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The Spatial Associations between Crime and Economy in Chicago 2015-2020

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The Spatial Associations between Crime and Economy in Chicago

2015-2020

Hongtao Huang

Department of Earth, Atmosphere and Environment

Abstract:

The severity of the crime is often the most intuitive reflection of whether a region is safe and the top factor for the public when evaluating a region. Economist's list of the safest cities in seven major North American cities, Chicago was ranked at six, just above Dallas. Chicago scored the lowest in personal security, which is closely tied to the crime. Against the backdrop of higher unemployment and prices, this study is interested in how property-based crimes are related to the economic decline in Chicago geographically. The study used the heterogeneity analysis tool Geodetector to investigate the correlation between property-related crimes and selected economic indicators; examine the interactions of economic indicators on the selected crimes and estimate the likelihood of occurrence of the crimes base on classifications of the economic indicators.

The results show that robbery, burglary, and Motor Vehicle Theft are less likely to occur in areas with stable economic environments such as high income, low housing vacancy rates, and low unemployment rates than in other areas, but not in Larceny. The spatial distribution of Larceny is not highly correlated with the distribution of either Median Household Income, Vacant Rate, or Unemployment Rate, but is correlated with the Median Household Income &

housing vacancy rate and housing vacancy rate & unemployment rate. but is highly correlated with the spatial distribution of the combination of Median Household Income & housing vacancy rate and housing vacancy rate & unemployment rate. Higher burglary crime risk is likely associated with higher unemployment rates whereas robbery and Motor Vehicle Theft have a greater association with the unemployment rate and housing vacancy than with the other factors.

The rates of vacant homes and unemployment are higher from 2015 to 2020. There is some level of association between higher crime risk and low income, high vacancy, and high unemployment rates in general, the increase in unemployment rates in 2020 is the dominant factor associated with high crime risk. Geodetector is not only able to identify the spatial associations between crimes and individual EIs but also how the interactions between EIs would affect crime risk at different levels.

Keywords:

crime, property-related crime, crime pattern analysis, spatial, spatial distribution, correlation, spatial correlation, spatial association, economy, economic indicators, EI, Geodetector, Chicago

Background:

There are many factors to consider when evaluating whether a city or region is safe, such as Digital security, Environmental security, Infrastructure security, etc. [1], but the most intuitive reflection of whether a region is safe or not is still the crime rate, which is the most priority factor for the public when evaluating a region. In the recent Economist's list of the safest cities in seven major North American cities (Economist 2021), Chicago was ranked at six, just above

Dallas. Chicago scored the lowest in personal security, which is closely tied to the crime. The severity of the crime is often the most intuitive reflection of whether a region is safe and the top factor for the public when evaluating a region. Over the past few years, economic growth has tended to slow down or even stagnate around the world due to the Covid pandemic. Against the backdrop of higher unemployment and prices, it becomes relevant to explore how property-based crimes are related to the economic decline geographically in the city of Chicago. Previous literature suggests that Crime pattern analysis can be used to elaborate the temporal and spatial distribution of cases for crime types with a high probability of recurrence.[2] The methods commonly used for Crime pattern analysis are K-means[3], Getis-Ord statistics[4], ANOVA[5], Moran' I, Local Geary's C, Gi, Gi*, Point Pattern Analysis[6], and Bayesian[7] etc.

Geodetector is a very popular tool for studying spatial heterogeneity in the last decade.[8] The applicable assumption of this tool is that if an independent variable has a significant effect on a dependent variable, then the spatial distribution of the independent and dependent variables should have similarity [9,10]. One advantage of using Geodetector is that it can detect numerical data as well as qualitative data. It can also detect two-factor interactions on the dependent variable. The general way to identify the interaction is to add the product term of the two factors to the regression model to test its statistical significance, especially when the interaction of the two factors is not necessarily multiplicative. By calculating the q-values of each single dependent variable and the q-values of the two dependent variables after superposition, we can determine whether there is an interaction between the two dependent variables, as well as the strength, direction, linearity or nonlinearity of the interaction, etc. In the case where multiple factors influence the dependent variable simultaneously, Geodetector can quickly identify the dominant factor at a specific spatio-temporal node [11].

