NICOLAUS COPERNICUS UNIVERSITY IN TORUŃ

Bulletin of Geography. Socio-economic Series, No. 59 (2023): 131-150
http://doi.org/10.12775/bgss-2023-0009

BULLETIN OF GEOGRAPHY. SOCIO–ECONOMIC SERIES

journal homepages:
https://apcz.umk.pl/BGSS/index
https://www.bulletinofgeography.umk.pl/

Property crime and violent crime in Detroit: spatial association with built environment before and during COVID-19

Ahmad Ilderim Tokey

The Ohio State University, Department of Geography, 154 N Oval Mall, Columbus OH 43210, United States of America, e-mail: tokey.1@osu.edu

How to cite:

Tokey, A.I. (2023). Property crime and violent crime in Detroit: spatial association with built environment before and during COVID-19. *Bulletin of Geography. Socio-economic Series,* 59(59): 131-149. DOI: http://doi.org/10.12775/bgss-2023-0009

Abstract. This study expands the literature by finding the associations of land use (LU) and road-related Built Environment (BE) with property and violent crime in Detroit from 2019 to 2021. It builds two spatial models with a wide range of built environment elements and sociodemographic information. Findings indicate that the retail and office LU proportion, bus stop density, and density of roads of less than 40 miles per hour are positively linked with crime rates. Conversely, block groups' median income, population density, and tenure length are inversely associated with crime rates. Single-family houses experienced more violent crime in low-income neighborhoods and less in high-income neighborhoods. Bus stop densities in downtown were more positively associated with violent crime in 2020–2021 than in the pre-pandemic time. This study advances understanding related to the BE–crime relationship during the pandemic, sheds new light on street-related BE, and leaves essential evidence for local policymakers in Detroit.

Article details:
Received: 2 January 2023
Revised: 22 February 2023
Accepted: 4 March 2023

Key words:
geography of crime,
built environment,
COVID-19,
spatial error model,
Geographically Weighted Regression

Contents:

1. Introduction

Crime rates and their severity have spatial and temporal dimensions in which scholars have long shown an interest. The physical features and Built Environment (BE) around this spatially concentrated phenomenon (i.e., crime) play vital roles in its generation (MacDonald, 2015). Over the last few decades, a large body of literature has underscored the effects of and associations between a wide range of BE elements. These studies have primarily focused on different land uses (Harrell, 1994; Taylor et al., 1995; Greenberg et al., 1982; Anderson, 2013; Sohn, 2016), schools (Matthews et al., 2010), business places (Wilcox, 2003), liquor stores, pawnshops, motels (Liggett et al., 2001; Loukaitou-Sideris, 2006), abandoned building (LaGrange et al., 1992), and poor visibility (MacDonald, 2015). Another major group of studies has discussed the roles of road-related BE variables. The micro-scale theorists have accentuated the importance of streets and their attributes in crime studies (Groff et al., 2010). These studies have revealed the effects of different types of streets, including thoroughfares (MacDonald, 2015), major streets and alleys (Brantingham & Brantingham, 1993; Loukaitou-Sideris, 2006; Johnson & Bowers, 2010), and street attributes, including lighting (Loukaitou-Sideris, 2006), bus stops (Loukaitou-Sideris et al., 2001), intersections (Sohn, 2016), and sidewalks (Hong and Chen, 2014). However, the understanding of the BE–crime relationship is not sufficiently studied in many major crime-prone US cities. Lately, the various types of crime have been affected due to COVID-19 in different ways (Ashby, 2020; Boman & Gallupe, 2020; Hodgkinson and Andersen, 2020; Syamsuddin et al., 2020; Payne et al., 2021). Some crimes have dropped or remained unchanged, while some other crimes have increased. This made the question more interesting as to whether the association of BE elements and crime rate changed during this pandemic.

The study area of this research is the city of Detroit, which is the largest city in Michigan state. This city is one of the most violent cities in the US (Fieldstadt, 2020; Schiller, 2021). Detroit has had a long history of continued outward migration, the foreclosure crisis, and bankruptcy over the last several decades (Larson et al., 2019). During the COVID-19 pandemic, Michigan has been moderately affected in the US. Criminologists have anticipated the future effects of the economic downturn on Detroit's social sphere (Felson et al., 2020).

We did not find too many studies discussing in detail the effects of BE on crimes in Detroit. Further, there is a dearth of literature on the relationship between BE and crime during this pandemic. The past studies are mostly limited to crime data from 2020 and insights during the later years (e.g., 2021) are scant. To fill the research gaps, the objective of this study is to (1) explore the spatial changes in property crimes and violent crime rates in 2020 and 2021 from 2019, (2) formalize the spatial association of BE and crimes rates in pre-COVID time (i.e., 2019) and during-COVID time (i.e., 2020 and 2021), and (3) look for the local changes in the association of BE with crime due to COVID-19 in Detroit.

The rest of the study is organized into four more sections. The next section discusses the literature on the relationship between BE and crime rates and changes amid this pandemic. The data sources, processing, variable description, and methodological descriptions are discussed in the third section. The fourth section reports the spatial analysis and model results. The discussion on the results and policy implications can be found in the Conclusion section.

2. Literature review

The literature in criminology is centered around several well-established theories, among which social disorganization theory (Shaw & McKay, 1942) and routine activity theory (Cohen & Felson, 1979) are very prominent and influential. The former theory assumes that individual behavior is shaped by its environment and the influential nature of a neighborhood or community. The routine activity theory underscores the recurrent activities of victims with a lack of guardianship as a favorable stage for offenders to commit crimes. In the following subsections, we discuss the built environment, including land use and street attributes and the changes in crime during COVID-19.

2.1. Crime and land-use-related Built Environment

Over the last few decades, there has been a noticeable resurgence of literature studying the impact of BE on crime and shedding light from multiple perspectives. Different land-use (LU) types and zoning are the most common aspects of BE that have widely received researchers' attention.

Among different LU types, most studies found that commercial LU attracts criminal activity. This LU was reported with a higher robbery rate in Washington DC. (Harrell, 1994), higher vandalism rate in Baltimore and Philadelphia (Taylor et al., 1995), and a higher violent crime rate in Indianapolis (Stucky & Ottensmann, 2009). In Atlanta, blocks with high commercial and non-residential land use are also associated with higher crime rates (Greenberg et al., 1982). Also, single and multi-commercial areas are more crime-prone than mixed land use (Anderson et al., 2013). Mixed LU with storefronts facing the streets helps to reduce criminal activity and acts as an eye on the street (Loukaitou-Sideris, 2006). When it comes to residential LU, single-use residential areas are reported to be safer than mixed-use areas (Greenberg et al., 1982; Anderson et al., 2013; Sohn, 2016). Interestingly, in some cases, high-density residential units can be associated with more violent crimes (Stucky & Ottensmann, 2009).

Several other land-use types are also considered to attract criminal activities. For example, physical signs of social incivilities including graffiti, litter, and abandoned buildings (LaGrange et al., 1992), liquor stores, pawnshops, and seedy motels (Liggett et al., 2001; Loukaitou-Sideris, 2006) can be considered as risk-prone establishments. With these, building height can increase crime by lowering the area's visibility and the sense of belongingness and responsibility (Chang, 2011).

2.2. Crime and street-related built environment

The features and environmental configurations of streets play an essential role in attracting or deterring crime. For example, the availability of different kinds of streets, alleys, and desolated areas in the vicinity of crime sites favors criminals being able to escape after committing a crime (Loukaitou-Sideris, 2006). Criminal activities near major streets are easy to perform for criminals (Brantingham & Brantingham, 1993; Johnson and Bowers, 2010; Sargin & Temurçin, 2010). Conversely, criminal activities (e.g., burglary, drive-by shooting) are significantly less common in cul-de-sacs and private roadways (Lasley, 1996; Johnson & Bowers, 2010), and streets away from highways or with no outlet (Hakim et al., 2001). High intersection density and street density are associated with lower residential crime density (Sohn, 2016). Findings related to transit stops are city-specific and not uniform. For example, bus stops are in close proximity to crime locations in Chicago and Bronx (Block & Block, 2000), whereas metros in Washington DC (Lavigne, 1997) and bus stops in Lansing (Kooi, 2013) are relatively safer. Bus stops are risky when they are close to alleys, multifamily housing, liquor stores, check-cashing establishments, vacant buildings, graffiti, litter, etc. (Loukaitou-Sideris et al., 2001).

2.3. Crime and COVID-19

The COVID-19 pandemic has caused enormous changes in people's activity, perception, movement, and economic condition. It consequentially impacted the crime patterns of cities. Scholarly articles have documented the effects of COVID-19 on crime around the world. Although the aggregate crime pattern shows a ubiquitous drop in crime in cities, studies have reported differing changes among different kinds of crime. With the increased level of staying at and working from home, the level of guardianship over personal property has increased, which has caused a decline in residential burglary, drug crimes, and theft (Abrams, 2021) in US cities. In contrast, domestic violence has increased in many parts due to extended staying at home (Leslie & Wilson, 2020; Mohler et al., 2020). Violent crimes like homicides did not increase (Boman & Gallupe, 2020; Abrams, 2021). In some cases, the decrease in crime is associated with a change in routine activities. Estévez-Soto (2021) reported associations – albeit weak – of declined crime with declined public transit usage in Mexico. In Detroit, in the early period of COVID-19 (March 2020), burglaries increased in mixed land use but not in residential land use (Felson et al., 2020). Commercial burglaries increased due to lockdown and decreased after reopening (Carter & Turner, 2021). Violence in Detroit was greater in less-privileged neighborhoods compared to the most privileged ones (Schleimer et al., 2022).

From this review, we have identified three major gaps in the literature. First, no study, to the best of our knowledge, has investigated the BE–crime relationship during the pandemic. So, it is unclear and a question of interest whether the theoretical relationship between built environment and crime has changed during COVID-19. Second, although several works documented the changes in crime in 2020, the insights during the later stages of the pandemic in 2021 are scant. Third, despite the high crime rate, Detroit has received less attention in the crime–BE literature and crime–COVID studies. This study attempts to mitigate these gaps in the following sections.

