



Article

# Spatial Patterns of COVID-19 Incidence in Relation to Crime Rate Across London

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**Abstract:** COVID-19 containment policies are not only curbing the spread of COVID-19 but also changing human behavior. According to the routine activity theory, owing to lockdown, the closure of entertainment sites (e.g., pubs and bars), an increase in stay-at-home time, and an increase in police patrols are likely to influence chance of committing a crime. In this study, we aimed to further examine the spatial association of COVID-19 infection rate and crime rate. Particularly, we empirically validated the speculation that increase in COVID-19 cases is likely to reduce crime rate. In the empirical study, we investigated whether and how COVID-19 infection rate is spatially associated with crime rate in London. As the spatial data used are mainly areal data, we adopted a spatial regression mode (i.e., the “random effects eigenvector spatial filtering model”) to investigate the spatial associations after controlling for the socioeconomic factors. More specifically, we investigated the associations for all the four crime categories in three consequent months (March, April, and May of 2020). The empirical results indicate that 1) crime rates of the four categories have no statistically significant associations with COVID-19 infection rate in March; 2) violence-against-the-person rate has no statistically significant association with COVID-19 infection rate; and 3) robbery rate, burglary rate, and theft and handling rate have a statistically significant and negative association with COVID-19 infection rate in both April and May.

**Keywords:** crime rate; COVID-19 infection rate; bivariate Moran’s I test; containment policies; spatial regression analysis



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## 1. Introduction

Global crises (e.g., global warming, financial crisis, and pandemic) have been reshaping the world. To draw proper responses and interventions, it is of great significance to first understand how the environment and society have been fundamentally influenced by such crises. Compared to global warming or financial crisis, COVID-19 pandemic that has a short-term but significant impact on environment and society requires faster responses. Unlike the last global pandemic, the “1918 flu” that occurred one century ago, COVID-19 occurred in a highly globalized modern society in which the interactions between people, society, and environment have become extremely complex. This leads to a number of important questions as a result, including whether and how the above interactions have to be reconsidered accordingly during and after pandemic. From a sociological perspective, it is of interest to investigate how COVID-19 is changing human behavior and how this may affect the approaches of urban governance. Particularly, compared with rural areas, urban areas are worth in-depth investigations, as they are main hotspots of COVID-19 infections, also with more complex interacting systems and more intensified human activities. After

the COVID-19 outbreak, a large number of emerging studies focused on the prediction of COVID-19 spread [1,2] and on identifying influential factors [3,4]. Meanwhile, the COVID-19 pandemic has greatly influenced urban environments and urban society. The large lockdown in urban areas has caused a series of chain reactions, such as the reduced air pollution [5] and the simultaneously increased housing waste [6]. Containment policies have great impact on people's lifestyles as well [7]. The closure of public places (e.g., pubs, bars, schools) and working from home are dramatically changing people's daily routine. Owing to stay-at-home and social distancing measures, public gatherings have dramatically dropped; meanwhile, police patrols have largely increased. According to the routine activity theory, the occurrence of crime is expectedly influenced by the change of daily routine as the result of this pandemic [8–10]. For instance, as people spend more time at home and less time on streets, it is likely to curb both violent crime (e.g., robbery) and property crime (e.g., burglary and thief). Moreover, as the impact of daily route activities on the occurrence of crime is likely to differ by category, the outbreak of the pandemic might have distinct effects on the occurrence of different crime categories. A number of countries, regions, or cities have reported a decline in total crimes after the outbreak of COVID-19 [8–10]. In recent months, a few studies found declines in some crime categories are associated with COVID-19 policies [8–10]. Surprisingly, in Spain and Portugal, thefts have decreased by 90.2% from the second half of March 2019 to the same period of 2020 [9]. Containment policies may also impact crime occurrence through changing human behavior. For instance, in the wake of official responses to COVID-19, mass lockdowns, and stay-at-home orders issued by state governments throughout the U.S., there has been a decline in crime [10].

Moreover, the effects of COVID-19 containment policies on crime are found to vary from one category to another [11–13]. For instance, in Los Angeles, there is a significant decline in the incidence of robbery, shoplifting, theft, and battery, whilst there is no significant decline in the incidence of vehicle theft, burglary, assault with a deadly weapon, intimate partner assault, and homicide [12]. Similarly, Gerell et al. [13] found that assaults, pick-pocketing, and burglary in Sweden have decreased significantly, while personal robberies and narcotics crime remained unchanged during the past spreading period of COVID-19. Payne et al. [14] found social distancing regulations are temporally correlated with reductions in certain violent crimes since social distancing is likely to have significantly limited interpersonal activities, especially in locations where violence is usually prevalent. Specifically, they found that rates of common, serious, and sexual assaults had declined to their lowest level in a number of years in Queensland, Australia [14]. Particularly, some studies investigated the drop in crime cases induced by the pandemic by comparing the observed real number of crime cases with a newly predicted number from an assumed non-pandemic normal time model based on historical data [12,14]. They used time-series models to predict the number of crime cases in the scenario of no COVID-19 prevention policies [12,14]. Additionally, Felson et al. [15] investigated the impact of containment policies on burglary incidence by taking land use into account. They found that burglaries in Detroit increased in urban blocks with mixed land use but not in blocks dominated by residential land use [15].