Although Geodetector is advantageous in detecting the dominant factor of the dependent variable, there is not yet a wealth of studies using Geodetector for Crime pattern analysis. Important recent studies have used the tool to explore crime rate changes at different time scales [12], and there is a complementary relationship with the methodology of my current research theme of exploring crime rate changes at different time points affecting specific crime types. This study will use common influencing factors used in previous literature: social, economic and demographic variables such as income diversity, vacant housing and population size [7] to explore the changes in crime rates in 2015 and 2020 and the dominant factors associated with crime rates.

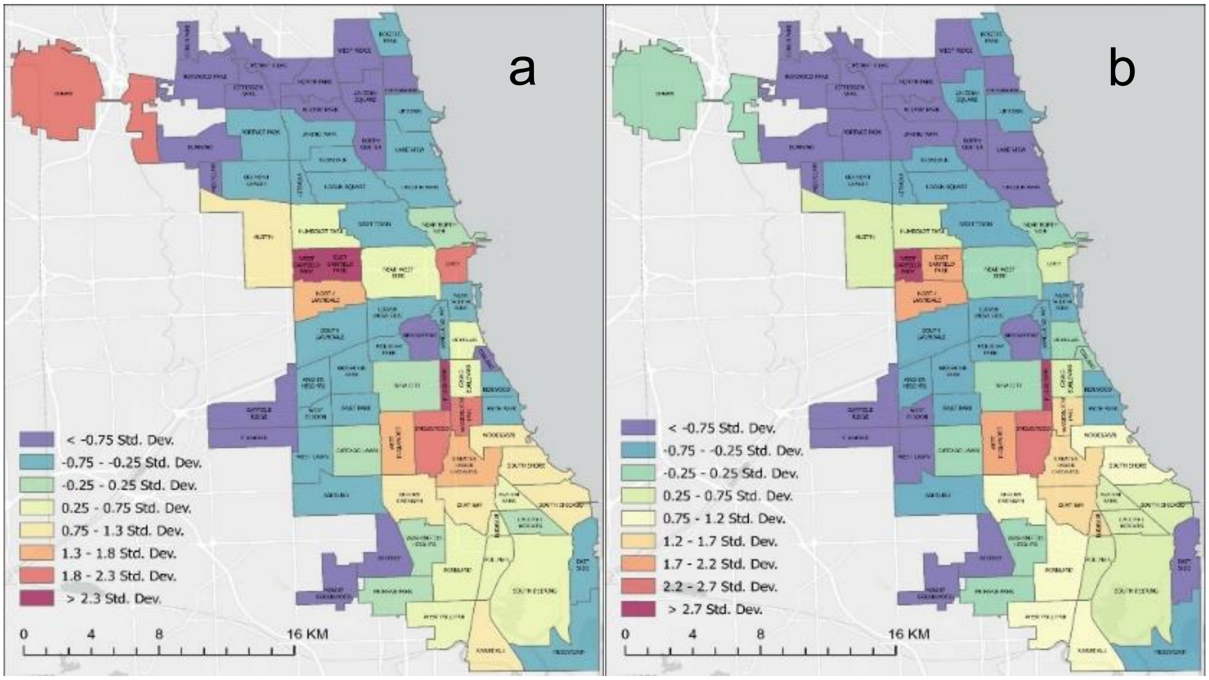
Study Area and Data Source (in 2015 and 2020):

Crime Data From Chicago Data Portal:

1. Robbery (FBI Code: 3)
2. Burglary (FBI Code: 5)
3. Larceny (FBI Code: 6)
4. Motor Vehicle Theft (MVT) (FBI Code: 7)

Economic Indicators Data From The Chicago Metropolitan Agency For Planning:

1. Median Household Income (MHI)
2. Vacant Rate
3. Unemployment Rate



Community Level Crime Rates: (a) 2015; (b) 2020

Methodology:

Spatial Association Analysis – Geodetector (Wang, J.F. et al. 2010):

1. Factor Detector

$$\mathrm{q} = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST},\ q \in [0,1]$$

Where:

L: A selected economic indicator *x*

h: the # of classes of *x*

N: number of units of y

σ^2: the variance of y in for a class of x

SSW: Sum of squares of y within zones

SST: Sum of squares total of y

If *q* is close to 1, then SSW/SST are closer to 0, indicating the spatial distributions of x and y are not similar; If *q* is close to 0, then SSW and SST are similar, indicating the spatial distributions of x and y are similar. In short, if q is small, it means that the spatial distribution of EI does not reflect the distribution of crime rate well. If q is larger, it means that the distribution of EI is highly similar to the actual distribution of crime rate, which can well reflect the association between EI and crime.

2. Interaction Detector

Reclassification of classes according to the intersection of the two Economic Indicators to analyze the level (q-value) of agreement of their spatial distribution with the property-related crimes'.

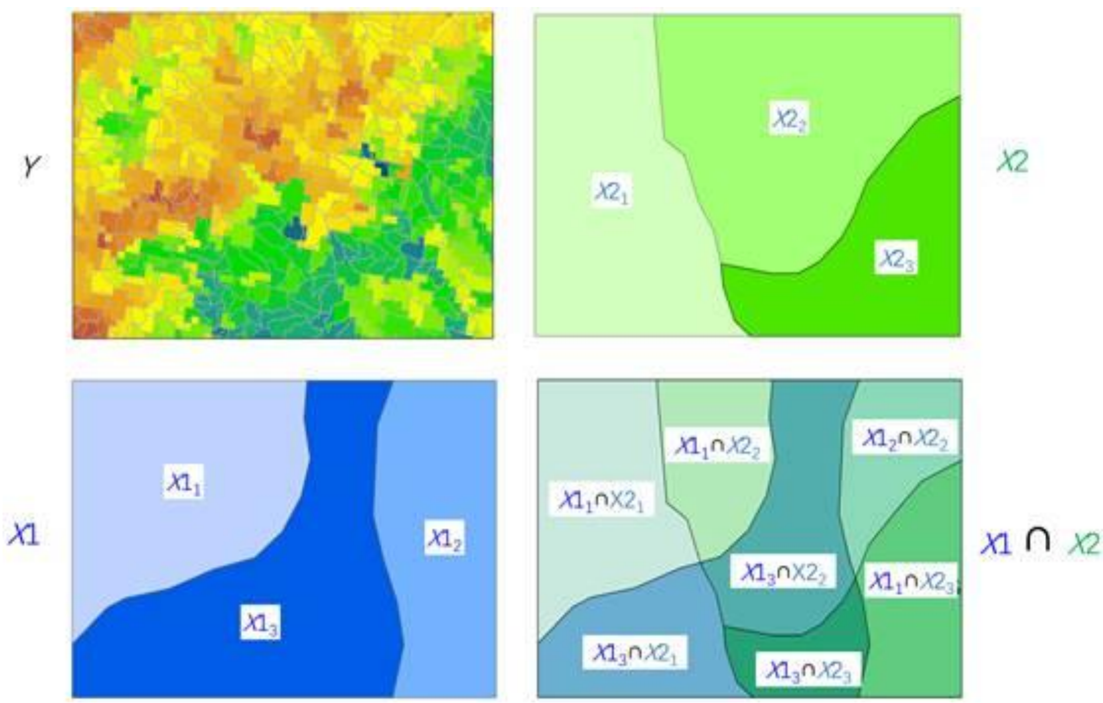


Figure 1 Principle of reclassification [8]