3. Data and method

3.1. Data source

We collected all the data from the City of Detroit (COD) Open Data Portal, Southeast Michigan Council of Governments (SEMCOG) portal, and American Community Survey (ACS). Table 1 shows the data sources and links. All the data except the sociodemographic data were downloaded as shapefiles.

3.2. Dependent variable

This study uses the census block group as the unit of analysis to aggregate all the independent and dependent variables, since it believes that this is a good trade-off between granularity, sociodemographic data availability, and the ability to represent a neighborhood perception of crime. As the dependent variable, we used data on property crimes (i.e., larceny, damage to property, burglary, stolen property, arson, and forgery) and violent crimes (homicide, justifiable homicide, assault, aggravated assault, robbery, and kidnapping) for Detroit. The numbers of property crimes in 2019, 2020, and 2021 are 32,184, 28,450, and 28,115, respectively. Similarly, the counts of violent crimes in Detroit are 27,776, 26,783, and 25,889 in these three years. We calculated the crime rate (incidents per 1000 persons in a block group) for three years (i.e., 2019–2021) and for property and violent crime. These six aggregated rates for block groups were used as the primary Dependent Variables (DVs). Throughout the study, we transformed the crime rates into logarithms to obtain a normal distribution of DVs and to readily compare the effect of each variable across models.

3.3. Independent variables

We used several LU-based and road-based BE variables as independent variables (IVs). The proportion of single-family residential, multifamily residential, retail, and office LU was used. The number of licensed liquor store and the median building height of block groups were also used as explanatory variables. Among the road-related BE variables, total Vehicle Mile Travelled (VMT) in a block group was used to express traffic flow. The density of roads with different posted speed limits in the block groups (unit: length of road per square mile) was also used, where the speed limits were broadly classified into four bins to accommodate the roadway types. The first category is below 30 miles per hour (mph) which mostly reflects residential areas, school zones, business districts, and alleys (Forbes et al., 2012). The second category includes 30 and 35 mph roads. These are mostly local roads, associated with a greater degree of physical activity, presence of people, and safe biking (Siddiqui et al., 2012; van Loon et al., 2014). The third and fourth categories comprise roads restricted to 40–55 mph (i.e., arterial and collector roads) and 60 mph and above (i.e., interstate highway or freeway). The density of bus stops in block groups (number of bus stops/square miles) was also used.

3.4. Control variables

Several socio-economic and sociodemographic controls are used in this study. The median income of individuals in the block group represents their socio-economic condition. Low income has been found to be more associated with crime, as these areas can have greater social disorganization and lesser community control (Cantor & Land, 1985; Loukaitou-Sideris et al., 2002; Madyun, 2011; Wong, 2012). Residential stability is represented by the

Table 1. Data sources

Data	Agency	Source
Crime data	COD	https://data.detroitmi.gov/datasets/rms-crime-incidents/data
Land use	SEMCOG	https://maps-semcog.opendata.arcgis.com/datasets/land-use/data
Non-residential use	SEMCOG	https://maps-semcog.opendata.arcgis.com/datasets/building-points
Traffic volume	SEMCOG	https://maps-semcog.opendata.arcgis.com/datasets/traffic-volume
Speed limit	SEMCOG	https://maps-semcog.opendata.arcgis.com/datasets/bicycle-network/
DDOT bus stop	COD	https://data.detroitmi.gov/datasets/ddot-bus-stops/data
sociodemographic	ACS	Median income (table B20017), tenure (B25003), median year householder moved (table B25039)

Source: own elaboration

percentage of owner-occupied households in block groups. Stability increases residents' attachment to the neighborhood, thus decreasing the crime rate (Oh, 2004). The third control is the length of residency, which can be equally crucial as stability in predicting crime (Boggess & Hipp, 2010). This is translated by the "median year householders in a block group moved to the area". We classified the moving years into three categories: on or after 2010 (decade10), from 2000 to 2009 (decade00), and before 2000 (decade90). The first category is used as the base category. The fourth control is the population density of the block groups, which can increase surveillance and guardianship, thereby reducing crime (Harries, 2006; Sohn, 2016). Finally, the male–female ratio of block groups is used to control the gender effect. Several other controls were in our initial consideration (e.g., race, education, age), but they were removed from our final analysis for their poor performance in the models and high multicollinearity with the selected controls mentioned here.

3.5. Descriptive statistics

Table 2 shows the descriptive statistics, description, and data type of the variables used in this study. The central values (i.e., mean and median) and diversity (i.e., standard deviation) of the crime rates gradually decreased from 2019 to 2021. There are on average 55% single-family residential LU units in Detroit, 4% multifamily residential LU units, 3% retail or commercial LU units, and 7.5% office LU units. The mean of block groups' median building height is 1.45 storeys, and the block groups have 2.27 liquor stores on average. Block groups have, on average, 22.3% of roads with a posted speed limit of below 30 miles per hour (mph), i.e., 10, 15, 20, 25 mph. The other three categories of roads with speed profile of 30–35 mph, 40–55 mph, and above 55 mph comprises, on average, 6.28%, 0.74%, and 1.12%, respectively, of the roads in block groups. There are around 40 bus stops per square mile in Detroit. The median individual income is around $21,000. The ratios of male–female and owner–renter are almost equal at the city level. In 60%, 27.6%, and 13.2% of the block groups, householders moved after 2010, from 2000 to 2009, and before 2000, respectively.

3.6. Statistical method

We have used two kinds of spatial models to account for the spatial dependence and heterogeneity in our study. The first model is the Spatial Error Model (SEM), which is global and assumes that the error term of regression of a spatial unit is correlated with that of its neighbor (Anselin, 1988). We used another model in this study: Geographically Weighted Regression (GWR). The usefulness of GWR is that it allows one to find how the influence of one variable can vary over space. This model has an enhanced benefit over the global model and can offer insights into local variations not revealed in global models. Crime literature has extensively used SEM (Kepple & Freisthler, 2015; Kelling et al., 2021) and GWR (E. Stein et al., 2016; Xu et al., 2019; Tavares & Costa, 2021) in examining crime and the wide variety of socio-spatial processes.

The functional form of SEM can be expressed with the following equations 1 and 2:

$$y = \beta_0 + X\beta + \varepsilon \tag{1}$$

$$\varepsilon = \lambda W\varepsilon + u \tag{2}$$

Here, y is an N×1 vector outcome where (N = 879 block groups), X is the independent variable in the form of 879×k matrix, β_0 is the intercept, and β is a k×1 vector of regression coefficients. ε is the error term, and the Wε is the spatially lagged error term where the lag is defined by the weight matrix W. λ is the spatial autoregressive parameter, and the null hypothesis is rejected when λ ≠ 0, which means the error is correlated. This model uses Queen's contiguity approach (order one) to define the spatial weight matrix.

The Geographically Weighted Regression (GWR) (Brunsdon et al., 1996) model uses the following form (Equation 3 and 4):

$$y_i = a_{i0} + \sum_{k=1}^{m} a_{ik}x_{ik} + \varepsilon_i \tag{3}$$

$$a(i) = (x^t w(i)x)^{-1} x^t w(i)y \tag{4}$$

Here, the equations are provided for *i* observation, where y_i is its dependent variable. a_{i0} is the intercept of it, and a_{ik} is the value of the k^{th} parameter at location *i* for the independent variable x_{ik}. For each of the independent variables (k=1……m), equation 4 is used to estimate a(i), which depends on the weight matrix w(i). The diagonal entries of this matrix are the weight set by the Gaussian weighting

Table 2. Descriptive statistics

Variable	Description	Min	Mean	Std. Dev	Median	Max
Log_p19	Log of property-related crime in 2019	0.00	3.808	0.708	3.819	6.629
Log_p20	Log of property-related crime rate in 2020	1.11	3.716	0.684	3.725	5.961
Log_p21	Log of property-related crime rate in 2021	0.37	3.699	0.705	3.704	6.058
Log_v19	Log of violent related crime rate in 2019	0.24	3.686	0.756	3.720	5.866
Log_v20	Log of violent related crime rate in 2020	0.00	3.639	0.770	3.697	5.963
Log_v21	Log of violent related crime rate in 2021	0.24	3.610	0.764	3.669	5.998
singl_p	Proportion of single-family LU	0.00	0.549	0.270	0.590	0.997
multi_p	Proportion of multi-family LU	0.00	0.040	0.086	0.009	0.711
retail_p	Proportion of retail LU	0.00	0.032	0.033	0.024	0.234
office_p	Proportion of office LU	0.00	0.075	0.099	0.043	0.740
Stories	Median number of stories	1.00	1.448	0.634	1.274	8.892
Liquor	Number of licensed liquor store	0.00	2.270	6.180	1.000	115.000
busstop_de	Bus stop density (per sq. mile)	0.00	40.043	25.171	37.494	297.397
Vmt	Vehicle mile traveled	0.00	20932.5	29096.6	11533.8	403369.4
speed_1_de	Road density with below 30 mph speed	4.04	22.383	5.572	22.562	37.339
speed_2_de	Road density with 30-35 mph speed	0.00	6.296	3.662	6.205	29.670
speed_3_de	Road density with 40-55 mph speed	0.00	0.747	1.801	0.000	16.789
speed_4_de	Road density with above 55 mph speed	0.00	1.191	2.521	0.000	19.968
median_inc	Median income of individuals	0.00	20989	12439	21964	72917
own_perc	% of owner-occupied households in block group	0.00	50.675	21.314	51.622	100.000
decade90	Median householder moved into unit before 2000	0.00	0.132	0.338	0.000	1.000
decade00	Median householder moved into unit in 2000-2010	0.00	0.276	0.447	0.000	1.000
Decade10	Median householder moved into unit after 2010	0.00	0.59	0.49	1.000	1.000
pop_dens	Population density	96.38	6181.9	3945.94	5367.240	25461.48
MF_ratio	Male-female ratio	0.00	1.213	6.304	0.907	186.500

Source: own elaboration

scheme that uses a distance band to consider features as neighbors and exponentially decrease the weights as the distance increases. We used distance band as neighborhood type, as opposed to the number of neighbors, to have a consistent extent.

