Mapping Spatial Crime Diffusion and Its Relation to Socioeconomic Factors: An Analysis for Fortaleza, Brazil

Fabrício Carneiro Linhares
Graduate Program in Economics at the Federal University of Ceará, CAEN/UFC
Postal Address: Universidade Avenue, 2762, 1st floor, Benfica, Fortaleza, Ceará, Brazil. Zip Code: 60.020-181
Phone: (85) 3366-7751
flinhares@caen.ufc.br

Marcus Vinicius Adriano Araujo
PhD candidate in the Graduate Program in Economics, Federal University of Ceará, CAEN/UFC
Graduate Program in Economics at the Federal University of Ceará, CAEN/UFC
Postal Address: Universidade Avenue, 2762, 1st floor, Benfica, Fortaleza, Ceará, Brazil. Zip Code: 60.020-181
Phone: (85) 3366-7751
marcusvinicius.bob@alu.ufc.br

Abstract

Purpose Much of the existing literature on the spatial displacement of crime focuses on specific times, locations, or the effects of targeted interventions. In contrast, this paper maps Fortaleza at the neighborhood level to identify areas that could influence crime patterns in other regions. Additionally, it examines the relationship between socioeconomic indicators and the emergence of these spatial interconnections.

Methods This study employs a panel data model with heterogeneous coefficients to analyze the spatiotemporal behavior of monthly theft and robbery rates across Fortaleza's neighborhoods. The model isolates pure spatial correlation from strong cross-sectional correlations and to identify neighborhoods with statistically significant impacts on crime occurrences in other areas. Additionally, a feature selection method utilizing a logistic regression model assesses the impact of socioeconomic indicators on a neighborhood's potential to spatially affect crime occurrences within the city.

Results The analysis indicates that spatial interconnections in crime occurrences across neighborhoods are more prevalent for robbery, with approximately 45% of neighborhoods showing statistically significant spatial correlations, compared to 25% for theft. Moreover, a notable proportion of neighborhoods exhibit negative correlations in crime between different parts of the city. This suggests that local interventions targeting these areas could unintentionally increase crime elsewhere. Five neighborhoods were identified as outliers; significantly influencing crime occurrences in other areas for both types of crime. Also, the study reveals that poverty and income inequality significantly increase the likelihood of a neighborhood becoming a hub that spatially diffuses crime in Fortaleza.

Conclusions The spatial interconnection of crime in Fortaleza is not uniform and uni-directional. Neighborhoods with strong spatial interconnections pose significant challenges for law enforcement efforts. Depending on the nature of this spatial interconnection, targeting crime in these neighborhoods can produce positive or negative spatial externalities due to spill-over effects. Thus, combating crime in these areas requires a more strategic approach than merely identifying crime occurrence hotspots. Additionally, these spatial interconnections are likely related to patterns of income distribution and deprivation. This finding enhances the existing literature by demonstrating that socioeconomic factors influence not only the frequency of crimes in specific areas but also how crime spreads across regions experiencing such conditions.

Keywords: crime spatial patterns; spatio-temporal model; common factors; Fortaleza;
JEL Codes: C21, C23, C38.

Mapping Spatial Crime Diffusion and Its Relation to Socioeconomic Factors: An Analysis for Fortaleza, Brazil

1. Introduction

The high incidence of criminal activities in Fortaleza,[1] a coastal city in Ceará, Brazil, persists despite the implementation of numerous community-oriented policing strategies and administrative improvements (Lima, 2017; Araújo, 2019). Politicians and scholars frequently cite the lack or inefficiency of law enforcement's intelligence infrastructure as a primary factor behind the shortcomings in Ceará's public security system (Dantas, 2020). In response, the state of Ceará has substantially enhanced its law enforcement intelligence infrastructure, established several agencies, and expanded scientific research into the causes and solutions for violence.

Ceará's intelligence program, led by the Superintendency of Public Security Research and Strategy (SUPESP, by its Portuguese initials), has focused much of its research efforts on geoprocessing criminal data, meticulously mapping high-crime areas in detail (Nogueira and Moraes, 2022). This practice is commonly known as "hotspot mapping". It is based on the principles of routine activities theory (Cohen and Felson, 1979; Felson, 1998) and the rational choice perspective (Cornish and Clarke, 1986, 1987; Clarke and Felson, 1993), which recognize that crimes tend to concentrate in specific areas and that criminal behavior within cities is highly structured and localized (Sherman et al., 1989; Brantingham and Brantingham, 1995; Chainey and Ratcliffe, 2005; Weisburd, 2015). Empirical evidence indicates that strategically deploying police resources in crime hotspots effectively and significantly reduces crime (Braga et al., 2014; Weisburd and Eck, 2004; Chainey et al., 2008).

This type of geographic criminological research plays a crucial role in improving law enforcement strategies and reducing crime. However, focusing solely on the geographic distribution of crime based on its intensity may ignore other crucial concerns, such as the potential for crime to spread to different areas or to influence crime elsewhere. The central insight behind the idea of crime geographic displacement is that thwarting criminally motivated offenders in one location does not deter but merely displaces their criminal behavior. In developing crime-combating policies, policymakers and law enforcement bodies must consider geographic displacement to ensure that it does not dilute or curb the benefits of local targeted enforcement. For an overview of these ideas, see Bowers and Johnson (2003), Bowers et al. (2011), Ratcliffe and Breen (2011), and Eck and Weisburd (2015).

This study contributes to both police administration in Ceará and research on geographic crime displacement by demonstrating the utility of a spatiotemporal model for analyzing the spatial diffusion of crime in urban settings like Fortaleza. Utilizing methodologies developed by Bailey et al. (2015) and Aquaro et al. (2021), the model explores the complex dynamics of monthly theft and robbery crime rates across Fortaleza's neighborhoods and highlights the heterogeneity in their spatial and temporal dependence structures. Through a detailed analysis of spatial correlation patterns in each area, the model identifies neighborhoods that act as potentially contagious crime hotspots. It also characterizes contagion patterns and distinguishes between positive and negative

[1] According to 2022 statistics from the Statista Research Department and 2023 data from Numbeo, Fortaleza has the second-highest homicide rate in Brazil and the ninth-highest in the world. It is also ranked sixth nationally in recorded thefts and robberies, as reported by the Onde Fui Roubado website, http://www.ondefuiroubado.com.br

spatial connections. This distinction is crucial because positive and negative spatial connections influence crime spread differently. Distinguishing between the two thus provides essential insights into how crime can evolve in response to police interventions, infrastructural changes, and socioeconomic shifts.

Numerous studies have developed theoretical frameworks for understanding the spatial displacement of crime and analyzed empirical evidence regarding its degree and significance. However, much of this literature focuses on specific times and locations or on the effects of specific interventions. Ratcliffe and Breen's (2011) and Bowers et al.'s (2011) review studies examine the impacts of geographically focused policing initiatives. Piza et al. (2019) assessed CCTV surveillance's effects on crime prevention, and Welsh et al. (2022) explored street lighting interventions' influence on public space crimes.

Unlike previous studies, this paper maps the city at the neighborhood level to identify neighborhoods with the potential to spatially influence crime in other areas. Such spatial connections in crime occurrences might develop over time as criminally motivated offenders assess benefits, opportunities, and risks in several similar places within their cognitive maps. In this context, long-term spatial correlation provides insights into how crime might migrate from one region to another. Understanding the overall pattern of spatial correlation within a city can aid police administrations in proactively assessing the general potential for negative and beneficial spillover effects from crime prevention efforts in specific neighborhoods. Proactive assessment can in turn enable law enforcement agencies to develop crime prevention strategies specifically tailored to the dynamics in their target neighborhoods.