Graphical representation	Description	Interaction
	$q(X1 \cap X2) < \mathrm{Min}(q(X1), q(X2))$	Weaken, nonlinear
	$\mathrm{Min}(q(X1), q(X2)) < q(X1 \cap X2) < \mathrm{Max}(q(X1)), q(X2))$	Weaken, uni-
	$q(X1 \cap X2) > \mathrm{Max}(q(X1), q(X2))$	Enhance, bi-
	$q(X1 \cap X2) = q(X1) + q(X2)$	Independent
	$q(X1 \cap X2) > q(X1) + q(X2)$	Enhance, nonlinear

Figure 2 Interaction Results Evaluation Criteria [8]

3. Risk Detector

Calculate the crime rate of each class in a single indicator separately.

Pearson Correlation Analysis:

Calculate the correlation coefficients of the crimes and economic indicators to verify the results from Geodetector.

Data preprocessing:

The principle of Geodetector is to detect the similarity between the patterns of crime partition and EI partition after classifying the data. In this experiment, the raw data of EI are classified according to the standard deviation:

1. Median Household Income (MHI): Higher income is assigned to a lower class and vice versa.
2. Vacant Rate: Lower vacancy rate is assigned to a lower class and vice versa.
3. Unemployment Rate: Lower unemployment rate is assigned to a lower class and vice versa.

Results:

Factor Detector & Interaction Detector:

Year	2015			2020		
Factor detector q-value	Income	Vacant	Unempl	Income	Vacant	Unempl
Robbery	0.6125	0.6990	0.6007	0.4501	0.6579	0.5538
Burglary	0.4778	0.6129	0.6614	0.3881	0.7186	0.5771
Larceny	0.2601	0.1970	0.3128	0.3790	0.5869	0.3436
Motor Vehicle Theft	0.6755	0.5814	0.6490	0.5269	0.7024	0.6732
Interaction factor q-value	I &V	I & U	V & U	I &V	I & U	V & U
Robbery	0.8649	0.7350	0.9011	0.7192	0.6596	0.7431
Burglary	0.7394	0.6967	0.8971	0.8144	0.7391	0.8103
Larceny	0.8289	0.4191	0.8636	0.7814	0.6753	0.7249
Motor Vehicle Theft	0.7817	0.7596	0.8357	0.7857	0.7825	0.8374

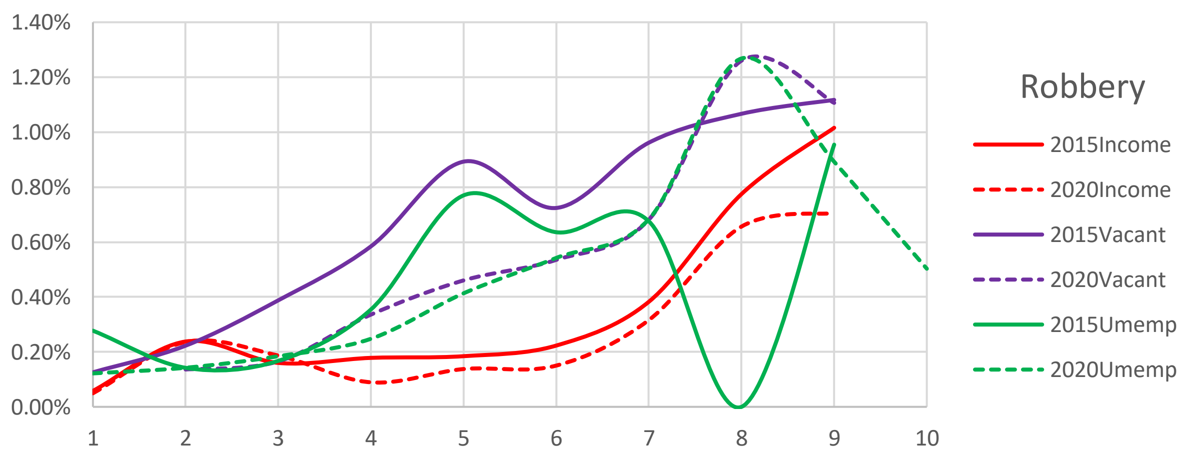
Globally, the data in the table shows that the classification of interactions based on two EIs given by the interaction detector gives a higher q value compared to the q value of individual EIs given by the factor detector. This suggests that the distribution of crime is determined by a variety of factors, in contrast to individual economic indicators that do not reflect the level of crime in a region very accurately.