Furthermore, some of those studies used routine activity theory to explain the impact of COVID-19 policies on crime trends. For example, commercial burglary increased during the COVID-19 lockdown because businesses were forced to close, and owners and employees were no longer present to act as capable guardians [16]. Assault may decline as there are fewer opportunities for motivated offenders and suitable targets to converge in certain locations, such as alcohol outlets (bars, pubs, etc.) or schools (fights) [16]. Similarly, Boman and Gallupe [10] offer an explanation on the contribution of COVID-19 policies to crime prevention across the United State. Since about half of crime in the U.S. is committed by young offenders, the fundamental reason why crime is down across the U.S. is probably because government-mandated lockdowns have temporarily removed the peer group as a viable means of providing available offenders [10].

Most relevant studies focused on the temporal variations in crime incidence in relation to COVID-19 incidence [8,10,11]. Those studies took no account of other socioeconomic factors affecting occurrence of crime. Although a recent study focused on spatial variations in crime trend, the influential factors fail to account for the extent of COVID-19 infection [17]. To abridge the research gaps, we investigated the spatial association of COVID-19 infection rate and crime rates after controlling for socioeconomic factors. In this study, we used the crime data and the COVID-19 data covering 3 months (March, April, and May of 2020) across the districts of London (i.e., 32 districts). Particularly, this study aimed to examine whether increase in COVID-19 cases is associated with decreased crime incidence. We speculate that increase in COVID-19 cases is likely to reduce crime rate because: (1) increasing COVID-19 cases enhance the fear of COVID-19, which could facilitate the implementation of COVID-19 containing policies according to the protection motivation theory (PMT) [18]; (2) areas with a higher infection rate are likely to be allocated with more police forces, which could curb crime incidence as well [19]. Therefore, we conducted a study to empirically validate this speculation. As a large number of previous studies uncovered that crime is spatially associated with socioeconomic factors such as poverty, unemployment, education level, and so forth [20–25], we need to examine the association of COVID-19 infection rate and crime rate over space after controlling the socioeconomic factors. Moreover, as the data we used are the areal data, spatial regression models (e.g., random effects eigenvector spatial filtering models) were deployed to investigate the spatial association between COVID-19 infection rate and crime rate. Compared with conventional spatial regression models (e.g., spatial lag model, spatial error model, and spatial Durbin model), random effects eigenvector spatial filtering models can effectively reduce model misspecification errors and increase model accuracy. Random effects eigenvector spatial filtering models have been reported to outperform all among spatial regression models in empirical studies [26,27].

## 2. Data and Research Methods

In this section, data on crime, COVID-19 cases, and socioeconomic factors are firstly introduced. This is then followed by how to explore the spatial association between two variables (COVID-19 infection rate and crime rate) without controlling for socioeconomic factors. Finally, this section presents how to explore their spatial association after considering socioeconomic factors. More specifically, the variables to be considered in our models and the spatial regression model devoted to the model estimation are briefly presented.

