVID-19 that only with significant Granger causality are

Fig. 5. Prediction of daily crime incidents numbers in different cities of the US. Black lines and points represent the real daily crime incidents numbers (Observed), red lines and points represent the predicted crime incidents numbers without conducting the COVID-19 cases (Predicted), while green lines and points represent the predictions with conducting the COVID-19 cases (Predicted with COVID-19).
Table 4
The results of the Granger causality test between crime incidents numbers and new cases of COVID-19 in different cities.

| City          | Null Hypothesis                                      | Optimal lags | AIC    | F-Statistic | p-value | Conclusion |
|---------------|------------------------------------------------------|--------------|--------|-------------|---------|------------|
| Washington DC | COVID-19 pandemic does not Granger cause theft       | 7            | 16.168 | 3.746       | 0.025∗ | Refuse     |
|               | COVID-19 pandemic does not Granger cause fraud        | 7            | 17.830 | 3.627       | 0.028∗ | Refuse     |
|               | COVID-19 pandemic does not Granger cause assault      | 7            | 13.407 | 1.591       | 0.139  | Accept     |
|               | COVID-19 pandemic does not Granger cause robbery      | 7            | 10.908 | 0.458       | 0.864  | Accept     |
|               | COVID-19 pandemic does not Granger cause burglary     | 7            | 12.534 | 0.416       | 0.892  | Accept     |
| Chicago       | COVID-19 pandemic does not Granger cause theft       | 10           | 21.740 | 2.407       | 0.010∗ | Refuse     |
|               | COVID-19 pandemic does not Granger cause fraud        | 10           | 20.450 | 0.849       | 0.582  | Accept     |
|               | COVID-19 pandemic does not Granger cause assault      | 9            | 20.651 | 3.727       | 0.000∗ | Refuse     |
|               | COVID-19 pandemic does not Granger cause robbery      | 14           | 19.952 | 0.794       | 0.684  | Accept     |
|               | COVID-19 pandemic does not Granger cause burglary     | 9            | 23.574 | 1.413       | 0.183  | Accept     |
| Los Angeles   | COVID-19 pandemic does not Granger cause theft       | 7            | 23.670 | 1.371       | 0.218  | Accept     |
|               | COVID-19 pandemic does not Granger cause fraud        | 7            | 22.406 | 2.068       | 0.040∗ | Refuse     |
|               | COVID-19 pandemic does not Granger cause assault      | 8            | 24.265 | 1.508       | 0.155  | Accept     |
|               | COVID-19 pandemic does not Granger cause robbery      | 7            | 21.753 | 2.293       | 0.028∗ | Refuse     |
|               | COVID-19 pandemic does not Granger cause burglary     | 7            | 24.280 | 0.438       | 0.878  | Accept     |
| New York City | COVID-19 pandemic does not Granger cause theft       | 7            | 24.813 | 2.361       | 0.032∗ | Refuse     |
|               | COVID-19 pandemic does not Granger cause fraud        | 7            | 20.920 | 0.852       | 0.546  | Accept     |
|               | COVID-19 pandemic does not Granger cause assault      | 7            | 24.679 | 2.142       | 0.042∗ | Refuse     |
|               | COVID-19 pandemic does not Granger cause robbery      | 7            | 22.520 | 2.130       | 0.043∗ | Refuse     |
|               | COVID-19 pandemic does not Granger cause burglary     | 3            | 25.063 | 0.348       | 0.791  | Accept     |

* Denotes a significance level lower than 0.05.

Table 5
Evaluations for the crime predictions.

| City          | Crime   | Crime prediction | Crime prediction (with COVID-19) |
|---------------|---------|------------------|----------------------------------|
|               |         | RMSE            | PRMSE               | RMSE          | PRMSE          |
| Washington DC | Theft   | 8.175           | 27.38%              | 7.220         | 24.18%         |
|               | Fraud   | 6.441           | 26.84%              | 5.268         | 25.13%         |
| Chicago       | Theft   | 15.434          | 13.03%              | 9.713         | 8.20%          |
|               | Assault | 6.853           | 15.47%              | 6.171         | 13.93%         |
| Los Angeles   | Fraud   | 4.427           | 38.50%              | 4.154         | 36.12%         |
|               | Robbery | 5.399           | 25.98%              | 4.973         | 23.93%         |
| New York City | Theft   | 84.877          | 27.40%              | 73.383        | 23.69%         |
|               | Assault | 28.924          | 17.33%              | 28.150        | 16.92%         |
|               | Robbery | 9.479           | 23.96%              | 8.927         | 22.56%         |

tried to improve the crime prediction by LSTM models. The results of ADF test are shown in Table A1, and the parameters of LSTM models are shown in Table A2.

Fig. 5 shows the predictions of daily crime incident numbers for two weeks in different cities of the US, in which both the results with and without conducting COVID-19 are shown. As shown in Fig. 5, the predicted values are approximately consistent with the observations. Moreover, the prediction results with and without conducting the new COVID-19 cases are quite close to each other.