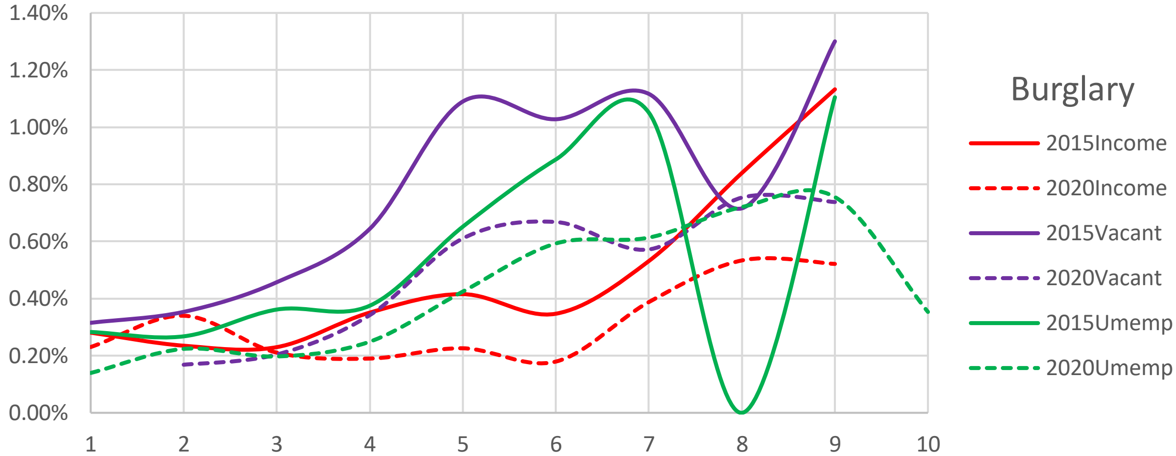
In the factor detector section, in 2015, among the three EIs, the spatial distribution of housing vacancy rate is most similar to Robbery's crime rate, the spatial distribution of unemployment rate is most similar to Burglary's crime rate, and the spatial distribution of MHI is most similar to the distribution of MVT's crime rate, while in contrast, all three EIs do not reflect the spatial distribution of Larceny well, meaning that none of the three EIs are informative when predicting the regional occurrence level of Larceny.

In contrast, in 2020, the housing vacancy rate becomes the EI with the highest correlation with all types of property-related crime among all EIs, and its spatial distribution can reflect the level of crime in an area to some extent.

In the interaction detector section, the increase between the data showed a large difference, except that the values were invariably higher than the corresponding individual q values in the factor detector. Overall, most of the data are between the single q-value and the sum of the q-values of the two EIs. However, it is worth noting that in 2015, the reclassification through the interaction of MHI and housing vacancy rate, as well as the reclassification through the interaction of housing vacancy rate and unemployment rate significantly improved the accuracy of the respondent region larceny's crime level. The q values of these two combinations are greater than the sum of the q values of the individual EIs, which means that the interaction of the two EIs is positively and nonlinearly enhanced.