Spatial correlation structures are widely employed in empirical models to account for the potential geographic spread or interconnection of crime occurrences and to manage the dependence of observations across spatially distinct units. These models are frequently employed for predicting crime (Haining et al., 2009; Zhao et al., 2022; Liesenfeld et al., 2017) and exploring relationships between crime data and socioeconomic variables (Kakamu et al., 2008; Kelling et al., 2021; Lin et al., 2022; Anselin, 1988; Oliveira, 2008; de Oliveira et al., 2019). Despite this literature's valuable contributions, the research is often constrained by the assumption of uniform and uni-directional spatial correlation across all geographic units in the data. While a detailed examination of the structure of spatial interconnections of crime is not those studies' primary focus, assuming identical spatial correlation across every geographic region within a city may oversimplify the issue and bias the estimators of interest.

Moreover, the literature often overlooks the impact of strong cross-correlation when estimating spatial correlations. Spatial dependencies in crime occurrence at the neighborhood level, for instance, may reflect broader economic and security policy changes affecting the entire city, which can introduce a strong form of cross-correlation into the data. Neglecting broader factors can obscure local crime diffusion patterns, distorting interpretations of ~~the~~ 'pure' spatial correlations (Pesaran et al., 2015; Bailey et al., 2016). As Wenger (2019) and Hipp et al. (2017) have noted, this bias underscores the importance of considering the macro-environment when analyzing crime in a city. Therefore, this study employs the two-step estimation procedure developed by Bailey et al. (2015) to account for factors common to both the city and regional level (the levels at which Fortaleza's policy administration structure is organized).

This study also contributes to the literature by exploring the potential relationship between socioeconomic indicators and a neighborhood's likelihood of becoming a spatial diffusion of criminal hub of criminal spatial diffusion. Drawing from research that correlates regional socioeconomic conditions with the formation of crime hotspots (Becker, 1968; Glaeser and Sacerdote, 1999; Pratt and Cullen, 2005; Chamberlain and Hipp, 2015), we hypothesize that such hubs emerge when criminals perceive similar crime opportunities and risks in different areas. Changes in socioeconomic factors could therefore create local dependencies that influence crime occurrence across neighborhoods. We seek to identify which socioeconomic indicators are associated with the formation of spatial interconnections for theft and robbery in Fortaleza.

This study provides new empirical evidence for the scant literature on the spatiotemporal dynamics of crime in large Brazilian cities. Some studies have examined determinants of homicide (Menezes et al., 2013; Pereira et al., 2017) and property crime (Faria et al., 2013) as well as the relationship with fear of crime (Alkimim et al., 2013) at the neighborhood level. The spatial distribution of urban crimes has also been investigated at the census tract and street levels (de Melo et al., 2015). Studies at such local levels have generally focused on cross-sectional analyses, possibly due to data scarcity.

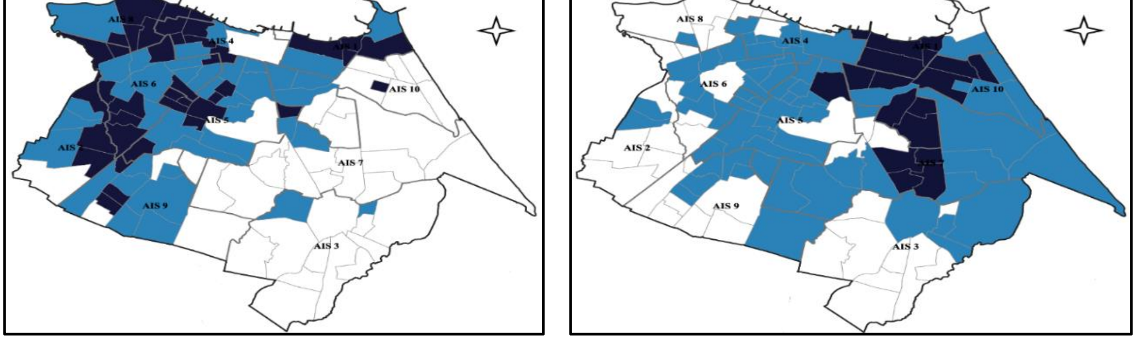
The remainder of this article is organized into five further sections. The subsequent two sections offer a detailed analysis of the socio-economic context, the database utilized, and the public security infrastructure in Fortaleza. The fourth section elaborates on the methodological framework employed. The fifth section is dedicated to presenting the primary findings of this study. Finally, the concluding section summarizes the research and discusses its contributions to the broader field of crime studies.

2. Socioeconomic Overview of Fortaleza's Neighborhoods

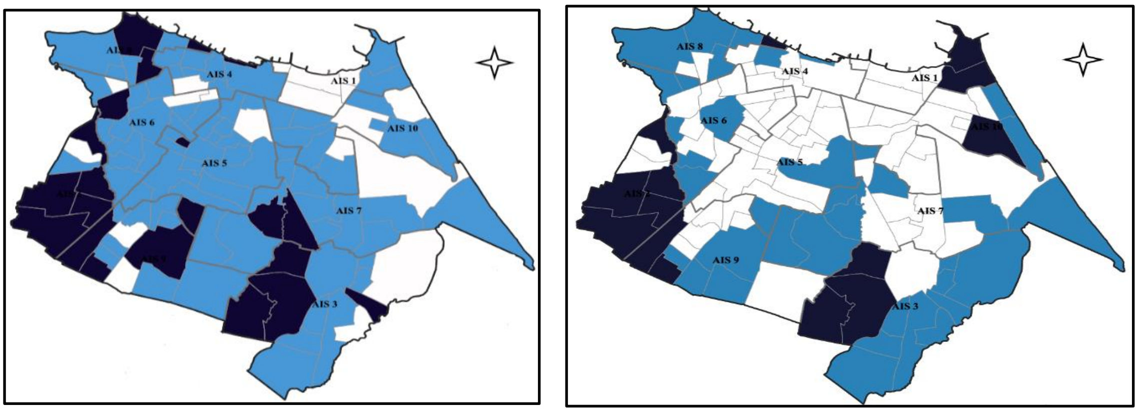
This section presents an overview of socioeconomic indicators and their spatial distribution across the neighborhoods of Fortaleza. Fortaleza, the capital of Ceará, located in the Northeast Region of Brazil, spans 312,353 km² and comprises 121 neighborhoods. With a 2021 population of 2.7 million and a 2020 GDP of approximately U$ 12,53 billion, Fortaleza is the fifth-largest city and has the eighth-largest economy among Brazil's state capitals. Figure 1 features a map that highlights Fortaleza's neighborhoods, displaying data on population size (panel a), monthly household per capita income in 2010 (panel b), income inequality (GINI) in 2010 (panel c), and extreme poverty rate (panel d).

Despite its economic significance, Fortaleza is ranked sixth from the bottom among Brazilian state capitals in terms of GDP per capita, with average monthly household per capita income across neighborhoods varying from \$112 to \$2,196. Contrary to the population distribution, which is denser in the north and western regions (Figure 1, panel a), neighborhoods with higher average incomes (Figure 1, panel b) are predominantly found in the central-eastern region. These areas, teeming with businesses, offices, shopping centers, tourist attractions, and public offices, are synonymous with zones of strong formal employment.