### 2.1. Case Study and Data

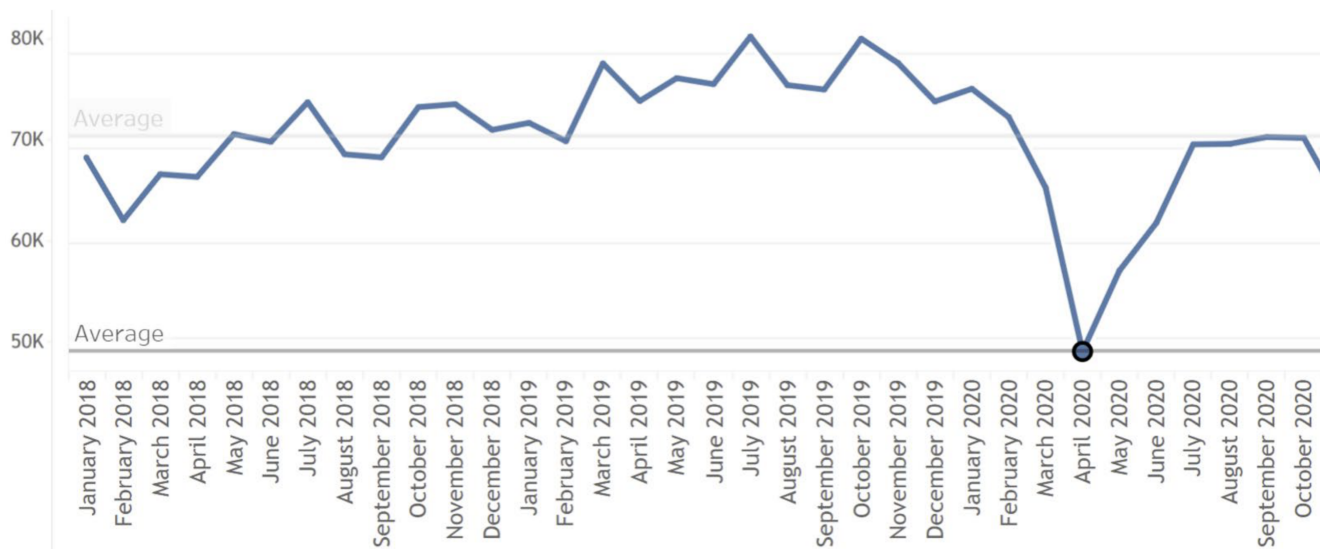
Monthly number of crime cases in London is available from the Metropolitan Police (<https://www.met.police.uk/sd/stats-and-data/met/crime-data-dashboard/>). We compared the monthly number of crime cases between 2020 and two previous years. Table 1 shows the monthly number of crime cases between March to August (i.e., 6 months) in 2018, 2019, and 2020. In each month, the number of crime cases decreased from 2019 to 2020 (see Table 1). Monthly number of crime cases in 2020 was smaller than that in 2018 as well. We conducted a paired *t*-test to compare the half year average monthly number of crime cases between the half year of 2018, 2019, and 2020. In Table 1, as the *p*-value of *t*-test was below 0.01, the half year average monthly number of crime cases in 2020 was statistically significantly lower than those in 2018 and 2019. In this study, we focused on the association of the variables of COVID-19 infection rate and crime rate across Greater London. Specifically, we took account of crimes from March to May 2020 since those three months had the smallest