The presence of significant clustering in the residual term denotes spatial autocorrelation in the model's error term, which is a common problem for non-spatial models. In our spatial models, we conducted Moran's I test to find the presence of significant clustering in model residual.

4 Results

4.1. Spatial changes in crime rate

Figure 1 shows the distributions of crime rates of block groups in Detroit. The first and second panels show the spatial distribution of property and violent crime rates, respectively. At the bottom of each panel, the temporal change in crime rates is also shown.

For property crime, the crime rate in 2019 is highest around downtown. If we think radially outwards from downtown, after the cluster of high property crime rates, there is an immediate chunk of block groups that has a substantially lower crime rate. The rate again increases as we radially move to the northern and the western areas. In 2020, many block groups around the downtown observed a fall in crime rate, and the high crime rates were more concentrated around downtown. The rates in the northern and western areas were also reduced. In 2021, the rates around downtown pertained, but the western areas showed more drops in property crime rates. These changes can further be understood with the trend of subtypes shown at the bottom. Among the top three subtypes of property crime (i.e., larceny, property damage, burglary), larceny and burglary dropped, and property damage had a slight increase in 2020. In 2021, the decrease in larceny and burglary was sustained, and property damage went to the same level as in 2019. Among the other subtypes, stolen property increased gradually from 2019 to 2021. Arson and forgery were reduced after 2019.

Violent crime shows a slightly different spatial pattern than property crime (panel 2). It depicts concentrations in the downtown, northern, and western parts of the city. However, the distinction in crime in downtown compared to the other parts was not as discernible for violent crime as it was for property crime. Violent crime dropped in 2020 all over the city, and no drastic change was observed in any specific part of the city. In 2021, the crime dropped in several places (mainly in the northwestern part), but concentrations in downtown and the southwest were sustained. The trends at the bottom of Figure 1 tell us that assault gradually declined from 2019 to 2021, whereas aggravated assault increased over the year. Robbery had a gradual decline from 2019, and sexual assault rebounded in 2021 after a drop in 2020. The other subtypes (i.e., homicide, kidnapping, and justifiable homicide) show no major trend.

4.2. BE–crime relation (model result) and changes

Six year-specific (2019–2021) models were fitted with BE and control variables, where three of them are for property crime, and the rest are for violent crime. Table 3 shows the regression output of the global SEM for property crime. Since we used the logarithm of crime rate, the parameter estimates of one variable can be compared across models. We found significant positive associations of single-family LU, multifamily LU, retail LU, and office LU with property crime rate. However, the effects of single-family, multifamily, and office LU diminished over the year. Building height is not significantly related to crime rates. Property crimes are consistently high in areas with greater densities of transit stops and higher traffic volumes, and higher densities of roads with speeds below 30 mph (speed_1_de) and 30 to 35 mph (speed_2_de). Intuitively, the density of highways, arterials, collector roads, and freeways does not affect property crime. In fact, freeway density (speed_4_de) is negatively associated with crime in 2021.

Interestingly, property crime did not vary with median incomes in 2019 whereas, in 2020 and 2021, poorer areas showed more property crimes than their richer counterparts. Areas with more renters are associated with more property crime in 2021, but not in 2019 and 2020. Compared to the new householder (i.e., moved in 2010 and later), older householders (i.e., those who moved in from 2000 to 2009) consistently experienced less crime. However, the crime rates in older areas (i.e., 1999 or earlier) are not significantly different from the areas with the newest householders (i.e., moved in 2010 and later). High population density is strongly related to less property crime, reflecting the effect of natural surveillance and policing in denser areas. We did not find the male–female ratio to be a significant parameter in any models.

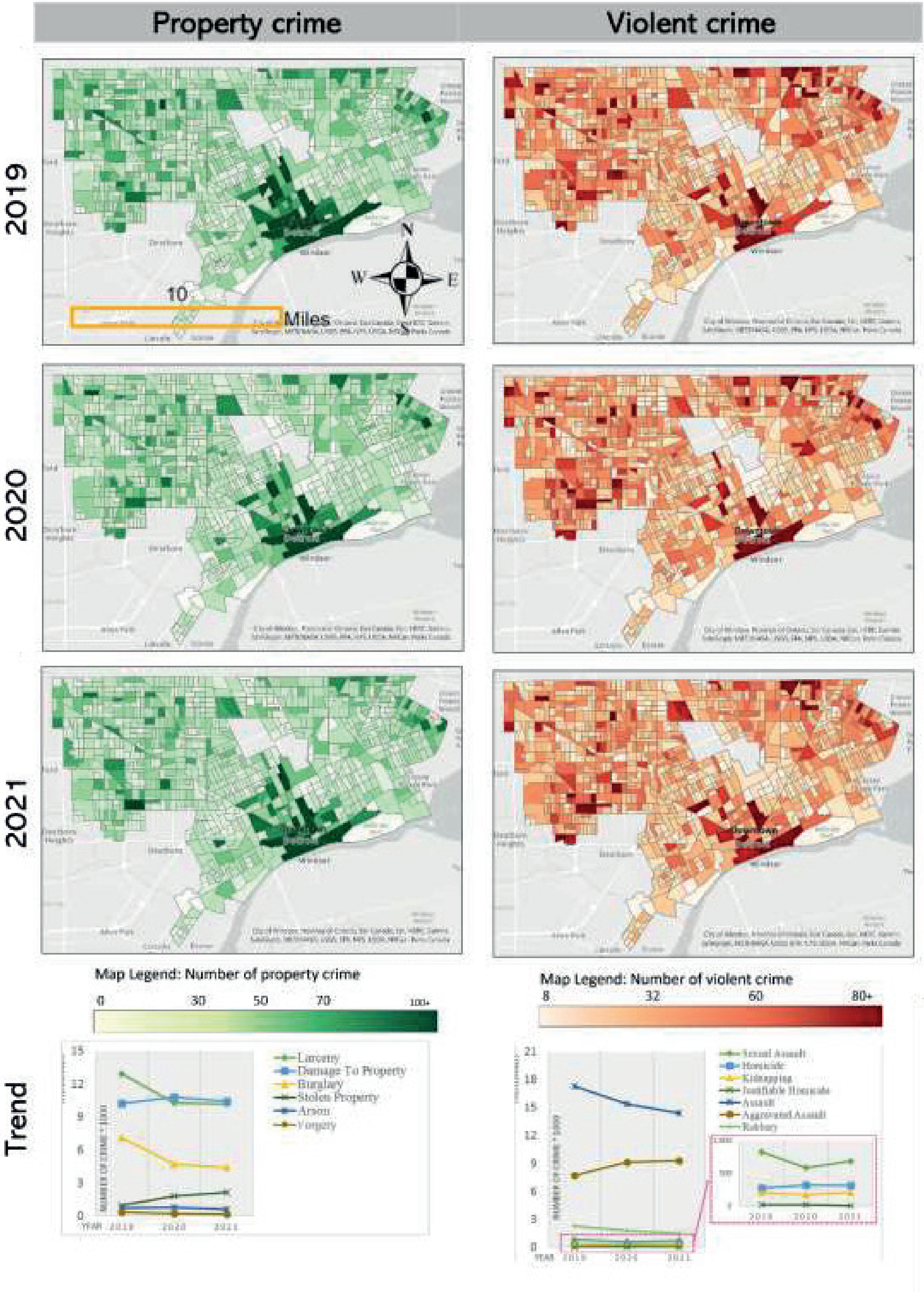

Fig. 1. Distribution of rates (2019–21) of property crime (left panel) and violent crime (right panel) and the trend of their subtypes (bottom)
Source: Author's analysis

Table 3. Regression output from SEM for property crime (DV: log of crime rate)

Variable	2019 coeff.	2019 SE	2020 coeff.	2020 SE	2021 coeff.	2021 SE	VIF
Constant	1.475***	0.064	1.515***	0.060	1.51***	0.063	NA
singl_p	0.217***	0.052	0.167***	0.049	0.122**	0.053	2.787
multi_p	0.536***	0.127	0.464***	0.121	0.379**	0.125	1.768
retail_p	1.1***	0.266	1.3***	0.256	1.093***	0.258	1.220
office_p	0.363***	0.093	0.261**	0.089	0.175*	0.090	1.341
Stories	0.029	0.019	0.023	0.018	0.025	0.019	2.187
Liquor	0.005**	0.002	0.003**	0.002	0.003	0.002	1.838
busstop_de	0.001**	0.000	0.001**	0.000	0.001**	0.000	1.573
Vmt	0.000002***	0.000	0.000001***	0.000	0.000002***	0.000	2.278
speed_1_de	0.008***	0.002	0.008***	0.002	0.009***	0.002	2.032
speed_2_de	0.01***	0.003	0.008**	0.003	0.01***	0.003	1.644
speed_3_de	-0.007	0.006	-0.007	0.005	-0.004	0.006	1.622
speed_4_de	-0.007	0.005	-0.012**	0.004	-0.013**	0.004	1.979
median_inc	-0.000001	0.000	-0.000002**	0.000	-0.000002**	0.000	1.141
own_perc	-0.001	0.001	0.000	0.000	-0.001*	0.001	1.920
decade90	0.021	0.027	-0.022	0.026	0.025	0.027	1.373
decade00	-0.047**	0.021	-0.064**	0.020	-0.025	0.020	1.377
decade10	base						1.755
pop_dens	-0.00005***	0.000	-0.00005***	0.000	-0.00005***	0.000	1.090
MF_ratio	-0.0007	0.001	-0.00089	0.001	0.00024	0.001	1.768
Lambda	0.16**	0.054	0.095*	0.056	0.243***	0.052	NA
Pseudo ρ^2	0.43		0.43		0.46		NA

* p<.10 ** p<.05 *** p<.001

Coeff.: coefficient; SE: Standard Error

Source: own elaboration

Table 4 reports the findings for violent crime. We found that single-family LU is significantly positively associated with violent crime in 2019 and 2020. In contrast, multifamily LU registered as a significant factor only in 2020, when the pandemic was at its peak. Retail LU and office LU were consistently found as positive factors across the years. Building height, liquor stores, and traffic volume were not significant in violent crime after controlling for other BE factors. Bus stop density is a consistent feature associated with higher crime. In addition, the high density of local roads, alleys, business districts, etc., creates avenues for violent criminals. Conversely, a high density of arterials does not affect violent crime, and more freeways often negatively affect violent crime.