Figure 1. Socioeconomic Overview of Fortaleza's Neighborhoods



(a) Population density (b) Average monthly household per capita income



(c) Income inequality (GINI) (d) Extreme poverty rate

Legends:

(a) ☐ 188 to 7,089 inhab./km² ■ 7,647 to 12,532 ■ 12,766 to 31,376 inhab./km²

(b) ☐ US$112 to 300 ■ US$ 301 to 809 ■ US$868 to 2,196

(c) ☐ GINI < 0.3 ■ 0.3 ≤ GINI < 0.5 ■ GINI ≥ 0.5

(d) ☐ Extreme poverty rate < 5% ■ 5% <= Extreme poverty rate < 8% ■ Extreme poverty rate > 8%

The spatial distribution of income inequality measured by the Gini coefficient in Fortaleza, as shown in Figure 1, panel c, reveals that the highest levels of inequality are concentrated in the neighborhoods of the western region, contrasting with the areas of highest average household per capita income, which are concentrated in the central-eastern region. Although not explicitly indicated on the map, it is worth highlighting that the Gini index for Fortaleza was 0.6267, according to the 2010 Census, placing it among the most unequal state capitals in the country.

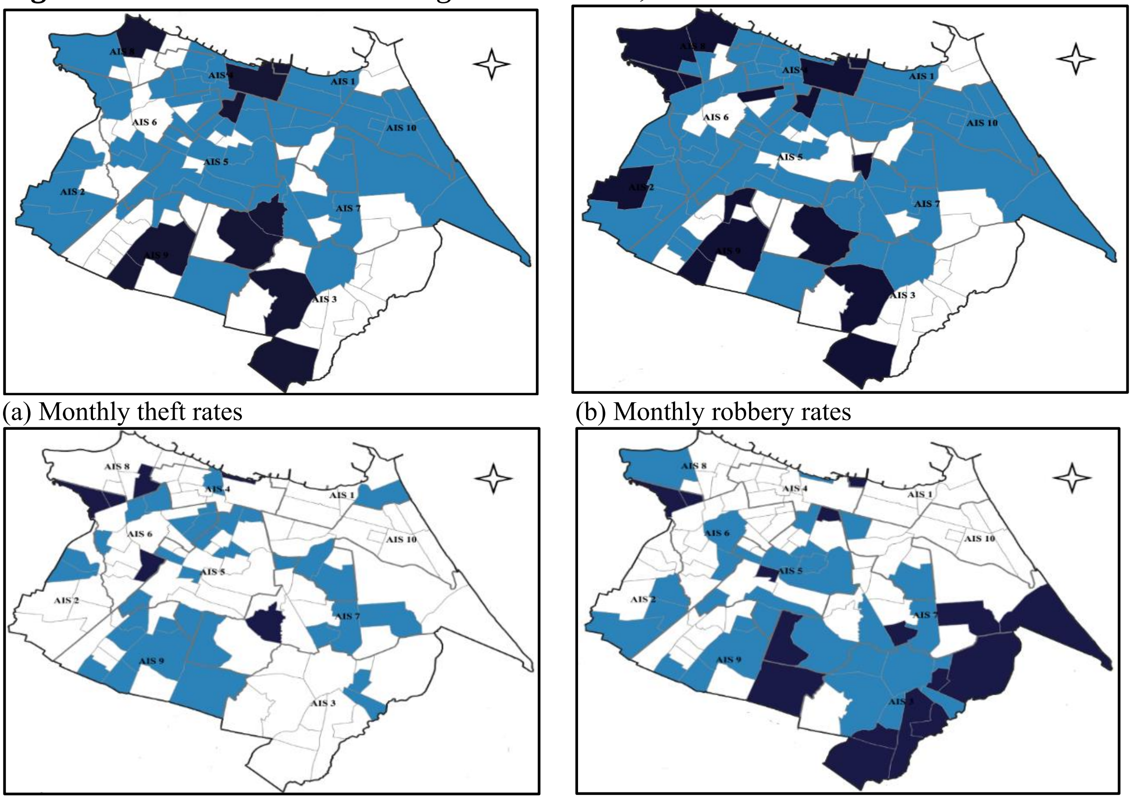
Regarding poverty, based on the federal government's extreme poverty line of US$42 per capita monthly income at the time, panel d of Figure 1 shows that areas with extreme poverty are typically located on the city's periphery. Three clusters of neighborhoods with high rates of extreme poverty emerge in the west, center-south, and upper-east regions. These clusters have extreme poverty rates above the national average of 6.6%, capturing as much as 26% of the population in some neighborhoods. Despite Fortaleza's economic prominence within the Northeast Region, these indicators underscore the city's social challenges.

3. Crime in Fortaleza: Database, Police Administration and Spatial Distribution.

This study utilizes a crime dataset comprising monthly neighborhood theft and robbery rates from 2009 to 2019, expressed per 1,000 inhabitants, obtained from the Secretariat of Security and Social Defense of the State of Ceará (SSPDS-CE). Theft is defined as property theft without violence or threat, whereas robbery entails property crimes that involve violence — excluding *latrocínio* (robbery followed by death), which is classified as an intentionally lethal violent crime. Although Fortaleza currently has 121 neighborhoods, our analysis relies on data for an older spatial division encompassing 114 neighborhoods, a decision dictated by data availability in the series' early years.

Figure 2 offers an overview of crime occurrences, showing monthly averages and growth rates for thefts and robberies. The Fortaleza police, under state government administration, is segmented into 10 Integrated Security Areas (AIS), each responsible for policing specified areas. This spatial division aims to boost the efficiency of security agencies by optimizing police deployment for crime prevention and investigation.

Figure 2. Crime Levels and Changes in Fortaleza, 2010–2019



(a) Monthly theft rates (b) Monthly robbery rates

(c) Average monthly growth rate (theft) (d) Average monthly growth rate (robbery)

Legends

For panels (a) and (b) ☐ Below 0.5 ■ Between 0.5 and 2.9 ■ Above 3

For panels (c) and (d) ☐ Between -1% and -0.004 % ■ Between 0% and 0.8 % ■ Above 0.81%

Theft and robbery rates exhibit considerable variability, with some neighborhoods experiencing rates as low as 0.01 (theft) and 0.04 (robbery), and others as high as 18.7 (theft) and 13.1 (robbery). For context, in 2019, Rio de Janeiro's monthly theft and robbery rates were approximately 0.72 and 0.41, respectively. About 52% of Fortaleza’s neighborhoods surpass Rio’s monthly theft rate, and 86% exceed its robbery rate. The spatial distribution of crime occurrences is somewhat uneven, but neighborhoods with higher rates appear to be concentrated in the upper and lower central parts of the city.

The trend in crime rates (particularly for theft) from 2009 to 2019 showed a significant decrease in many neighborhoods, as depicted in Figure 3, panels c and d. On average, theft and robbery rates in these neighborhoods declined by about 5% annually over this period. However, 36% of neighborhoods experienced an increase in theft rates, and 43% saw a rise in robbery rates. Notably, in neighborhoods located primarily in the AIS 3 and 7 areas (in the city’s southwest), robbery rates surged — nearly thirteenfold — as indicated in dark blue in Figure 3, panel d. Interestingly, increases in crime occurrences were not confined to neighborhoods with historically high crime rates. For instance, several southwestern neighborhoods with low average monthly crime rates witnessed significant increases, suggesting a spread of crime to these areas.

Visually, there is no straightforward correlation between high-crime areas, AIS boundaries, and the variables levels presented in Figure 1. An exception may be the growth rates of the robbery series, which appear to correlate with extreme poverty in the southeast region.