number of crimes in our dataset (see Figure 1). The outbreak of COVID-19 pandemic in the UK started from the end of March 2020, and the first wave of the pandemic in London was from March as well. In the meantime, the crime counts in those three months were also lower than the following months (see Figure 1). Particularly in London, April saw the smallest number of crimes with the largest number of COVID-19 cases (see Figure 1). Crime cases occurred from March to May of 2020 experienced a sub-

stantial drop in comparison with those occurred in the same period of 2019. This indicates that the decrease in city-level crime cases is likely to be associated with the increase of COVID-19 infections.

**Table 1.** Paired *t*-test of COVID-19 infection rate and crime rate for three months.

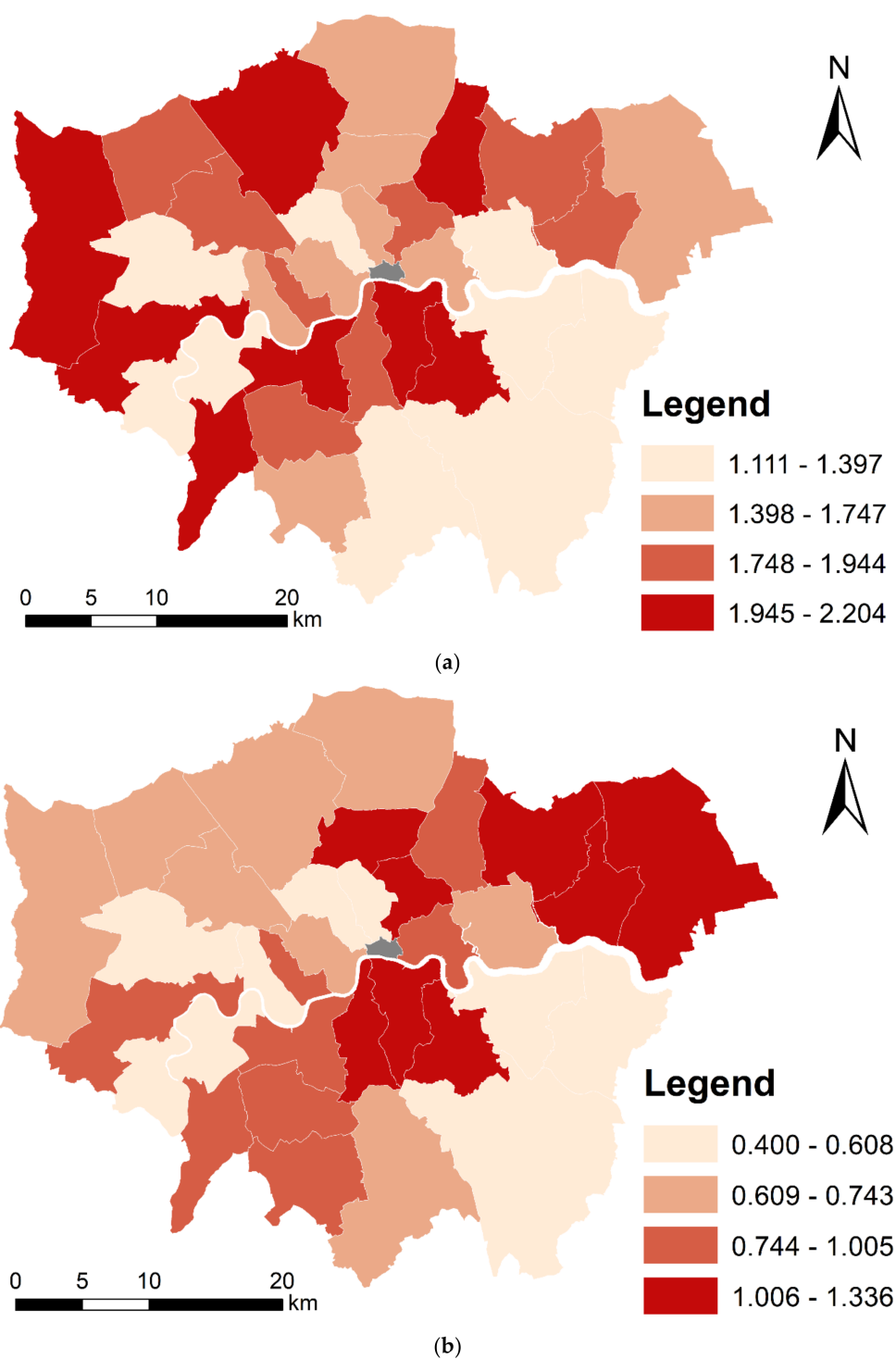
Crime Cases	March	April	May	June	July	August	Mean
2018	67,232	66,953	71,461	70,653	74,819	69,332	70,075
2019	78,906	74,947	77,354	76,721	81,740	76,618	77,714.3
2020	65,819	48,570	57,083	62,112	70,377	71,156	62,519.5
<i>t</i> -test	2018 vs. 2020					0.031 *	
<i>p</i> -value	2019 vs. 2020					0.002 **	