The median income is negatively associated with crime rates in all models. The areas with fewer renters had fewer crimes in 2019, not after the pandemic started. Areas with most householders moved from 2000 to 2009 experienced consistently less crime than the new areas. Violent crime is negatively related to population density, and gender composition does not affect it.

Table 4. Regression output from SEM for violent crime (DV: log of crime rate)

Year	2019		2020		2021	
Variable	coeff.	SE	coeff.	SE	coeff.	SE
Constant	1.452***	0.070	1.558***	0.074	1.539***	0.073
singl_p	0.132**	0.060	0.174**	0.062	0.095	0.062
multi_p	0.109	0.140	0.312**	0.148	0.136	0.145
retail_p	1.105***	0.284	1.1***	0.303	1.156***	0.295
office_p	0.234**	0.099	0.227**	0.106	0.253**	0.103
stories	0.018	0.022	-0.028	0.023	-0.003	0.022
liquor	0.0001	0.002	0.001	0.002	0.002	0.002
busstop_de	0.001**	0.000	0.001**	0.000	0.001**	0.000
vmt	0.000001	0.000	0.00000003	0.000	0.00000001	0.000
speed_1_de	0.014***	0.002	0.01***	0.002	0.011***	0.002
speed_2_de	0.015***	0.003	0.009**	0.003	0.009**	0.003
speed_3_de	-0.004	0.006	0	0.007	0.004	0.007
speed_4_de	-0.005	0.005	-0.005	0.005	-0.01*	0.005
median_inc	-0.000002**	0.000	-0.000003***	0.000	-0.000002**	0.000
own_perc	-0.001**	0.001	-0.001	0.001	-0.001	0.001
decade90	-0.005	0.029	-0.013	0.031	-0.017	0.030
decade00	-0.038*	0.022	-0.053**	0.023	-0.041*	0.023
decade10	base					
pop_dens	-0.00006***	0.000	-0.00005***	0.000	-0.00005***	0.000
MF_ratio	0.00017	0.001	-0.00022	0.001	0.00015	0.001
Lambda	0.307***	0.049	0.252***	0.051	0.283***	0.050
Pseudo ρ^2	0.44		0.38		0.40	

* p<.10 ** p<.05 *** p<.001

Coeff.: coefficient; SE: Standard Error

Source: own elaboration

Table 5. Model diagnosis of OLS, SEM, and GWR

		Property crime			Violent crime		
Measure	model	2019	2020	2021	2019	2020	2021
AIC	SEM	-33.30	-96.14	-86.86	86.41	198.62	153.18
	GWR	-43.64	-101.25	-96.75	72.89	183.16	134.25
Moran's I	SEM	-0.02	-0.01	-0.01	-0.02	-0.02	-0.02
	GWR	0.02	0.00	0.03	0.05*	-0.02	0.02

* p<0.001

Source: own elaboration

Table 5 reports the Moran's I indices of the residuals of SEM and GWR. All the models except for violent crime in 2019 are free from significant spatial autocorrelation. This table also reports the Akaike Information Criterion (AIC), where the lower AIC (most desirable) is achieved in GWR models. The selected variables in our models are free from multicollinearity issues. We reported the Variance Inflation Factor (VIF) of the explanatory variables in Table 3, where the maximum VIF is 2.8. A VIF value greater than 7 indicates the presence of multicollinearity.

4.3. Spatial distribution of local effects

This section discusses the findings from GWR and shows how the parameter estimates vary across the city. Figure 2 presents the distribution of parameters for each of the six models (i.e., property and violent crime for 2019, 2020, and 2021). We used the scattered dots beside the boxplots to show the significant estimates.

The single-family LU is mostly positively associated. For violent crime in 2020 and 2021, the variability of estimates increased, and a few block groups have negative estimates as well. For multifamily LU, retail LU, and the first two speed categories (i.e., below 30 mph and 30–35 mph), the significant estimates are all positive for both crimes. However, the estimates are quite consistent for property crime but have high variability for violent crime (in 2020 and 2021). The third (i.e., 40–55 mph) and fourth speed (i.e., 60 mph and above) categories are negative in all significant block groups. The density of freeways is associated with fewer crimes after 2019. For office LU, the relationship gradually decreased for property crime but increased for violent crime from 2019 to 2021. For building height parameters, the significant block groups are all positive (and fewer) for property crime and mostly negative for violent crime. We further plotted the coefficient with the median heights (Appendix A, Fig. A). The plot clearly shows that the buildings that are three-storied or taller attract violent criminals. Notably, areas with one-storied buildings are safer than areas with two-storied ones. The findings of GWR models for liquor stores and traffic volume are similar to the findings of the SEM – liquor stores and VMT are positively associated with property crimes. For violent crimes, liquor stores are not a significant factor. Interestingly, VMT showed a wide range of positive local coefficients in violent crime rate GWR model although it turned out insignificant in global model. Areas with dense bus stops are consistently prone to crime, but the effects are greatly increased for violent crime in 2020 and 2021. The control variables have expected associations very similar to SEM findings.

Since local parameters have far greater variability for violent crime than for property crime, we explored the spatial variation of the effects of four important factors. The following four figures, with the distribution of the variables, show their parameter estimates in models for violent crime in three years. The gray areas indicate the statistically insignificant block groups.

The northwest and the northeast of Detroit have the highest concentration of single-family LU (Fig. 3). However, in 2019, a strong association was found only in the east of Detroit. With this, in 2020, a cluster in the north part registered a negative association, meaning that higher single-family LU was associated with fewer violent crimes. In 2021, that cluster was diminished, and another cluster with a negative association was found in areas close to downtown – an area with a low proportion of single-family LU.

The retail LU is distributed across the city (Fig. 4), and so is its significant positive association with violent crime in 2019. The northwestern part and the downtown areas show the weakest association, whereas the southern part (from Hamtramck to south Detroit) is strongly associated with violent crime. In 2020 and 2021, the northwestern areas turned insignificant, and east Detroit and central Detroit (Dexter Linwood to Barton McFarland) had a strong positive association.

The high bus stop density is radially distributed from downtown to northwest Detroit (Fig. 5). The positive association of bus stops with violent crime in 2019 was not along this corridor. Rather, bus stops in northeast Detroit had the strongest association. In 2020 and 2021, this association turned insignificant, and the downtown areas became significantly related to violent crime.

Finally, Fig. 6 shows the distribution of road density with a speed limit below 30 mph, and it is well-distributed in the city. This road density in areas close to downtown and northwest residential areas was highly associated with violent crime in 2019. The effect changed in 2020 and 2021. That is, the areas with the weakest association turned insignificant after 2019. In contrast, areas where the effect was strong in 2019 had an even stronger association in later years.

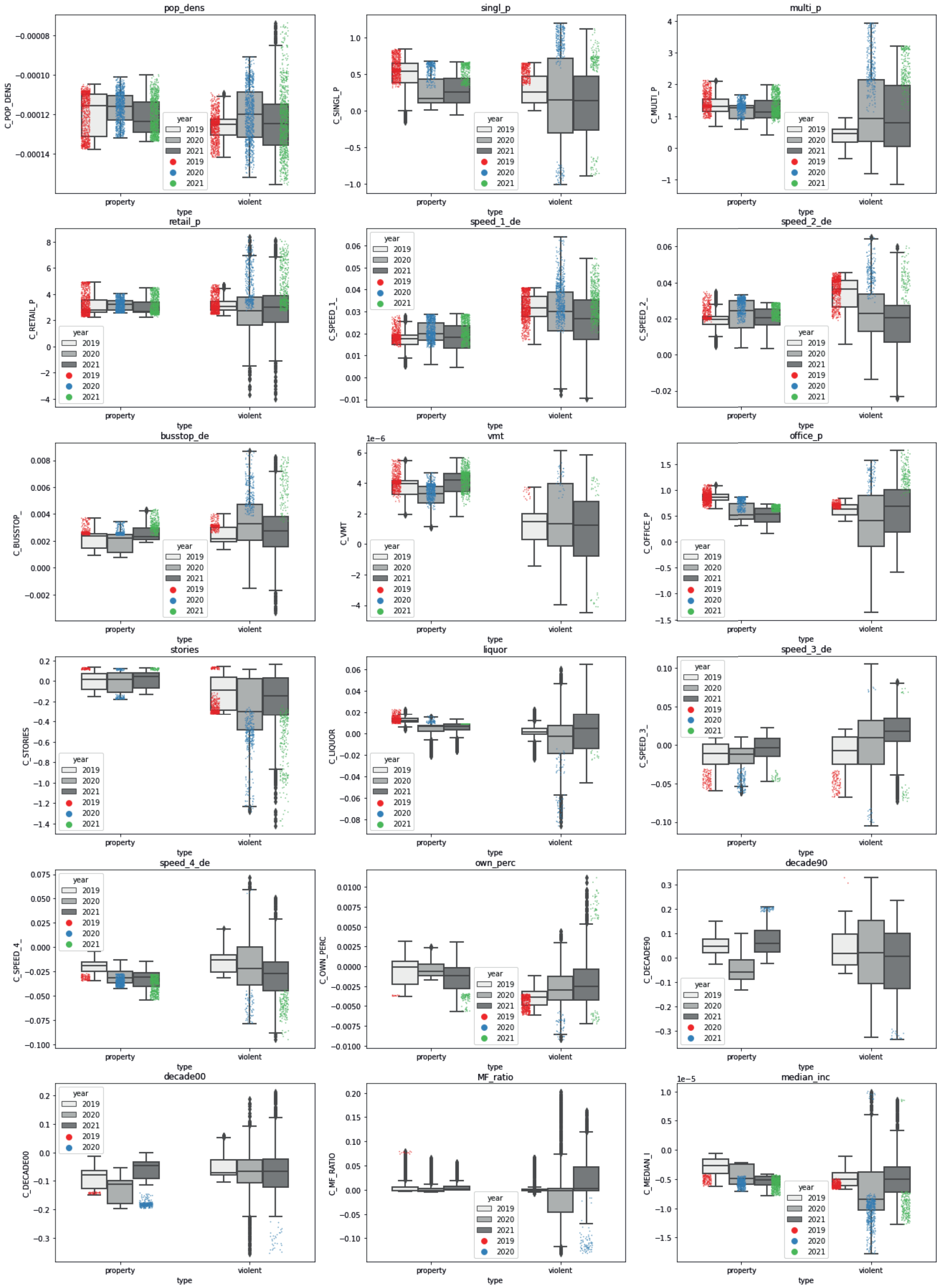

Fig. 2. Boxplot of GWR parameter estimates with strip plot for significant estimates
Source: Author's analysis