To conclude, it is worth highlighting that there are few studies on the spatial behavior of crime in the city of Fortaleza. Generally, these studies have found an inverse association between homicide rates and neighborhood human development levels, with a concentration of crimes in the western region of the city, characterized by neighborhoods with the lowest HDIs (De Oliveira, De Medeiros and Carvalho, 2019). Three areas with high homicide rates were identified, showing significant spatial dependence within a radius of up to 2 km (Oliveira and Simonassi, 2019). Evidence indicates that locations with high rates of violence are spatially correlated with more socioeconomically vulnerable locations, demographic factors, and urban disorder (De Oliveira et al, 2019; Dantas and Favarin, 2021). There is a notable spatial relationship between the locations of homicides and nearby slums (De Medeiros et al., 2013). This article aims to complement these findings by analyzing other types of crime in the city.

4. Methodology

4.1. The Spatiotemporal Model: Structure and Estimation

The equation $\pi_{\mathrm{it}} = \psi \mathrm{W} \pi_{\mathrm{it}} + \beta \mathrm{X}_{\mathrm{it}} + \varepsilon_{\mathrm{it}}$ represents a typical spatial panel model widely used in applied analyses. In this model, π_{it} denotes the variable of interest, and X_{it} comprises a set of explanatory variables in the spatial area *i* (*i* = 1, 2, …, N) across time *t* (*t* = 1, 2, …, T). *W* is an NxN row-standardized spatial matrix, usually sparse, with its non-zero elements determined a priori, often based on physical or economic distance. ψ represents the spatial correlation coefficient and $\varepsilon_{\mathrm{it}}$ is the error term. Recent crime literature has increasingly adopted this model as the primary empirical approach. Typical applications include crime prediction (Haining et al., 2009; Zhao et al., 2022; Liesenfeld et al., 2017) and exploring the relationships between crime occurrences and socio-economic variables (Kakamu et al., 2008; Kelling et al., 2021; Lin et al., 2022).

A prevalent issue within this body of work using spatial panel model application is the assumption that parameters are equal across all geographic areas. Additionally, there's often an oversight of the impact of strong cross-correlation when estimating the models, leading to biased results in spatial correlation parameters (Pesaran and Tosetti, 2011). This type of bias was also discussed in Wenger (2019) and Hipp et al. (2017), reinforcing the need to control the broader macro-environment when focusing the study on crime events across neighborhoods or micro-geographic units in a specific city.

The model adopted in this study, inspired by Bailey et al. (2015), leverages the relatively large *T* (time periods) available in our panel data crime series to tackle these issues. It incorporates more complex temporal and spatial dynamics by accommodating heterogeneous coefficients across geographic units, considering the influence of common determinants, and recognizing both negative and positive spatial connections.[2] The model is expressed as follows:

$$\pi_{\mathrm{it}} = \lambda_i \pi_{\mathrm{it}-1} + \psi_{0i}^{+} \mathrm{W}^{+} \pi_{\mathrm{it}} + \psi_{0i}^{-} \mathrm{W}^{-} \pi_{\mathrm{it}} + \psi_{1i}^{+} \mathrm{W}^{+} \pi_{\mathrm{t}-1} + \psi_{1i}^{-} \mathrm{W}^{-} \pi_{\mathrm{it}-1} + \varepsilon_{\mathrm{it}} \quad (1)$$

where λ_i measures the temporal persistence of shocks in crime rates of neighborhood *i*. W^{+} and W^{-} are NxN network matrices for positive and negative connections, respectively such that $W = W^{+} + W^{-}$. The coefficients ψ_{0i}^{+} e ψ_{0i}^{-} capture the contemporaneous positive and negative spatial correlations for neighborhood *i*, while ψ_{1i}^{+} and ψ_{0i}^{-} represent the lagged positive and negative spatial correlations, respectively. This equation also accounts for spatial heterogeneity in the error term's variance, $\sigma_{i\varepsilon}^{2} = var(\varepsilon_{\mathrm{it}})$.

[2] A limitation of our model is the absence of explanatory variables. Due to the granularity of our geographic unit being the neighborhood, we were unable to source any related variables that matched both the frequency and time span of our data.

Aquaro et al. (2021) define the sum of the coefficients $\psi_{0i}^{+} + \psi_{0i}^{-} + \psi_{1i}^{+} + \psi_{1i}^{-}$ as a measure of the net temporal spatial correlation in neighborhood i. In this study, following the interpretation by LeSage and Chih (2016), the net temporal spatial correlation would indicate how crime occurrences in neighborhood i influence crime occurrences in nearby areas as delineated in W. A positive net correlation implies that positive (negative) exogenous shocks in crime occurrences in neighborhood i tend to increase (decrease) crime occurrences in other areas, whereas a net negative correlation suggests the reverse[3].

However, as mentioned above, the analysis of such pure temporal spatial correlations is complex because the observed dependencies between neighborhood crime occurrences might reflect a citywide commonality in crime trends, influenced by unique factors such as economic shifts and comprehensive security policies. Consequently, the coefficients ψ_{0}^{+}, ψ_{0}^{-}, ψ_{1}^{+} and ψ_{1}^{-}, which aim to capture the weak cross-sectional dependence in the data, may be biased.

To address this issue, the estimation of equation (1) follows a two-stage strategy proposed by Bailey et al (2015). In the initial stage, we employ the cross-sectional dependence (CD) test developed by Pesaran (2004, 2014) on the raw crime panel series, y_{it}, to determine the strength of cross-sectional dependence. Additionally, we employ the cross-sectional dependence exponent (α) introduced by Bailey et al (2014) to assess the extent of cross-sectional dependence within the series. If the null hypothesis of weak cross-sectional dependence is rejected, indicating the presence of (semi) strong cross-sectional dependence, we proceed to model it using the following factor model.

$$y_{\mathrm{it}} = a_i + \gamma_i F_{\mathrm{t}} + \sum_{r=1}^{R} \gamma_{\mathrm{ir}} F_{\mathrm{rt}} D_{ir} + \pi_{\mathrm{it}},\ r = 1,2,\ldots,R, \tag{2}$$

where y_{it} represents the crime rate in neighborhood *i* at period *t*, a_{i} is a fixed effect, F_{t} is the global factor that captures commonalities in the temporal behavior of crime rates citywide, γ_i represents the factor loadings associated with F_{t}, and F_{rt} is a regional factor that captures commonalities in the temporal behavior of crime rates in the neighborhoods of the AIS *r*. These commonalities may result from the administrative characteristics of this command unit, and γ_{ir} denotes the factor loadings associated with F_{rt}. D_{ir} is an indicator variable such that D_{ir} = 1 if neighborhood *i* belongs to AIS *r* and 0 otherwise, and π_{it} represents the defactored crime series.

Following the approach utilized in Bailey et al (2015), we estimate equation (2) sequentially using the Principal Components Analysis (PCA) method.[4] Assuming the presence of only one global factor and one regional factor within each AIS,[5] F_{t} represents the strongest principal component extracted from the dataset, while each F_{rt} corresponds to the strongest principal components extracted independently from the data within each AIS. The hierarchical factors F_{t} and $(F_{\mathrm{1t}}, \ldots, F_{\mathrm{Rt}})$ are derived through rescaling the

---

[3] It should be noted that this direct interpretation considers only the first-order effects of exogenous shocks, as higher-order effects would depend on the power expansions of $\psi_{0i}^{+} + \psi_{0i}^{-} + \psi_{1i}^{+} + \psi_{1i}^{-}$ and the spatial profile specified in *W*. For more details on the interpretation of higher-order effects in spatial models, refer to Whitten et al. (2021).