Risk detector: Trends in crime rates by class in 2015 and 2020:

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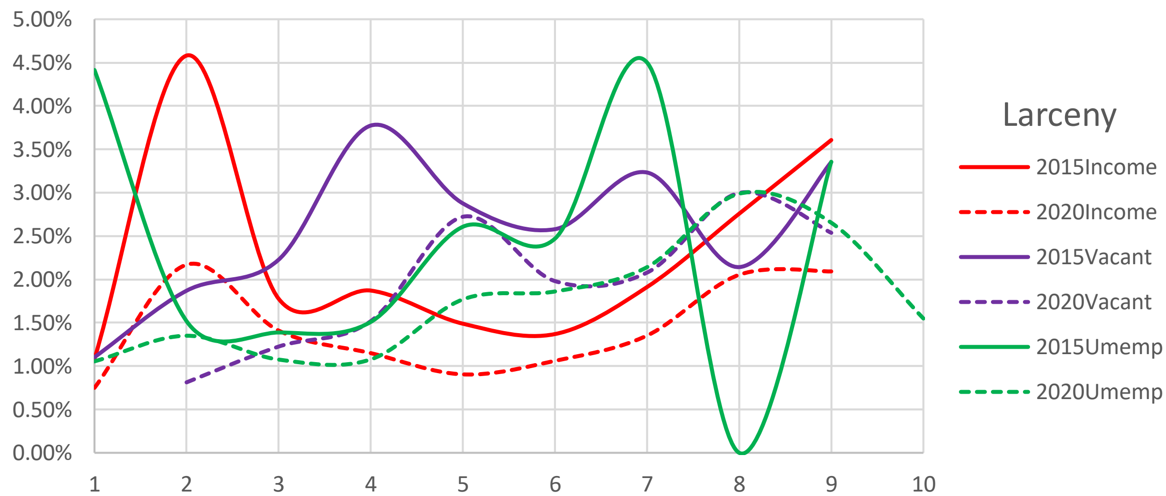
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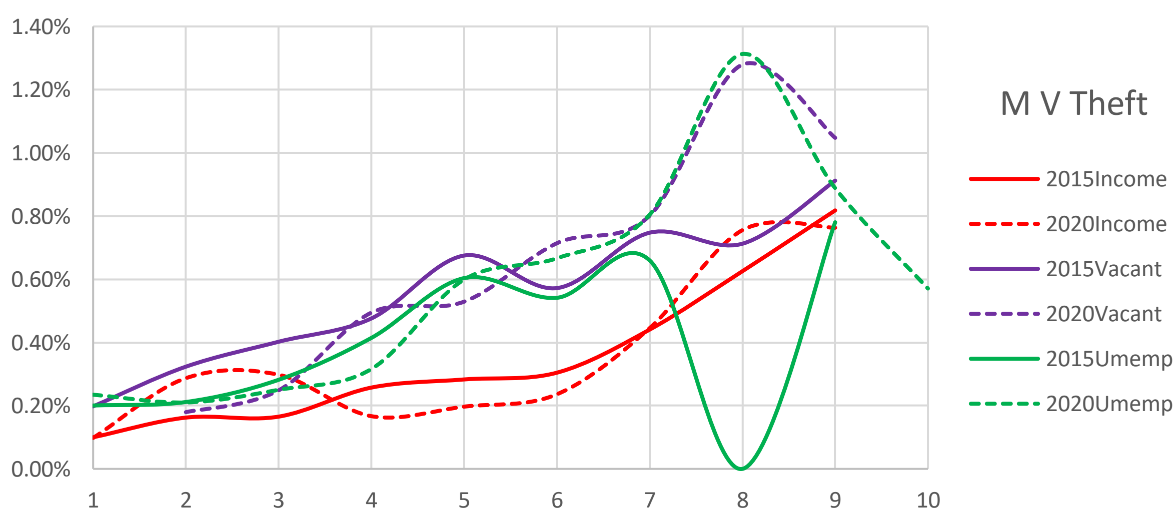
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According to the data preprocessing section, the lower class represents the community belongs to high MVI low housing vacancy rate low unemployment rate (AKA, high-end community) and the higher class represents low MVI high housing vacancy rate high unemployment rate (AKA, Poor Community).