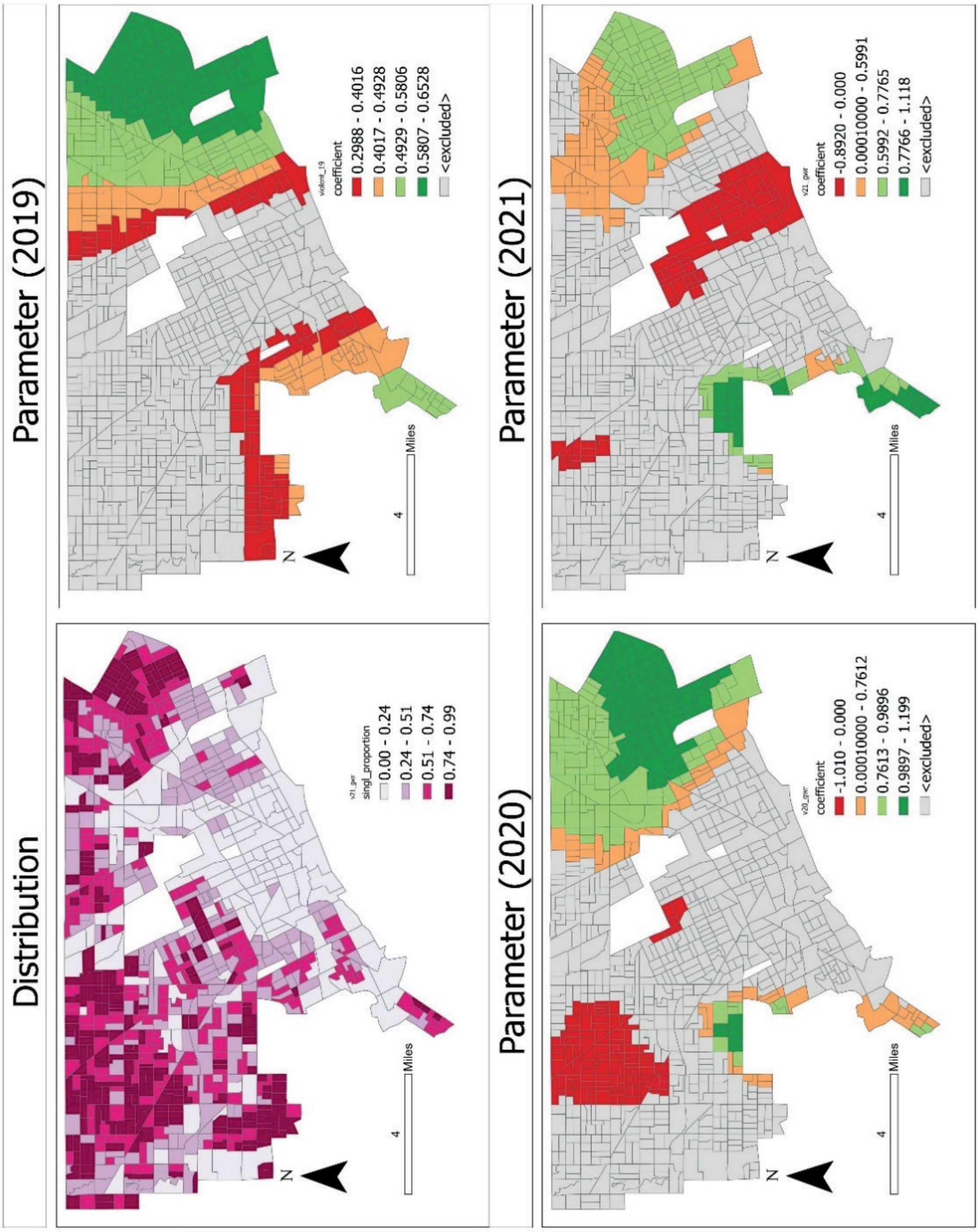

Fig. 3. Spatial distribution of single-family LU proportion (top-left) and its local estimates where the dependent variable is violent crime in 2019 (top-right), 2020 (bottom-left), and 2021 (bottom-right)
Source: Author's analysis

5 Discussion and conclusion

This study seeks to understand the relationship of land-use-related and transport-related built environment elements with the crime rates in Detroit, MI. By using crime incident data for 2019, 2020, and 2021, this study finds the spatial association of these BE factors and their inter-year changes after controlling for sociodemographic characteristics. Property crime declined in 2020–2021, whereas violent crime does not show much spatial variation in the city. This pattern is consistent with many other US cities (Boman & Gallupe, 2020; Campedelli et al., 2020; Abrams, 2021). For formalizing the association with BE, this study uses Spatial Error and GWR model.

The findings first show some general differences and similarities of BE-effect between property and violent crime. The association of single-family LU is more strongly positive for property crime than for violent crime. Multifamily LU is mostly associated

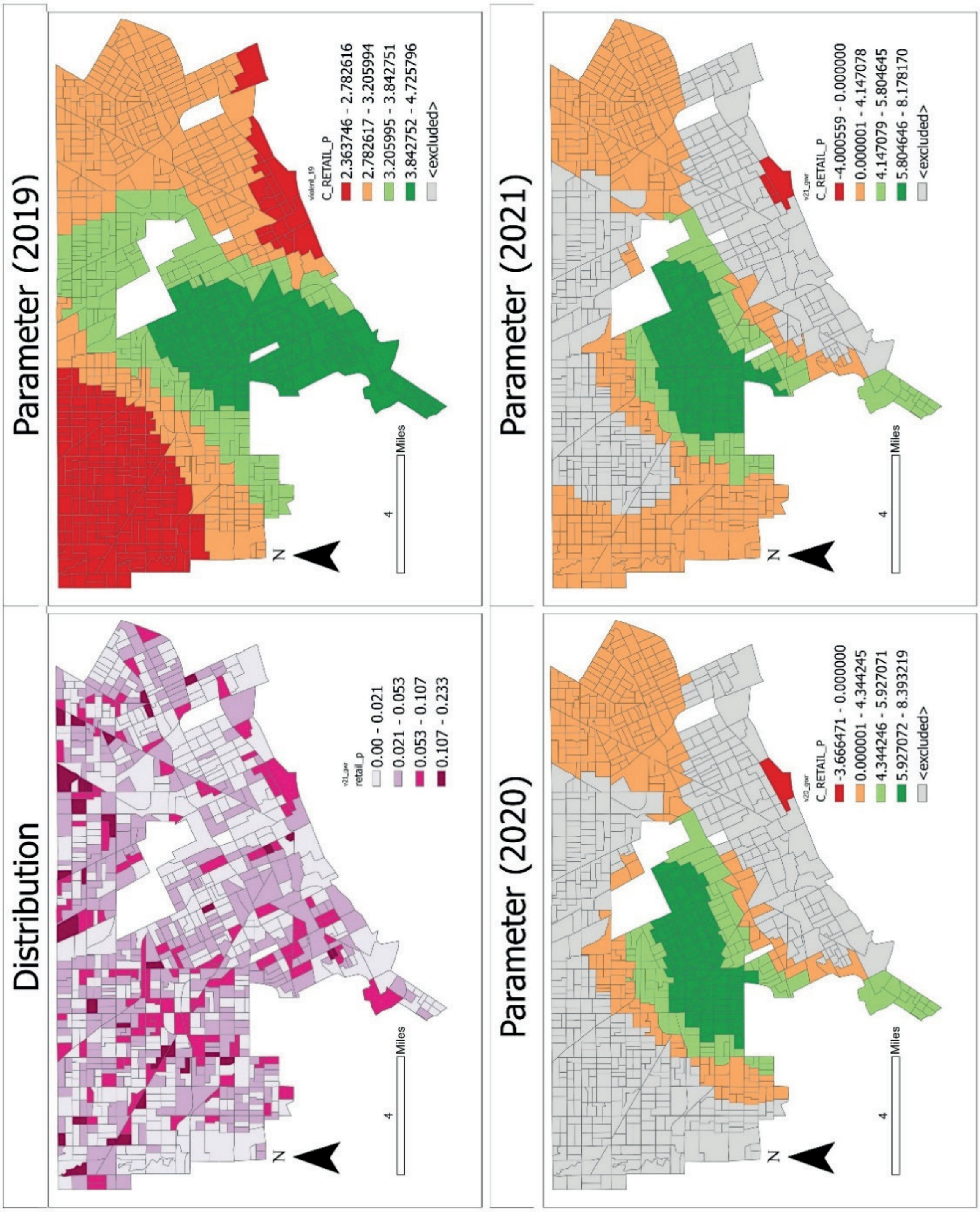

Fig. 4. Spatial distribution of retail LU proportion (top-left) and its local estimates where the dependent variable is violent crime in 2019 (top-right), 2020 (bottom-left), and 2021 (bottom-right)
Source: Author's analysis

with property crime but not with violent crime. Unlike violent crime, property crimes are involved with liquor stores. This is particularly intuitive as alcohol consumption facilitates quick aggression and immediately incites people to commit crimes like property damage, breaking and entering, etc. (Fagan, 1990), while most violent crimes are usually more organized. A high proportion of retail and office LUs and bus stop density increase both types of crime, and these findings are in line with other studies (Carter & Turner, 2021; Anderson et al., 2013; Wilcox, 2003; Matthews et al., 2010). This study uniquely finds the positive association of slower streets after controlling for land use. Moreover, the positive association of VMT – which is consistent with Wilcox & Eck, (2011) – implies that a greater traffic volume may offer a safe exit to property criminals. High median income, high