[4] According to Bai (2003), PCA estimation remains consistent even with limited cross-sectional dependence and heteroscedasticity in the error term. Monte Carlo simulations assessed principal component-based estimators in the presence of strong factor loadings and weak or semi-strong common factors, demonstrating satisfactory performance in separating cross-sectional dependence. For further details, refer to Chudik et al. (2011) and Bailey et al. (2014).

[5] The number of principal components can be determined using various information criteria, as proposed by Bai and Ng (2002), among others. Given the data's dimension, we adopted a parsimonious approach and assumed the presence of one global and one regional factor.

variance-covariance matrix of the data via the PCA method, yielding factor loadings that exhibit strong correlations across all AIS.

To assess whether the strong dependence in y_{it} is adequately controlled, we examine the CD test and the cross-sectional dependence exponent (α) in the defactored series π_{it}. If they do not indicate strong forms of cross-sectional dependence, we proceed to estimate the remaining weak cross-dependencies in π_{it} as defined in the spatial model (1).

Consistent estimates of the parameters of equation (1) are obtained by the quasi-maximum likelihood method (QML), using the following log-likelihood function:

$$\ell(\psi_0^+, \psi_0^-) \propto Tln|-\psi_0^+ W^+ - \psi_0^- W^-| - \frac{T}{2}\sum_{i=1}^{N} \ln\left(\frac{1}{T}\tilde{x}_i' M_i \tilde{x}_i\right) \tag{3}$$

where:
$\tilde{x}_i = x_i - \psi_{i0}^+ x_i^+ - \psi_{i0}^- x_i^-$, $M_i = I_T - Z_i\left(Z_i' Z_i\right)^{-1} Z_i'$, $Z_i = (x_{i,-1}, x_{i,-1}^+, x_{i,-1}^-)$, $\psi_0^+ = (\psi_{10}^+, \psi_{20}^+, \ldots, \psi_{N0}^+)'$ e $\psi_0^- = (\psi_{10}^-, \psi_{20}^-, \ldots, \psi_{N0}^+)'$. $\ell(\psi_0^+, \psi_0^-)$. This is the log-likelihood function that we are trying to maximize; it depends on the parameters we are trying to estimate, which are ψ_{i0}^+ and ψ_{i0}^-. T represents the sample size or the number of observations in our data. $ln|-\psi_0^+ W^+ - \psi_0^- W^-|$ is part of the log-likelihood function that contains weighted spatial matrices. M_i is a matrix that involves operations with the matrix Z_i and is used to consider the presence of residual correlation, and Z_i is used to capture the spatial structure in the observations.

Additionally, maximum likelihood estimation weights were used to account for spatial heterogeneity present in the positive and negative spatial weight matrices ($\tilde{x}_i = x_i - \psi_{i0}^+ x_i^+ - \psi_{i0}^- x_i^-$). This approach also considers the presence of residual correlation ($M_i = I_T - Z_i\left(Z_i' Z_i\right)^{-1} Z_i'$), which improves the consistency of the spatial weight matrix estimates.

The estimation of spatial weight matrices W^+ and W^- follows Bailey et. al. (2014 and 2015) multiple testing procedure. This technique diverges from the traditional construction of W matrices based on geodesic distances. Instead, it emphasizes the development of a graphical model for “marginal dependencies,” represented by marginal correlations, offering a deeper understanding of the complexities of spatial interactions by allowing each spatial unit to exhibit a positive, negative, or null connection. This approach, combined with the permitted heterogeneity in spatial correlation parameters, addresses some limitations in spatial models discussed in Neumayer and Plümper (2016). Specifically, it accounts for the relative relevance of spatial dependence in each unit, the directionality of spatial effects, and helps avoid possible misspecification of spatial connectivity that could arise from using simple geographical proximity measures to construct W.

4.2. Analyzing the Socioeconomic Determinants of Spatial Correlation in Crime

The relationship between socioeconomic determinants and crime has been extensively studied, with a primary focus on their influence on crime levels. However, no econometric studies have yet explored how these determinants might affect the spread of crime across different geographic areas. This gap may be due to the complexity of developing an econometric model that allows for heterogeneity in spatial parameters and determines their values based on regional characteristics. In our case, a more rigorous approach would require the spatial parameters (ψ_{0i}^+, ψ_{0i}^-, ψ_{1i}^+, ψ_{1i}^-) in equation (1) to be dependent on socioeconomic variables at the neighborhood level, which is beyond the scope of this study. Instead, we conducted a simplified forecasting analysis to identify socioeconomic indicators as significant predictors that may designate a region as a spatial diffusion hub — a neighborhood with a statistically significant nonzero net spatial correlation.

This analysis employs a feature selection method based on the performance of a logistic regression model, following the methodologies of Gevert et al. (2010) and Chang et al. (2022). It involves training and testing data subsets, calculating the contribution of each feature to optimize prediction with different model configurations, and removing irrelevant ones. These authors demonstrated its effectiveness in precision and computational efficiency. For instance, Gevert et al. (2010) successfully applied this method to identify key predictors in assessing the creditworthiness of corporate clients, achieving 98.5% accuracy, which proved useful for bank credit analysts.

In our analysis, we calculate the predictive contribution of each socioeconomic indicator by averaging the results from 200 rounds of the feature selection procedure. In each round, we randomly use 80% of the data to train logistic regression models for the dependent variable, defined as 1 if the neighborhood exhibits a nonzero net spatial correlation and 0 otherwise, using different sets of socioeconomic indicators $(X_1, X_2, \dots, X_n)$. We select the best model using the remaining 20% of the data through a stepwise method based on the Akaike Information Criterion (AIC) and calculate the expected change in the odds ratio for each X_i, holding other features constant. The predictive contribution of each indicator is the average of these changes across all rounds.

5. Results

In this section, we highlight crucial aspects of our findings. Firstly, we investigate the cross-sectional dependence in both the original and defactorized series of crime rates, providing rationale for our chosen methodology. Next, we discuss the temporal persistence and spatial dependence as determined in the spatiotemporal model outlined in equation (1). Our subsequent focus is on examining the relationship between temporal persistence, spatial dependence, and socioeconomic factors, employing an explanatory approach independent of a specific model. Lastly, we aggregate the key insights from our analysis, emphasizing the most impactful findings.

5.1. Analysis of the Cross-sectional Dependence

Following the methodology, we examined the dependence between the original crime rate series y_{it} using the CD test. The test statistics for theft and robbery rates were 140.75 and 243.7, respectively. Compared to a critical value of 1.96 at the 5% significance level, these results indicate strong dependence in both series. Likely influenced by common factors, the values of the cross-sectional dependence exponent (α) were 0.935 and 0.967, respectively,[6] confirming a strong correlation between theft and robbery rates in the neighborhoods of Fortaleza.

In a similar analysis for the defactored series π_{it}, using one global and one local factor for each AIS area, the CD test values decreased significantly to 1.14 for theft and 6.45 for robbery. The estimates of the cross-sectional dependence exponents also decreased to 0.702 and 0.601, respectively,[7] close to the threshold of 0.5, indicating the presence of weak cross-sectional dependence, possibly due to pure spatial dependencies.

---

[6] The standard error for both is 0.02.
[7] The standard errors are 0.01 and 0.02.

This suggests that the PCA defactoring method effectively reduced much of the strong cross-sectional dependence in the original series.