Note: Significance codes: '\*\*\*' 0.01; '\*\*' 0.05.

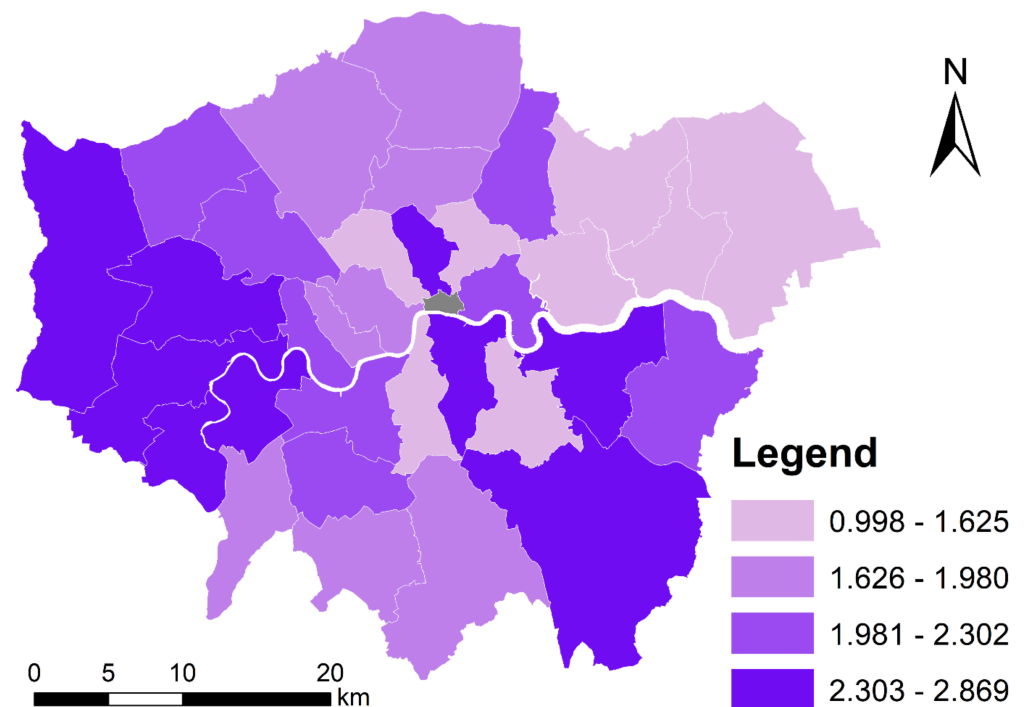


**Figure 1.** Monthly crime counts in London from January 2018 to October 2020 (source: Metropolitan Police).

The historical crime data were downloaded from the official Datastore ([https://data.london.gov.uk/dataset/recorded\\_crime\\_summary](https://data.london.gov.uk/dataset/recorded_crime_summary)). The original crime data are available from the data.police.uk (<https://data.police.uk/data/archive/>). Although the original crime data are at the street level, our analysis was performed at district level. This is because the occurrence of zero crime case in some finer grained units (e.g., streets or census areas) is likely to produce biased results of analysis. Figure 2 maps district-level crime rate (per 1000 persons) across London in April 2020. It is noted that one district (City of London) is excluded in this study as it has a relatively small number of residents. The most up-to-date demographic data, including population, income, and employment data, were downloaded from the Office for National Statistics (<https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/populationestimatesforukenglandandwalesscotlandandnorthernireland>), the Tower Hamlets ([https://www.towerhamlets.gov.uk/Documents/Borough\\_statistics/Income\\_poverty\\_and\\_welfare/income\\_2019\\_1.pdf](https://www.towerhamlets.gov.uk/Documents/Borough_statistics/Income_poverty_and_welfare/income_2019_1.pdf)), and the London Datastore (<https://data.london.gov.uk/dataset/model-based-unemployment-estimates>) respectively. COVID-19 data was downloaded from the London Datastore (<https://data.london.gov.uk/dataset/coronavirus-covid-19-cases>). Figure 3 maps district-level COVID-19 infection rate (cases per 1000 persons) across London in April 2020.



**Figure 2.** District-level crime rates (cases per 1000 persons) across London in April 2020. (a) Violence-against-the-person rate (values grouped into quantiles); (b) Theft and handling rate (values grouped into quantiles)



**Figure 3.** District-level COVID-19 infection rates (cases per 1000 persons) across London in April 2020 (Note: values grouped into quantiles).

## 2.2. Spatial Clustering of Crime Rate

To explore the spatial clustering of crime rate over months, we applied univariate Moran's  $I$  test, which is known as a measure of spatial autocorrelation. A positive Moran's  $I$  test value means a positive spatial autocorrelation, thereby high (low) values are likely to be surrounded by high (low) values as well. A  $p$ -value is produced to indicate the statistical significance of the spatial autocorrelation.

## 2.3. Spatial Association of Crime Rate and COVID-19 Infection Rate

In this study, we first explored spatial association of crime rate and COVID-19 infection rate without controlling for socioeconomic factors. Specifically, we can use bivariate Moran's  $I$  test to explore spatial association of crime rate and COVID-19 infection rate. The observed Moran's  $I$  value is used to quantify the spatial association between two variables. Specifically, a positive association (a positive Moran's  $I$  value) indicates high (low) values of one variable is surrounded by high (low) values of the other variable, whilst a negative association (a negative Moran's  $I$  value) indicates high (low) values of one variable is surrounded by low (high) values of the other variable.

## 2.4. Modeling of Crime Rate

To further examine the association of COVID-19 infection rate and crime rate, we applied regression analysis controlling for socioeconomic factors.

### 2.4.1. Model Variables

In this study, we selected four crime categories as typical crime categories: violence-against-the-person, robbery, burglary, and theft and handling. They are distinct and representative types among all crime categories. Violence-against-the-person and robbery are violence-related types, whilst burglary and theft and handling are property-related types. Violence-against-the-person, robbery, and theft and handling are the most popular crime types in London. Besides, robbery is a typical violent crime which usually occurs on streets. Although some studies suggested replacing population-standardized measure with area-standardized measure due to the possible presence of ecological fallacy or modifiable

areal unit problems [28], this study selected population-standardized crime rate because most of the explanatory variables are population-standardized measures (see Table 2a). The rate of new COVID-19 cases (the number of new COVID-19 cases per population) was used to represent COVID-19 infection rate. In addition to COVID-19 infection rate, socioeconomic factors were considered as the explanatory variables to be controlled (see Table 2b). The socioeconomic factors were used as confounding factors in this study. Moreover, as the observations of crime rate (i.e., VAP\_R, ROB\_R, BUG\_R, and TH\_R) are unlikely to follow a normal distribution according to Shapiro–Wilk normality test, we conducted a logarithmic transformation of those observations to reduce skewness. Therefore, we replaced crime rates (i.e., VAP\_R, ROB\_R, BUG\_R, and TH\_R) with natural logarithm of crime rates (i.e., Ln\_VAP\_R, Ln\_ROB\_R, Ln\_BUG\_R, and Ln\_TH\_R) as the explanatory variables eventually in this study (see Table 2a). In this study, each regression model was set up based on 32 observations (32 districts).

**Table 2.** Introduction and descriptive statistics of variables considered in this study. (a) Response variables; (b) Explanatory variables.