In general, although the curve fluctuates, except for larceny, the high-end community has a much smaller chance of experiencing robbery, burglary, and motor vehicle theft than poor community. Overall, the curve for 2020 is more shifted to the right than that of 2015, which indicates a worse economic environment and more severe associated crime in the community as a whole in 2020.

In the chart set, the data on unemployment rates are particularly unusual: in the 2015 data, no communities are classified as Class8, while in the 2020 data, communities are divided into ten classes according to the variance differences in unemployment rates. This phenomenon indicates that in 2015, there is already a large disparity in unemployment rates among Chicago's neighborhoods, with some of the neighborhoods experiencing the highest unemployment rates being far higher than others and creating a disconnect with other neighborhoods. The situation gets worse in 2020: not only are there neighborhoods classified as class 8, but there are even class 10 neighborhoods with extremely high

unemployment rates, three times the standard deviation above the regional level. It is also for this reason that the curve of the chart becomes irregular.

Result verification:

Since Geodetector is not a common tool for crime studies, it is necessary to verify the results obtained through Geodetector by other methods. With Pearson Correlations, the same results can still be obtained, except that the spatial information is missing: in 2015, the spatial distribution of housing vacancy rate is most similar to Robbery's crime rate, the spatial distribution of unemployment rate is most similar to Burglary's crime rate, and the spatial distribution of MHI is most similar to the distribution of MVT's crime rate, all three EIs are failed to reflect the spatial distribution of Larceny as the correlation is weak; in 2020, the housing vacancy rate becomes the EI with the highest correlation with all types of property-related crime among all EIs.

Pearson Correlations		15Robbery	15Burglary	15Larceny	15MVTheft	20Robbery	20Burglary	20Larceny	20MVTheft
MEDINC	Correlation	-.618**	-.574**	-.005	-.522**	-.408**	-.233*	-.583**	-.750**
	Sig. (2-tailed)	.000	.000	.968	.000	.000	.041	.000	.000
	N	77	77	77	77	77	77	77	77
VacantRate	Correlation	.807**	.730**	.324**	.772**	.781**	.667**	.798**	.737**
	Sig. (2-tailed)	.000	.000	.004	.000	.000	.000	.000	.000
	N	77	77	77	77	77	77	77	77
UnempRate	Correlation	.704**	.772**	.212	.667**	.679**	.459**	.739**	.776**
	Sig. (2-tailed)	.000	.000	.064	.000	.000	.000	.000	.000
	N	77	77	77	77	77	77	77	77

Conclusion and Discussion:

In both years, the factor detectors suggest that the spatial distributions of the individual EIs were more related to robbery, burglary, and MVT than to larceny.

Higher burglary crime risk was likely associated with higher unemployment rates whereas robbery and MVT had a stronger association with unemployment rate and housing vacancy than with the other factors.

The interaction detectors suggest that in 2015, the interactions between two EIs (MHI & housing vacancy rate and housing vacancy rate & unemployment rate) had stronger impacts on larceny than their individual influences combined. While such effects were reduced in 2020, the interactions of EIs still persisted and showed greater impacts on larceny than their individual influences.

According to the risk detector charts, communities with the indicator associated with stable economic environments tended to have lower crime risk in general other than larceny.

The economy went downward from 2015 to 2020 with higher rates of housing vacancy and unemployment. While we observed some level of association between high crime risk and low income, high vacancy and high unemployment rates in general, the rise of unemployment rates in 2020 was obviously the dominant factor associated with high crime risk.

Findings from Geodetector are consistent with the results from the correlation analysis of EIs and crimes. Both suggest much stronger correlations between vacant rates, unemployment and crimes.

This study demonstrated that Geodetector is able to not only identify the spatial associations between crimes and individual EIs but also capture how the interplays between EIs would compound crime risk at different levels.

Different classification schemes may result in different variations of the factors in each class. Future studies will examine how different classification schemes might affect the results.

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