5.2. Spatiotemporal Model Results

Given the specification of the spatiotemporal model (Equation 1), we have 114 estimates for each coefficient (λ_i, ψ_{0i}^{+}, ψ_{0i}^{-}, ψ_{1i}^{+}, ψ_{1i}^{-}), corresponding to a specific neighborhood. For comprehensive analysis, we summarize the results by calculating the mean and identifying the percentage of coefficients that are statistically significant at a level of 5%. The consolidated results for theft and robbery rates are presented in Table 1. Additionally, the estimates of the net spatiotemporal correlation ($\psi_{0i}^{+} + \psi_{0i}^{-} + \psi_{1i}^{+} + \psi_{1i}^{-}$) are illustrated on maps, facilitating visualization of result heterogeneity across the city and highlighting neighborhoods with notably high net spatial correlations.

Table 1. QML Estimates from the Spatiotemporal Model.

Theft Rate	$\boldsymbol{\lambda}$	$\boldsymbol{\psi_0^+}$	$\boldsymbol{\psi_0^-}$	$\boldsymbol{\psi_1^+}$	$\boldsymbol{\psi_1^-}$
Mean of non-zero estimates	0.177 (0.013)	0.114 (0.067)	-0.363 (0.065)	0.051 (0.037)	-0.063 (0.056)
% of significant coefficients at 5% level	42.1	45.8	61.1	0.0	22.2
Robbery Rate					
Mean of non-zero estimates	0.220 (0.012)	0.210 (0.047)	-0.288 (0.056)	0.154 (0.068)	-0.035 (0.059)
% of significant coefficients at 5% level	61.4	46.8	53.7	14.9	18.5

Note: Numbers in parentheses represent the standard errors for the means.

The proportion of statistically significant estimates of λ_i indicates that the impacts of shocks on theft and robbery crime rates are persistent in 42.1% and 61.4% of Fortaleza's neighborhoods, respectively (as detailed in Table 1, column 2, rows 5 and 9). The average estimates of λ_i for theft and robbery series in these neighborhoods are 0.177 and 0.220, respectively (Table 1, column 2, rows 3 and 7). These figures allow us to determine the duration for the impact of a shock to be considered negligible, defined as a reduction to less than 5% of its initial value, using the formula $\ln(0.05)/\ln|\lambda i|$. Accordingly, the estimated average persistence durations for shocks are 1.73 months for theft and 1.98 months for robbery. This suggests that the effects of shocks on crime rates diminish relatively quickly. However, it's important to note that the degree of persistence in the original series may be higher as these estimates are derived from the defactorized series.

The parameters (ψ_{0i}^{+}, ψ_{0i}^{-}, ψ_{1i}^{+}, ψ_{1i}^{-}) measure the strength and direction of both contemporaneous and lagged spatial correlations among neighborhood crime rates. In the theft series, the contemporaneous correlation estimates for ψ_{0i}^{+} and ψ_{0i}^{-} are statistically significant for approximately 45% and 60% of neighborhoods, respectively. For the robbery series, ψ_{0i}^{+} and ψ_{0i}^{-} are statistically significant in about 46% and 63% of neighborhoods, respectively. The lagged spatial correlations, represented by ψ_{1i}^{+} and ψ_{1i}^{-}, are not statistically significant for most neighborhoods, especially in the case of ψ_{1i}^{+} related to theft.

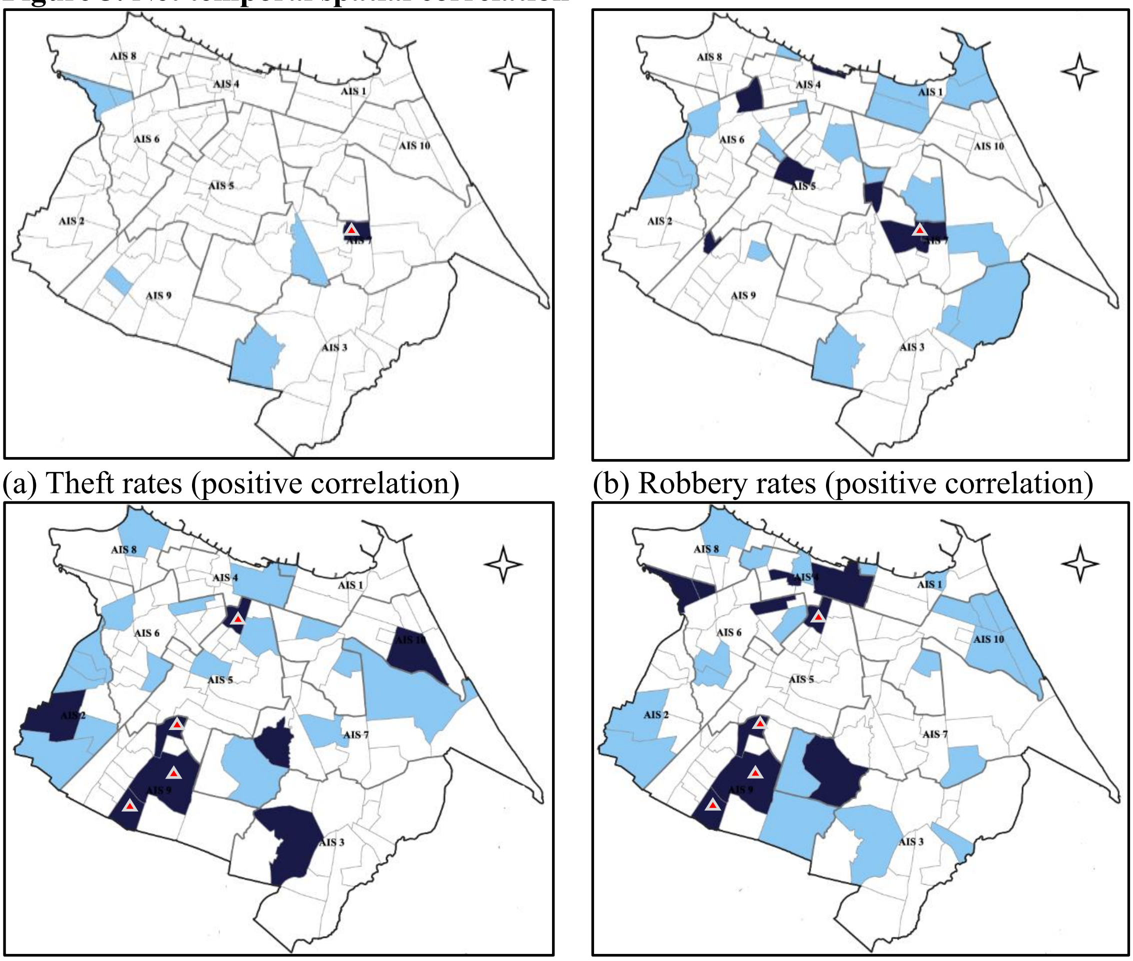
Considering only the significant results, the average estimates for ψ_{0i}^{+} and ψ_{0i}^{-} are 0.114 and -0.363 for the theft series, and 0.21 and -0.288 for the robbery series. The estimates for ψ_{1i}^{+} and ψ_{1i}^{-} are significantly smaller, and appear more relevant for ψ_{1i}^{+} in the case of the robbery series. Spatial correlation in crime occurrences within Fortaleza's neighborhoods appears considerably stronger in the contemporaneous scenario and more spatially prevalent for robbery occurrences (a relatively more violent type of crime).