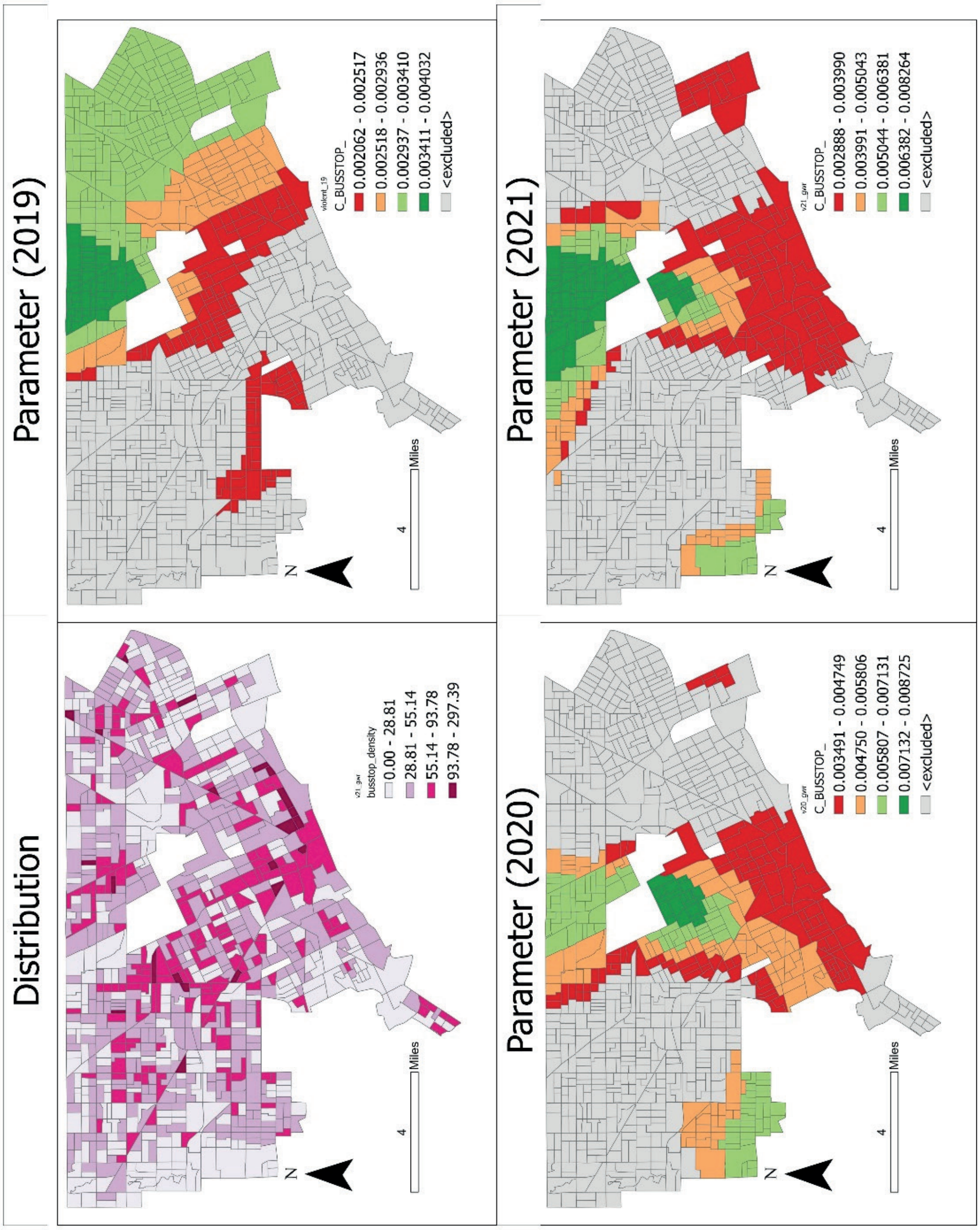

Fig. 5. Spatial distribution of bus stop density (top-left) and its local estimates where the dependent variable is violent crime in 2019 (top-right), 2020 (bottom-left), and 2021 (bottom-right)
Source: Author's analysis

population density, and old neighborhoods are generally associated with less property and violent crime among the sociodemographic controls, which corroborates with the social disorganization theory (Taniguchi et al., 2011) and routine activity theory (Harries, 2006).

From the GWR estimates, the variation in property crime was minimal. However, we found differences in the distribution of the local estimates for violent crime over the year. The association between single-family LU and violent crime in the eastern areas (with low median income) is positive and increased during the pandemic. In contrast, a northern high-income area registered a negative association during the pandemic. One reason behind increased violence in the eastern area could be increased domestic violence and batteries with partners during the pandemic, as suggested by Boman & Gallupe (2020). For retail LU, the areas where the association was strong in 2019 obtained a stronger association after 2019. The bus stops in downtown areas did not register a positive

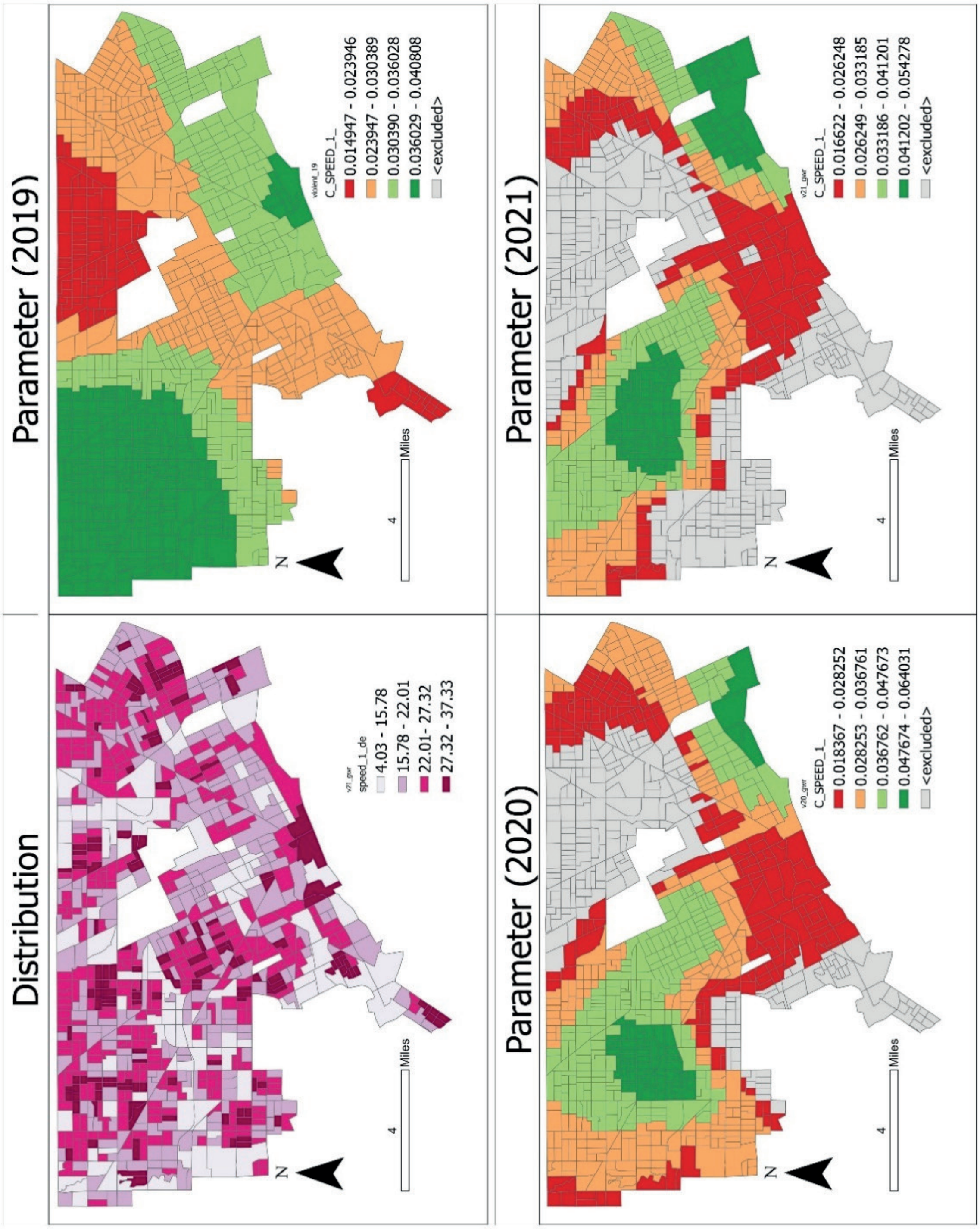

Fig. 6. Spatial distribution of road density with speed below 30 mph (top-left) and its local estimates where the dependent variable is violent crime in 2019 (top-right), 2020 (bottom-left), and 2021 (bottom-right)
Source: Author's analysis

association in 2019. However, they did after 2019, perhaps because there were fewer people at bus stops due to the pandemic and working from home.

This study has several limitations that future studies could overcome. First, the data do not provide information that would allow the separation of residential from non-residential crimes (e.g., burglary, violent crime), limiting our ability to conclude more precisely. Second, there are some limitations regarding crime-reporting, as many crimes are not reported to the police (Anderberg et al., 2022). Finally, this study does not claim any causal inference or threshold effect for the BE variables, which might be of interest to future researchers.