		(a)					
Variables	Full Names	March 2020		April 2020		May 2020	
		Mean	SD	Mean	SD	Mean	SD
VAP_R	Violence-against-the-person rate (cases per 1000 persons)	1.96	0.4	1.71	0.29	1.98	0.36
ROB_R	Robbery rate (cases per 1000 persons)	0.3	0.18	0.12	0.06	0.15	0.06
BUG_R	Burglary rate (cases per 1000 persons)	0.6	0.17	0.41	0.13	0.43	0.13
TH_R	Theft and handling rate (cases per 1000 persons)	1.71	1.44	0.82	0.25	1.01	0.3
		(b)					
Variables	Full Names	Time		Mean	SD		
A_P	Asian percent	2018		17.82	12.39		
B_P	Black percent	2018		11.35	6.18		
YP_P	Young people percent	2019		10.93	1.05		
INC_M	Median household income (1000£)	2019		31.38	4.98		
UNE_R	Unemployment rate (1000 persons/hectare)	2019		4.57	0.75		
NCC_R	Rate of new COVID-19 cases (cases per 1000 persons)	March 2020		1.12	0.3		
		April 2020		1.98	0.47		
		May 2020		0.49	0.18		

#### 2.4.2. Model Estimation

In this study, spatial regression models were estimated to analyze crime rate based on areal data. We used the random effects eigenvector spatial filtering (RE-ESF) model to investigate the association of variables. Moran’s eigenvector-based spatial regression approach is called eigenvector spatial filtering (ESF) [29] in regional science, and ESF with a small number of eigenvectors (e.g., small  $L$ ) can greatly reduce model misspecification errors and increase model accuracy [30,31]. Furthermore, a specification called random effects ESF (RE-ESF) had been recently developed to enhance model estimation because of its usefulness for spatial dependence analysis considering spatial confounding [26,32]. As a new type of spatial regression models, RE-ESF model has been recently applied to geospatial analysis [29,30].

### 3. Empirical Results and Discussion

We report the results of our empirical study in this section with some further discussions. Firstly, we exhibit results on exploratory spatial data analysis. Subsequently, the model estimation results and the contributions of explanatory variables are discussed. The estimates of all the models used in this study were all implemented in R. Specifically, an R package named “spmoran” was developed to implement estimates of eigenvector spatial filtering (ESF) models (<https://cran.r-project.org/web/packages/spmoran/index.html>). Besides, the implementations of univariate and bivariate Moran’s *I* tests can be performed in the open software GeoDa (<https://spatial.uchicago.edu/geoda>).

#### 3.1. Spatial Clustering of Crime Rate

We calculated the univariate Moran’s *I* tests of rates of the four crime categories from March 2020 to May 2020. Table 3 shows the univariate Moran’s *I* testing results for the three months separately in which the computed Moran’s *I* values can be found. We implemented an inference with 999 permutations in each Moran’s *I* test, thereby yielding a pseudo *p*-value to indicate the statistical significance. As Table 3 shows, for all the three months, the spatial autocorrelation of crime rate in London was statistically significant and positive for the two crime categories (i.e., burglary and theft and handling). This indicates that spatial clustering of burglary and theft and handling cases existed during all the three months across London.

**Table 3.** Univariate Moran’s *I* test of crime rate for three months. (a) March 2020 ( $N = 32$ ); (b) April 2020 ( $N = 32$ ); (c) May 2020 ( $N = 32$ ).

(a)				
Moran’s <i>I</i>	VAP_R	ROB_R	BUG_R	TH_R
Value	0.012	0.120 .	0.180 *	0.301 **
(b)				
Moran’s <i>I</i>	VAP_R	ROB_R	BUG_R	TH_R
Value	−0.063	−0.055	0.306 **	0.288 *
(c)				
Moran’s <i>I</i>	VAP_R	ROB_R	BUG_R	TH_R
Value	0.001	−0.177	0.313 **	0.358 **

Note: Significance codes: ‘\*\*\*\*’ 0.001; ‘\*\*\*’ 0.01; ‘\*\*’ 0.05; ‘.’ 0.1.

#### 3.2. Spatial Association of Crime Rate and COVID-19 Infection Rate

Firstly, we explored the spatial association between COVID-19 infection rate and crime rate by performing bivariate Moran’s *I* tests. Specifically, we performed the bivariate Moran’s *I* tests of COVID-19 infection rate and rates of the four crime categories for the three months separately. Table 4 shows bivariate Moran’s *I* testing results for three months separately in which the bivariate Moran’s *I* values can be seen. Similarly, we implemented an inference with 999 permutations in each Moran’s *I* test, thereby yielding a pseudo *p*-value to indicate the statistical significance. As Table 4 shows, the infection-crime spatial association is statistically significant and negative for both the crime categories of burglary and theft and handling and for the two months of April and May.



**Table 4.** Bivariate Moran's *I* test of COVID-19 infection rate and crime rate for three months. (a) March 2020 (*N* = 32); (b) April 2020 (*N* = 32); (c) May 2020 (*N* = 32).