In order to quantitatively evaluate and compare the prediction results, the indices RMSE and PRMSE are calculated and their values are shown in Table 5. As indicated by them, models conducting COVID-19 cases perform slightly better than those without the cases. This demonstrates that involving new cases of COVID-19 as a variable can improve the performance of crime prediction in terms of some specific types of crime.

4. Conclusion

This study investigates the impact of COVID-19 pandemic on crimes in four large cities (namely Washington DC, Chicago, New York City and Los Angeles). The differences in crime incident numbers before and during the pandemic are investigated, and the Granger causal relationships between crime incident numbers and new cases of COVID-19 are examined. Then, significant correlations between COVID-19 and crimes are used to improve the crime prediction performance.

Overall, the result shows that crime is indeed impacted by the COVID-19 pandemic, but it varies in different cities and also with different crime types. Most types of crimes have seen fewer incidents numbers during the pandemic than before. For example, theft numbers decrease significantly in these cities. Moreover, in three of the US cities, theft numbers are proved Granger caused by the new cases of COVID-19. For some other crime types and cities, similar results are reported. This may be partially explained by the Routine Activity theory and Opportunity theory that people may prefer to staying at home to avoid being infected with COVID-19 during the pandemic, giving fewer chances for crimes.

Although providing some new insights on the relation between the COVID-19 pandemic and crimes, our work comes with some limitations. For the reason of data limitation, the research area only involves American cities. For future work, more data from other large cities around the world are recommended to use for investigating the impact of the pandemic on crime. This may be more helpful in comparing the results between different countries all through the world. Apart from that, some other variables are expected to be extracted from the COVID-19 pandemic as new indices (such as variations of travel frequency, individual income, etc.), which may be useful to explore deeper relations and laws between pandemic and crime as well as to improve the crime prediction performance.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests.
Appendix A

Figs. A1, A2, A3 and A4, Tables A1 and A2.

Fig. A1. The distributions of daily fraud incidents numbers before and during the COVID-19 pandemic in different cities of the U.S. The green boxplots represent the daily fraud incidents numbers before the pandemic (2019) while the yellow ones are during the pandemic (2020).

Table A1
The results of the Augmented Dickey-Fuller test for different crime incidents numbers during the COVID-19 pandemic in different cities.

| City          | Variable | ADF statistic | p-value | Critical Values | Conclusion       |
|---------------|----------|---------------|---------|-----------------|------------------|
|               |          |               |         | 1% Level  | 5% Level  | 10% Level  |               |
| Washington, DC| Theft    | −3.523        | 0.007*  | −3.432      | −2.862      | −2.567      | Stationary    |
|               | Fraud    | −4.552        | 0.000*  | −3.432      | −2.862      | −2.567      | Stationary    |
| Chicago       | Theft    | −2.025        | 0.276   | −3.432      | −2.862      | −2.567      | Non-stationary|
|               | D(Theft) | −15.279       | 0.000*  | −3.432      | −2.862      | −2.567      | Stationary    |
| Los Angeles   | Fraud    | −4.279        | 0.000*  | −3.432      | −2.862      | −2.567      | Stationary    |
|               | Assault  | −3.810        | 0.003*  | −3.432      | −2.862      | −2.567      | Stationary    |
|               | Robbery  | −3.972        | 0.002*  | −3.432      | −2.862      | −2.567      | Stationary    |
| New York City | Theft    | −4.600        | 0.000*  | −3.432      | −2.862      | −2.567      | Stationary    |
|               | Assault  | −4.423        | 0.000*  | −3.432      | −2.862      | −2.567      | Stationary    |
|               | Robbery  | −3.516        | 0.001*  | −3.432      | −2.862      | −2.567      | Stationary    |

* Denotes a significance level lower than 0.05. D (Theft) represents the first difference of the theft time series.
Fig. A2. The distributions of daily assault incidents numbers before and during the COVID-19 pandemic in different cities of the U.S. The green boxplots represent the daily assault incidents numbers before the pandemic (2019) while the yellow ones are during the pandemic (2020).

Table A2
The parameters of LSTM models.

| City              | Variable | Batch Size | Epochs | Hidden Neurons |
|-------------------|----------|------------|--------|----------------|
| Washington, DC    | Theft    | 1          | 50     | 3              |
|                   | Fraud    | 1          | 50     | 1              |
| Chicago           | Theft    | 1          | 20     | 2              |
|                   | Assault  | 1          | 10     | 6              |
| Los Angeles       | Fraud    | 1          | 30     | 8              |
|                   | Robbery  | 1          | 20     | 1              |
| New York City     | Theft    | 1          | 10     | 3              |
|                   | Assault  | 1          | 10     | 3              |
|                   | Robbery  | 1          | 20     | 7              |
Fig. A3. The distributions of daily robbery incidents numbers before and during the COVID-19 pandemic in different cities of the U.S. The green boxplots represent the daily robbery incidents numbers before the pandemic (2019) while the yellow ones are during the pandemic (2020).
Fig. A4. The distributions of daily burglary incidents numbers before and during the COVID-19 pandemic in different cities of the U.S. The green boxplots represent the daily burglary incidents numbers before the pandemic (2019) while the yellow ones are during the pandemic (2020).
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