The unique contribution of this article to the body of literature is threefold. First, this presents a comprehensive understanding of the relationship between BE and crime for a well-known crime-prone city – Detroit. Second, one strong focus of this article is street-related BE elements, where we uniquely incorporated the understanding of road speed and traffic volume. Third, no article before this, to the best of our knowledge, has assessed the global and local association of BE during COVID-19 within a three-year timeframe. With these contributions, we expect that the spatial association of BE with the crime rate revealed for Detroit will help city planners and crime prevention officials to formulate policies centering on different BE elements and targeting the particular area. Moreover, the locations identified in this study where crime rates were changed during COVID will stimulate researchers to look for other mechanisms or factors behind the changes and have a baseline for future epidemiological, financial, political, or natural disaster-related events similar to COVID.

References

Abrams, D.S. (2021). COVID and crime: An early empirical look. *Journal of Public Economics*, 194: 104344. DOI: https://doi.org/10.1016/j.jpubeco.2020.104344.

Anderberg, D., Rainer, H. & Siuda, F. (2022). Quantifying domestic violence in times of crisis: An internet search activity-based measure for the COVID-19 pandemic. *Journal of the Royal Statistical Society, Series A. Statistics in Society*, 185(2): 498-518. DOI: https://doi.org/10.1111/rssa.12780.

Anderson, J.M., MacDonald, J.M., Bluthenthal, R. & Ashwood, J.S. (2013). Reducing crime by shaping the built environment with zoning: An empirical study of Los Angeles, 699-756. University of Pennsylvania Law Review.

Anselin, L. (1988). Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. *Geographical analysis*, 20(1): 1-17.

Ashby, M.P. (2020). Initial evidence on the relationship between the coronavirus pandemic and crime in the United States. *Crime Science*, 9: 1-16.

Biagi, B. & Detotto, C. (2014). Crime as Tourism Externality. *Regional Studies*, 48(4): 693–709. DOI: https://doi.org/10.1080/00343404.2011.649005.

Block, R. & Block, C.R. (2000) The Bronx and Chicago: Street Robbery in the Environs of Rapid Transit Stations. In: V. Goldsmith et al. (Eds.), Analyzing Crime Patterns: Frontiers in Practice, 137-152. New York, NY: Sage. DOI: https://doi.org/10.4135/9781452220369.n11.

Boggess, L.N. & Hipp, J.R. (2010). Violent Crime, Residential Instability and Mobility: Does the Relationship Differ in Minority Neighborhoods? *Journal of Quantitative Criminology*, 26(3): 351–370. DOI: https://doi.org/10.1007/s10940-010-9093-7.

Boman, J.H. & Gallupe, O. (2020). Has COVID-19 changed crime? Crime rates in the United States during the pandemic. *American Journal of Criminal Justice*, 45(4): 537-545.

Brantingham, P.L. & Brantingham, P.J. (1993). Nodes, paths and edges: Considerations on the complexity of crime and the physical environment. *Journal of Environmental Psychology*, 13(1): 3-28.

Brunsdon, C., Fotheringham, A.S. & Charlton, M.E. (1996). Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity. *Geographical Analysis*, 28(4): 281–298. DOI: https://doi.org/10.1111/j.1538-4632.1996.tb00936.x.

Campedelli, G.M., Favarin, S., Aziani, A. & Piquero, A.R. (2020). Disentangling community-level changes in crime trends during the COVID-19 pandemic in Chicago. *Crime Science*, 9(1): 21. DOI: https://doi.org/10.1186/s40163-020-00131-8.

Cantor, D. & Land, K.C. (1985). Unemployment and Crime Rates in the Post-World War II United States: A Theoretical and Empirical Analysis. *American Sociological Review*, 50(3): 317–332. DOI: https://doi.org/10.2307/2095542.

Carter, T.M. & Turner, N.D. (2021). Examining the immediate effects of COVID-19 on residential and commercial burglaries in Michigan: An interrupted time-series analysis. *Journal of Criminal Justice*, 76: 101834. DOI: https://doi.org/10.1016/j.jcrimjus.2021.101834.

Chang, D. (2011). Social Crime or Spatial Crime? Exploring the Effects of Social, Economical, and Spatial Factors on Burglary Rates. *Environment and Behavior*, 43(1): 26–52. DOI: https://doi.org/10.1177/0013916509347728.

Cohen, L.E. & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review*, 1: 588–608.

Stein, R.E., Conley, J.F. & Davis, C. (2016). The differential impact of physical disorder and collective efficacy: A geographically weighted regression on violent crime. *GeoJournal*, 81(3): 351–365. DOI: https://doi.org/10.1007/s10708-015-9626-6.

Estévez-Soto, P.R. (2021). Crime and COVID-19: Effect of changes in routine activities in Mexico City. *Crime Science*, 10(1): 15. DOI: https://doi.org/10.1186/s40163-021-00151-y.

Fagan, J. (1990). Intoxication and Aggression. *Crime and Justice*, 13: 241–320. DOI: https://doi.org/10.1086/449177.

Felson, M., Jiang, S. & Xu, Y. (2020). Routine activity effects of the Covid-19 pandemic on burglary in Detroit, March, 2020. *Crime Science*, 9(1): 1-7.

Fieldstadt. E. (2021). The most dangerous cities in America, ranked. CBS News. Available at: https://www.cbsnews.

com/pictures/the-most-dangerous-cities-in-america/ (Accessed: 6 May 2021).

Forbes, G.J., Gardner, T., McGee, H. & Srinivasan, R. (2012). Methods and Practices for Setting Speed Limits: An Informational Report – Safety | Federal Highway Administration (FHWA-SA-12-004). Federal Highway Administration. Available at: https://safety.fhwa.dot.gov/speedmgt/ref_mats/fhwasa12004/.

Greenberg, S.W., Rohe, W.M. & Williams, J.R. (1982). Safety in urban neighborhoods: A comparison of physical characteristics and informal territorial control in high and low crime neighborhoods. *Population and Environment*, 5(3): 141-165.

Groff, E.R., Weisburd, D. & Yang, S.M. (2010). Is it important to examine crime trends at a local "micro" level?: A longitudinal analysis of street to street variability in crime trajectories. *Journal of Quantitative Criminology*, 26(1): 7-32.

Hakim, S., Rengert, G.F. & Shachmurove, Y. (2001). Target search of burglars: A revised economic model. *Papers in Regional Science*, 80(2): 121-137.

Harrell, A.V. (1994). Community Decay and Crime: Issues for Policy Research.

Harries, K. (2006). Property Crimes and Violence in United States: An Analysis of the influence of Population density. *International Journal of Criminal Justice*, 1(2): 1-12.

Hodgkinson, T. & Andresen, M.A. (2020). Show me a man or a woman alone and I'll show you a saint: Changes in the frequency of criminal incidents during the COVID-19 pandemic. *Journal of Criminal Justice*, 69: 101706.

Hong, J. & Chen, C. (2014). The role of the built environment on perceived safety from crime and walking: examining direct and indirect impacts. *Transportation*, 41(6): 1171-1185.

Johnson, S.D. & Bowers, K.J. (2010). Permeability and burglary risk: Are cul-de-sacs safer?. *Journal of Quantitative Criminology*, 26(1): 89-111.

Kelling, C., Graif, C., Korkmaz, G. & Haran, M. (2021). Modeling the Social and Spatial Proximity of Crime: Domestic and Sexual Violence Across Neighborhoods. *Journal of Quantitative Criminology*, 37(2): 481–516. DOI: https://doi.org/10.1007/s10940-020-09454-w.

Kepple, N.J. & Freisthler, B. (2015). Exploring the Ecological Association Between Crime and Medical Marijuana Dispensaries. *Journal of Studies on Alcohol and Drugs*, 73(4): 523–530. DOI: https://doi.org/10.15288/jsad.2012.73.523.

Kim, S., Ulfarsson, G.F. & Hennessy, J.T. (2007). Analysis of light rail rider travel behavior: Impacts of individual, built environment, and crime characteristics on transit access. *Transportation Research Part A: Policy and Practice*, 41(6): 511-522.

Kooi, B. (2013). Assessing the Correlation between Bus Stop Densities and Residential Crime Typologies. *Crime Prevention and Community Safety*, 15(2): 81–105.

LaGrange, R.L., Ferraro, K.F. & Supancic, M. (1992). Perceived risk and fear of crime: Role of social and physical incivilities. *Journal of research in crime and delinquency*, 29(3): 311-334.

Larson, M., Xu, Y., Ouellet, L. & Klahm IV, C.F. (2019). Exploring the impact of 9398 demolitions on neighborhood-level crime in Detroit, Michigan. *Journal of Criminal Justice*, 60: 57-63.

Lasley, J.R. (1996). Using traffic barriers to design out crime. Report to the National Institute of Justice. Fullerton: California State University.

LaVigne, N.G. (1997). Visibility and Vigilance: Metro's Situational Approach to Preventing Subway Crime. Research in Brief. Washington, DC: US Department of Justice, National Institute of Justice.

Leslie, E. & Wilson, R. (2020). Sheltering in place and domestic violence: Evidence from calls for service during COVID-19. *Journal of Public Economics*, 189: 104241. DOI: https://doi.org/10.1016/j.jpubeco.2020.104241.

Liggett, R., Loukaitou-Sideris, A. & Iseki, H. (2001). Bus Stop-Environment Connection: Do Characteristics of the Built Environment Correlate with Bus Stop Crime? *Transportation Research Record: Journal of the Transportation Research Board*, 1760: 20–27. DOI: 10.3141/1760-03.

Loukaitou-Sideris, A. (2006). Is it Safe to Walk?1 Neighborhood Safety and Security Considerations and Their Effects on Walking. *Journal of Planning Literature*, 20(3): 219–232. DOI: 10.1177/0885412205282770.

Loukaitou-Sideris, A., Liggett, R. & Iseki, H. (2002). The Geography of Transit Crime: Documentation and Evaluation of Crime Incidence on and around the Green Line Stations in Los Angeles. *Journal of Planning Education and Research*, 22(2): 135–151. DOI: https://doi.org/10.1177/0739456X02238443.