(a)				
Moran's <i>I</i>	VAP_R	ROB_R	BUG_R	TH_R
NCC_R	0.043	0.025	−0.008	−0.029
(b)				
Moran's <i>I</i>	VAP_R	ROB_R	BUG_R	TH_R
NCC_R	0.002	−0.101	−0.174 *	−0.278 **
(c)				
Moran's <i>I</i>	VAP_R	ROB_R	BUG_R	TH_R
NCC_R	−0.058	0.003	−0.245 *	−0.301 **

Note: Significance codes: '\*\*\*\*' 0.001; '\*\*\*' 0.01; '\*\*' 0.05; '.' 0.1.

### 3.3. Modelling of Crime Rate: Regression Model Estimation

We further examined the infection–crime correlation over space, controlling for socioeconomic factors. As one district (City of London) was excluded in this study due to a relatively small number of residents, 32 observations (32 districts) were used in the model estimation. In our regression models, the response variables are natural logarithm of violence-against-the-person rate (Ln\_VAP\_R), natural logarithm of robbery rate (Ln\_ROB\_R), natural logarithm of burglary rate (Ln\_BUG\_R), and natural logarithm of theft and handling rate (Ln\_TH\_R) respectively. The explanatory variables are Asian percent (A\_P), Black percent (B\_P), young people percent (YP\_P), median household income (INC\_M), unemployment rate (UNE\_R), and rate of new COVID-19 cases (NCC\_R). Specifically, we estimated models for all the four crime categories and the three months (4 categories × 3 months = 12 models).

Table 5 shows estimation results for the spatial regression models (i.e., RE-ESF models). *R*-squared and Akaike information criterion (AIC) were used to measure model performance. In addition, variance inflation factor (VIF) values for all the explanatory variables were below five, which indicated that no serious multicollinearity existed in the models estimated. Specifically, the RE-ESF models estimated show that (1) crime rates of the four categories had no statistically significant associations with COVID-19 infection rate in March; (2) violence-against-the-person rate had no statistically significant association with COVID-19 infection rate; and (3) robbery rate, burglary rate, and theft and handling rate were all reported to have a statistically significant and negative association with COVID-19 infection rate in both April and May. Particularly, COVID-19 infection rate was negatively associated with burglary rate and theft and handling rate after controlling for socioeconomic factors in April and May. This is consistent with the above finding without taking account of socioeconomic factors; spatial association of COVID-19 infection rate and crime rate was statistically significant and negative for all the three crime categories (robbery, burglary, and theft and handling) and the two months (April and May) (see Section 3.1).

In addition, we found that socio-demographic factors play different roles in explaining different crime categories. Specifically, the percent of Black population exhibited a statistically significant and positive association with all the four crime categories in March and April. Median household income was found to have a statistically significant and positive association with burglary rate and theft and handling rate in March. Unemployment rate had a statistically significant and positive association with burglary rate in March.

**Table 5.** Estimation results for the regression models. (a) Dependent variable: Ln\_VAP\_R; (b) Dependent variable: Ln\_ROB\_R; (c) Dependent variable: Ln\_BUG\_R; (d) Dependent variable: Ln\_TH\_R.

(a)			
Independent Variables	Coefficient		
	March	April	May
Intercept	−0.036	0.595	0.127
A_P	0.003	0.002	0.001
B_P	0.016	0.012 *	0.012
YP_P	0.001	−0.015	0.015
INC_M	0.006	−0.009	−0.002
UNE_R	0.098 .	0.077 .	0.076
NCC_R	−0.159	−0.074	−0.167
Adjusted R-squared	0.356	0.564	0.499
AIC	31.925	15.024	20.925
(b)			
Independent Variables	Coefficient		
	March	April	May
Intercept	−3.981 .	0.696	−3.023 .
A_P	0.015 .	0.014 .	0.006
B_P	0.054 *	0.052 *	0.027
YP_P	−0.016	−0.155	0.095
INC_M	0.055 .	−0.024	0.012
UNE_R	0.112	−0.025	−0.037
NCC_R	−0.257	−0.640 **	−1.328 **
Adjusted R-squared	0.604	0.637	0.456
AIC	75.273	77.159	65.081
(c)			
Independent Variables	Coefficient		
	March	April	May
Intercept	−3.800 ***	−0.756	0.193
A_P	−0.001	0.003	0.001
B_P	0.017 *	0.027 *	0.006
YP_P	0.050	−0.057	−0.053
INC_M	0.057 ***	0.017	0.000
UNE_R	0.177 **	0.044	0.004
NCC_R	−0.040	−0.351 **	−1.217 ***
Adjusted R-squared	0.672	0.538	0.837
AIC	23.120	47.928	26.563
(d)			
Independent Variables	Coefficient		
	March	April	May
Intercept	−1.110	−0.617	0.467
A_P	0.011	0.007	0.0004
B_P	0.039 .	0.024 *	0.005
YP_P	−0.083	−0.025	−0.018
INC_M	0.067 *	0.019	0.002
UNE_R	0.049	0.066	0.011
NCC_R	−0.518	−0.334 ***	−1.011 ***
Adjusted R-squared	0.434	0.551	0.739
AIC	77.905	43.516	31.165

Significance codes: '\*\*\*' 0.001; '\*\*' 0.01; '\*' 0.05; '.' 0.1.