These results highlight the importance of the adopted approach, which considers common behaviors in the series and allows for variations in parameters across neighborhoods, resulting in a significant reduction in the spatial correlation of crime. For comparison, estimates of a single spatial correlation parameter ψ in the model $\pi_{it} = \lambda_i \pi_{it-1} + \psi W \pi_{it} + \varepsilon_{it}$, without defactoring, are approximately 0.5 for theft and 0.7 for robbery. Furthermore, the variation in the spatial correlation parameter reveals that this characteristic may not be consistent across all geographic units — potentially being either positive or negative — indicating that the spatial connectivity between neighborhood crime rates does not necessarily follow a single direction.

To efficiently visualize the heterogeneity of results across the city, we will focus on discussing the net temporal spatial correlation $(\psi_{0i}^{+} + \psi_{0i}^{-} + \psi_{1i}^{+} + \psi_{1i}^{-})$ for each neighborhood. Figure 3 presents maps illustrating the estimates of net temporal spatial correlations, simplified into three levels to enable a direct comparison between crime types and neighborhoods in Fortaleza. Areas in dark blue in panels (a) and (b) indicate positive net temporal spatial correlations exceeding 0.5, while panels (c) and (d) feature areas with negative net temporal spatial correlations below -0.5. Non-significant correlations are marked in white, with intermediate values shown in light blue.

First, it is crucial to reiterate that due to the parameter heterogeneity allowed in our model, Figure 3 shows that not every neighborhood exhibits significant spatial correlation, echoing earlier findings presented in Table 1. Moreover, consistent with the results from Table 1, negative spatial correlation is more noticeable across neighborhoods than positive spatial correlation, particularly in cases of theft.

Figure 3. Net temporal spatial correlation



(a) Theft rates (positive correlation)

(b) Robbery rates (positive correlation)

(c) Theft rates (negative correlation)

(d) Robbery rates (negative correlation)

Note: The net temporal spatial correlation is determined by the sum of the coefficients $\psi_{0i}^{+}, \psi_{0i}^{-}, \psi_{1i}^{+}$ and ψ_{1i}^{-}.
Legend:
☐ No correlation ■ $0 < |\psi_{0i}^{+} + \psi_{0i}^{-} + \psi_{1i}^{+} + \psi_{1i}^{-}| \leq 0.5$ ■ $|\psi_{0i}^{+} + \psi_{0i}^{-} + \psi_{1i}^{+} + \psi_{1i}^{-}| > 0.5$

Aquaro et al. (2021) describe regions with positive net temporal spatial correlation as "spill-out" areas, where shocks in a geographic unit spill over to its neighbors. In our analysis, this implies that neighborhoods highlighted in panels (a) and (b) of Figure 3 tend to influence crime occurrences in other areas in the same direction as the shock. Consequently, negative shocks in these neighborhoods would lead to decreases in crime occurrences throughout the city. Arguably, targeting crime in these areas could generate positive spatial externalities due to these spill-over effects.

This dynamic, where crime prevention efforts may diffuse benefits beyond the initially targeted areas, is discussed in Eck and Weisburd (2015). They reference empirical studies such as Green (1995), which found improvements not only at the "nuisance" addresses targeted by the Oakland Beat Health Unit but also in the surrounding housing units, and Weisburd and Green (1995), which found evidence of spatial diffusion benefits in the Jersey City Drug Market Analysis Experiment.

However, our results also identify areas characterized by negative net spatial correlation, which Aquaro et al. (2021) term "spill-in" areas. Shocks in the series for these regions tend to inversely influence the behavior of series in nearby areas, concentrating their temporal effects within themselves. Thus, the neighborhoods in panels (c) and (d) of Figure 3 act as crime concentrators, potentially drawing in criminal activities from other areas within the city. Contrary to the spatial diffusion benefits discussed in Eck and Weisburd (2015), the negative spatial correlation suggests that efforts to reduce crime in these areas, constituting a negative shock, could inadvertently increase crime occurrences in other parts of the city. Given that there appears to be a relatively higher number of neighborhoods with negative net spatial correlation in Fortaleza, particularly concerning theft, these results suggest that defining strategic interventions in specific areas to reduce crime poses a challenge.

Finally, several neighborhoods identified as outliers in these analyses require careful evaluation by police administration to devise effective policing strategies. One outlier neighborhood, marked with a red triangle in panels (a) and (b), along with four neighborhoods marked with red triangles in panels (c) and (d), demonstrate a strong influence on crime occurrences in other areas for both types of crime. Three of this form a significant cluster in the south-central part of the city, as shown in Figure 2, with high rates of both crime types.

5.3. Analyzing the Link Between Spatial Correlation and Socio-Economic Indicators: Results and Insights

According to Eck and Weisburd (2015) in "Crime Places in Crime Theory," there is consistent evidence indicating that crime concentrations in specific areas are influenced by rational choice and routine activity. This theoretical framework highlights how socio-economic variables affect local crime occurrence, influencing crime opportunities, expected returns, and the probability of capture. For example, Glaeser and Sacerdote (1999) argue that areas with higher population density offer more crime opportunities, whereas Jacobs (1961) suggests that dense urban areas may inhibit criminal behavior by increasing the risk of capture.

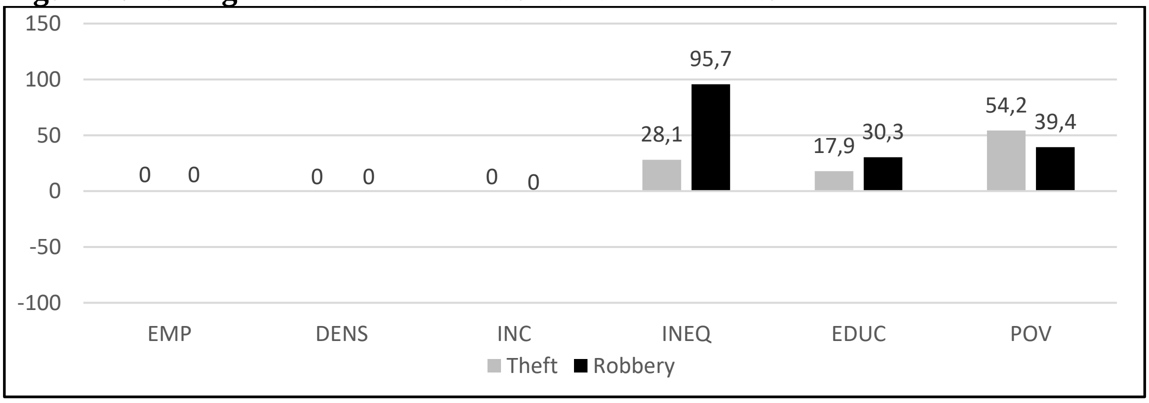
Furthermore, local household income levels and their distribution can simultaneously increase the expected benefits of committing a crime and enhance informal social control within communities (Bursik and Grasmick, 1995; Hipp, 2011). Additionally, individuals in regions with higher education levels often have more opportunities for legitimate earnings and a greater willingness to conform to social norms. However, these regions, typically wealthier and hosting more commercial activities, also present greater opportunities and expected returns for committing crimes (Nguyen, 2019; Groot and van den Brink, 2010). For a more detailed discussion, see Cohen and Felson (1979), Pratt and Cullen (2005), and Newburn (2016).