Loukaitou-Sideris, A., Liggett, R., Iseki, H. & Thurlow, W. (2001). Measuring the Effects of Built Environment on Bus Stop Crime. *Environment and Planning B: Planning and Design*, 28(2): 255–280. DOI: https://doi.org/10.1068/b2642r.

MacDonald, J. (2015). Community Design and Crime: The Impact of Housing and the Built Environment. *Crime and Justice*, 44(1): 333–383. DOI: 10.1086/681558.

Madyun, N.H. (2011). Connecting Social Disorganization Theory to African-American Outcomes to Explain the Achievement Gap. *Educational Foundations*, 25: 21–35.

Matthews, S.A., Yang, T.-C., Hayslett, K.L., & Ruback, R.B. (2010). Built Environment and Property Crime in Seattle, 1998–2000: A Bayesian Analysis. *Environment and*

Planning A: Economy and Space, 42(6): 1403–1420. DOI: https://doi.org/10.1068/a42393.

Mohler, G., Bertozzi, A.L., Carter, J., Short, M.B., Sledge, D., Tita, G.E., Uchida, C.D. & Brantingham, P.J. (2020). Impact of social distancing during COVID-19 pandemic on crime in Los Angeles and Indianapolis. *Journal of Criminal Justice*, 68: 101692. DOI: https://doi.org/10.1016/j.jcrimjus.2020.101692.

Oh, J.-H. (2004). Race/ethnicity, homeownership, and neighborhood attachment— – ScienceDirect. *Race and Society*, 7(2): 63–77.

Payne, J.L., Morgan, A. & Piquero, A.R. (2021). Exploring regional variability in the short-term impact of COVID-19 on property crime in Queensland, Australia. *Crime Science*, 10(1): 1-20.

Sargin, S. & Temurçin, K. (2010) Crimes and Crime Dispersion in Urban Areas in Turkey. *Bulletin of Geography. Socio-economic Series*, 13: 59-77. DOI: https://apcz.umk.pl/BGSS/article/view/v10089-010-0005-2.

Schiller. A. (2021). NeighborhoodScout's Most Dangerous Cities – 2021. Neighborhoodscout. Available at: https://www.neighborhoodscout.com/blog/top100dangerous (Accessed: 6 May 2021).

Schleimer, J.P., Buggs, S.A., McCort, C.D., Pear, V.A., Biasi, A.D., Tomsich, E., Shev, A.B., Laqueur, H.S., & Wintemute, G.J. (2022). Neighborhood Racial and Economic Segregation and Disparities in Violence During the COVID-19 Pandemic. *American Journal of Public Health*, 112(1): 144–153. DOI: https://doi.org/10.2105/AJPH.2021.306540.

Sciandra, M., Sanbonmatsu, L., Duncan, G.J., Gennetian, L.A., Katz, L.F., Kessler, R.C., Kling, J.R. & Ludwig, J. (2013). Long-term effects of the Moving to Opportunity residential mobility experiment on crime and delinquency. *Journal of Experimental Criminology*, 9(4): 451–489. DOI: https://doi.org/10.1007/s11292-013-9189-9.

Shaw, C.R. & McKay, D.H. (1942). Juvenile delinquency in urban areas. Chicago: University of Chicago Press.

Siddiqui, C., Abdel-Aty, M. & Choi, K. (2012). Macroscopic spatial analysis of pedestrian and bicycle crashes. *Accident Analysis & Prevention*, 45: 382–391. DOI: https://doi.org/10.1016/j.aap.2011.08.003.

Sohn, D.W. (2016). Residential crimes and neighbourhood built environment: Assessing the effectiveness of crime prevention through environmental design (CPTED). *Cities*, 52: 86-93.

Stucky, T.D. & Ottensmann, J.R. (2009). Land use and violent crime. *Criminology*, 47(4): 1223-1264.

Syamsuddin, R., Fuady, M.I.N., Prasetya, M.D. & Umar, K. (2021). The Effect of the Covid-19 Pandemic on the Crime of Theft. *International Journal of Criminology and Sociology*, 10: 305-312.

Taniguchi, T.A., Ratcliffe, J.H. & Taylor, R.B. (2011). Gang Set Space, Drug Markets, and Crime around Drug Corners in Camden. *Journal of Research in Crime and Delinquency*, 48(3): 327–363. DOI: https://doi.org/10.1177/0022427810393016.

Tavares, J.P. & Costa, A.C. (2021). Spatial Modeling and Analysis of the Determinants of Property Crime in Portugal. *ISPRS International Journal of Geo-Information*, 10(11): 731. DOI: https://doi.org/10.3390/ijgi10110731.

Taylor, R.B., Koons, B.A., Kurtz, E.M., Greene, J.R. & Perkins, D.D. (1995). Street blocks with more non-residential land use have more physical deterioration: Evidence from Baltimore and Philadelphia. *Urban Affairs Review*, 31(1): 120-136.

van Loon, J., Frank, L. D., Nettlefold, L. & Naylor, P.-J. (2014). Youth physical activity and the neighbourhood environment: Examining correlates and the role of neighbourhood definition. *Social Science & Medicine*, 104: 107–115. DOI: https://doi.org/10.1016/j.socscimed.2013.12.013.

Wilcox, P. & Eck, J.E. (2011). Criminology of the Unpopular: Implications for Policy Aimed at Payday Lending Facilities Investigating the Social Ecology of Payday Lending: Policy Essay. *Criminology and Public Policy*, 10(2): 473–482.

Wilcox, P., Quisenberry, N. & Jones, S. (2003). The Built Environment and Community Crime Risk Interpretation. *Journal of Research in Crime and Delinquency*, 40(3): 322–345. DOI: 10.1177/0022427803253801.

Wong, S.K. (2012). Youth crime and family disruption in Canadian municipalities: An adaptation of Shaw and McKay's social disorganization theory. *International Journal of Law, Crime and Justice*, 40(2): 100–114. DOI: https://doi.org/10.1016/j.ijlcj.2011.09.006.

Xu, Y.-H., Pennington-Gray, L. & Kim, J. (2019). The Sharing Economy: A Geographically Weighted Regression Approach to Examine Crime and the Shared Lodging Sector. *Journal of Travel Research*, 58(7): 1193–1208. DOI: https://doi.org/10.1177/004728751879719.

Appendix I

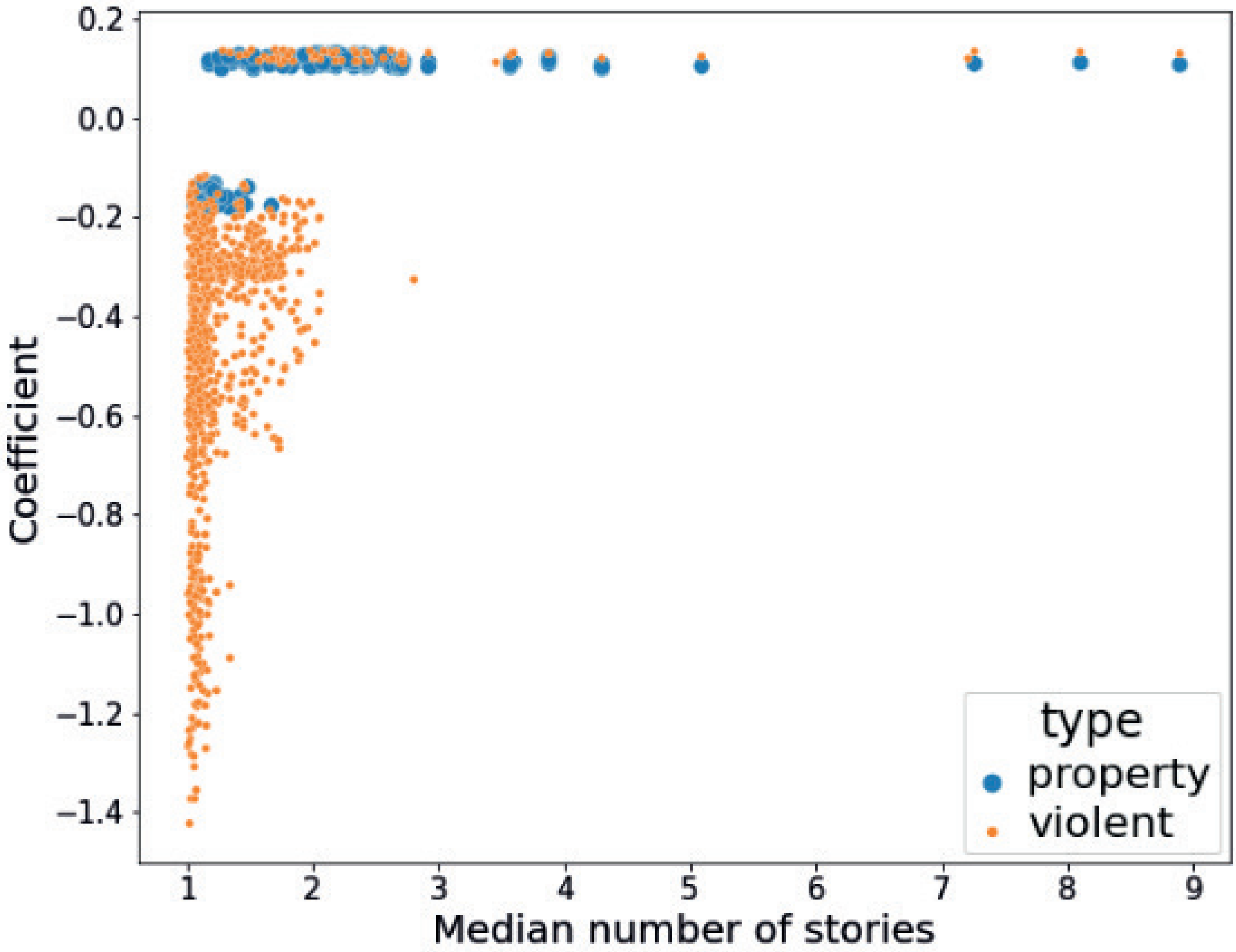

Fig. A. Scatterplot of GWR coefficients of building height (from six models) and the median building height of block groups
Source: Author's analysis