### 3.4. Discussions

In this study, empirical results indicate in April and May increasing COVID-19 infection rate associated with a decline in robbery rate, burglary rate, and theft and handling rate across London. Previous studies found a decline in the incidence of crime after the implementation of COVID-19 containment policies, which is consistent with results of this study. However, this study derived some different findings with previous studies in certain specific crime categories. For instance, a study found that, in Los Angeles, there was a significant decline in the incidence of robbery, shoplifting, theft, and battery, whilst there was no significant decline in the incidence of vehicle theft, burglary, assault with a deadly weapon, intimate partner assault, and homicide [12]. However, in this study, the increase of the number of COVID-19 cases was found to be associated with the decline in the incidence of burglary. Another study found that, in Sweden, assaults, pickpocketing, and burglary decreased significantly, while personal robberies and narcotics crime were unchanged [13]. Although one of the findings of Gerell et al. [13]—the decline in the incidence of burglary—is consistent with results of this study, its other finding that personal robberies were unchanged is inconsistent with our findings.

According to routine activity theory, there are several reasons behind the discussions of COVID-19 infection rate and crime rate. First, the incidence of residential crime (e.g., burglary and theft) decreases because people have spent much more time staying at home. Second, as Boman and Gallupe [10] explained, public crime is likely to decrease because the young people who are thought to be main offenders lose the opportunity to constitute peer groups after alcohol outlets (bars, pubs, etc) and schools (fights) have been closed due to the large lockdown. Third, owing to increasing police patrols in support of COVID-19 social distancing measures, people are less likely to commit crime on streets (e.g., robbery, commercial burglary, or commercial theft). In London, stricter lockdown measures are likely applied to the districts with a higher COVID-19 infection rate, leading to an increase in stay-at-home time periods and police patrols. The longer the residents stay at home or the more the police patrols there are, the less people are likely to commit a crime (e.g., burglary, robbery, or theft). In addition, since COVID-19 began to outbreak in London since the second half of March in 2020, a lot of people failed to adapt themselves to COVID-19 containment policies (e.g., social distancing measures). Meanwhile, police patrols have not dramatically increased in the most districts of London. Therefore, COVID-19 infection rate and crime rate are found not to be associated in March across London.

### 4. Conclusions and Future Work

In this paper, we examined the spatial association between the two variables of COVID-19 infection rate and crime rate across Greater London. The results empirically validated the speculation that the increase in COVID-19 cases is likely to reduce local crime rate. Although the bivariate Moran's *I* test results indicate that the COVID-19 infection rate appears to be positively associated with the crime rates of all the four crime categories, we found that these associations differ from one crime category to another after controlling for socioeconomic factors. Specifically, the empirical results indicate that (1) the crime rates of the four categories have no statistically significant associations with the COVID-19 infection rate in March; (2) one crime group, the violence-against-the-person rate, has no statistically significant association with the COVID-19 infection rate; and (3) the other three crime groups, to be explicit, robbery, burglary, and theft and handling rates, have a statistically significant and negative association with COVID-19 infection rate in both April and May.

There are some limitations in this study. First, this study focused mainly on exploring spatial association rather than spatiotemporal association, since local socioeconomic data are not updated on a monthly basis. Second, as the data used are aggregate data, there might exist some ecological fallacies. More specifically, the issue of modifiable areal unit (MAUP) often exists in geographical research. Results might change if areal units are changed. Third, the proposed theoretical explanations on research results and such reported

associations lack a validation by realistic human mobility and behavior changes that are supposed to be induced by COVID-19 containment policies. However, this validation cannot be added at present due to the lack of necessary data on real-time human activities. Fourth, our empirical study has only worked on one city, London. Repeating similar studies in more cities across the UK and Europe will enhance the understanding of association between COVID-19 and crime in urban areas. Fifth, exiting studies lack explorations on smaller cities and cities in developing countries, as their situations may be different from the megacity London.

In the future, some further aspects could be considered. First, we would examine the association over space and time simultaneously if monthly updated socioeconomic data could be available in the near future. Second, we would attempt to investigate how COVID-19 containment policies affect human mobility and behavior, which might become measurable by using some emerging new data sources such as cell phone location data or social media data. Third, we would further attempt to examine the impact of human mobility and behavior changes on criminal behavior after the implementation of COVID-19 containment policies. Fourth, we would attempt to extend the study to more cities in the UK or Europe in support of comparative studies. Fifth, since the vast majority of developing countries do not release their spatially fine-grained crime and COVID-19 data, repeating this study and its research methods in developing countries may still be difficult at present. We would attempt to include more cases in developing countries once relevant data become available in the future.

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