In this context, a pertinent question for this section is how socioeconomic factors could contribute to designating an area as a spatial diffusion hub of crime. Similar to the rationale applied in studies of crime hotspots, a spatial diffusion hub arises when criminals consider areas with similar opportunities, risks, and benefits as nearby areas. Consequently, significant changes in these socioeconomic factors could both spread and attract crime from other areas, reflecting the spatial displacement effects discussed in Eck and Weisburd (2015).

To explore the relationship between socio-economic factors and the likelihood of a neighborhood being identified as spatial diffusion hub of crime, we consider the following variables: formal local employment opportunities (**EMP**), population density (**DENS**), average household per capita income (**INC**), income inequality (**INEQ**), the percentage of the illiterate population (**EDUC**), and the percentage of poor households (**POV**).[8] These variables were selected based on data availability and their frequent use in empirical spatial studies assessing crime determinants, sourced from the 2010 Census.

Figure 4 presents a bar plot illustrating the average predictive contribution of each feature to the likelihood of a neighborhood being a spatial crime contagion hub for theft (in gray) and robbery (in black).

Figure 4: Average Predictive Contribution of Each Feature



The results indicate that the local number of formal employees, population density, and average household per capita income do not significantly predict whether a neighborhood is a potential spatial diffusion hub for either theft or robbery. Interestingly, studies by De Oliveira et.al. (2016) found a positive relationship between per capita household income and violent crime rates in Fortaleza, although population density was not a relevant factor in their analyses. It is important to note that the present study differs from this literature in both methodological approach and the dependent variable, which, in our case, is spatial correlation.

The results in Figure 4 highlight the critical importance of poverty (POV) and inequality (INEQ) in determining the likelihood of a neighborhood becoming a spatial diffusion hub of crime. In the case of theft, the percentage of poor households has an

[8] The variable POV represents the percentage of individuals with per capita household income equal to or less than U$42.00 per month, in 2010.

average odds ratio of 1.542, indicating that a one-unit increase in the percentage of the population living below the poverty line increases the odds of spatial correlation by 54.2%. For robbery, a more violent type of crime, the impact of poverty is slightly less pronounced, with an average odds ratio of 1.394. Inequality also plays a significant role, particularly in the context of robbery, where it has an odds ratio of 1.957—while for theft, the odds ratio is 1.287.

There is substantial evidence in the literature suggesting that poverty and inequality are closely related to crime occurrences in cities or neighborhoods (Paul-Phillippe and Felson, 2014; Wenger, 2019; and Xu et al., 2024 for a recent review). In addition to the increased expected benefit of committing crimes in poor and unequal areas, these factors may further influence crime due to their association with greater social disorganization and a lack of social control (Hipp, 2011). According to our results, these factors are also critically important for the spatial diffusion of crime across neighborhoods.

The variable related to education also proves relevant in this analysis. A one-unit increase in the percentage of the literate population increases the average odds of spatial correlation by 17.9% for theft and 30.3% for robbery. It is worth mentioning that many empirical studies assessing the influence of education on crime typically utilize data on average years of schooling at the regional level. For example, studies by Buonanno and Leonida (2006), Nguyen (2019), and Rakshit and Neog (2020) identified a negative relationship between educational attainment and crime occurrences at state levels in Italy, India, and Indonesia, respectively. However, in our case, this variable did not show sufficient variability across neighborhoods within a specific year to be viable for use. Nevertheless, using our proxy, the relevance of education for the spatial diffusion of crime is evident.

6. Conclusion

This study employs a panel data model with heterogeneous coefficients to examine the spatiotemporal behavior of monthly theft and robbery crime rates across 114 neighborhoods in Fortaleza, one of the most violent cities in the world. The model structure filters out pure spatial correlation from strong cross-sectional correlations and identifies potential spatial contagion hubs of crime. This is crucial to avoid biases in the analysis of crime rates due to common factors in the region and the assumption of spatial correlation in each cross-sectional unit of the data.

The results show that spatial correlation is relatively more prevalent for robbery, with approximately 45% of neighborhoods exhibiting statistically significant spatial correlation (compared to 25% for theft). These neighborhoods, identified as spatial diffusion hubs of crime, pose a challenge for police efforts because interventions in local crime occurrences tend to be accompanied by changes in crime occurrences in other areas. Depending on the nature of the spatial correlation, targeting crime in these neighborhoods may generate positive or negative spatial externalities due to spill-over effects. Therefore, combating crime in these neighborhoods demands a more strategic approach than one based solely on the identification of crime occurrence hotspots.

Through straightforward explanatory analysis, this study discovered that poverty and income inequality can heighten the likelihood of a neighborhood becoming a crime diffusion hub. This complements existing literature by showing that income deprivation not only affects the frequency of crimes in specific areas but also influences how crime spreads across regions facing such adverse conditions.

Lastly, it is crucial to acknowledge certain limitations of this study. Due to the lack of monthly socioeconomic or police-action data at the neighborhood level, the econometric model cannot directly control for these effects. It is hoped that using fixed effects, factors to account for shocks across the city, the regional structure of police administration, and lagged dependent variables as explanatory regressors will help reduce the influence of possible omitted factors. The results also highlight the need for future research to develop more structural approaches to simultaneously estimate spatial correlation in neighborhoods and its relationship with socioeconomic indicators.

References

ALKIMIM, A., CLARKE, K., & OLIVEIRA, F. (2013). Fear, crime, and space: The case of Viçosa, Brazil. **Applied Geography**, 42, 124±132.

ANSELIN, L. (1988). **Spatial Econometrics: Methods and Models.** Boston: Kluwer Academic.

ANSELIN, A. COHEN, J., COOK, D., GORR, W & TITA, G. (2000). Spatial Analyses of Crime. **Criminal Justice**, 4(2), 213-262.

ANSELIN, Luc; GRIFFITHS, Elizabeth; TITA, George. Crime mapping and hot spot analysis. In: **Environmental criminology and crime analysis.** Willan, 2013. p. 119-138.

AQUARO M., BAILEY, N. and PESARAN, M. H., "Estimation and Inference for Spatial Models with Heterogeneous Coefficients: An Application to U.S. House Prices", **Journal of Applied Econometrics**, Vol. 36, No. 1, 2021, pp. 18-44.

BAI, J. and NG, S. Determining the Number of Factors in Approximate Factor Models. **Econometrica**,70, 191-221, 2002.

BAILEY, Natalia; HOLLY, Sean; PESARAN, M. Hashem. A two-stage approach to spatio-temporal analysis with strong and weak cross-sectional dependence. **Journal of Applied Econometrics**, v. 31, n. 1, p. 249-280, 2016.

BAILEY, N., KAPETANIOS, G. and PESARAN, H. M. (2014). **Exponent of Cross-Sectional Dependence: Estimation and Inference.** Jan 2012, revised Apr 2014. Cambridge Working Paper 1206.

BECKER, G. **Crime and Punishment: An Economic Approach.** Journal of Political Economy. Vol.76, n. 2, mar/1968.

BOWERS, K., JOHNSON, S., GUERETTE, R. T., SUMMERS, L., & POYNTON, S. (2011). Spatial Displacement and Diffusion of Benefits among Geographically Focused Policing Initiatives: A Meta-Analytical Review. **Journal of Experimental Criminology**, 7(4), 347–374.

Bowers, K.J.; Johnson, S.D. Measuring the geographical displacement and diffusion of benefit effects of crime prevention activity. **Journal Quantitative Criminology**, 2003, 19, 275–301.

BUONANNO, P. and LEONIDA L. (2006). Education and crime: Evidence from Italian regions. **Applied Economics Letters** 13: 709–13.

BURSIK, R. J., GRASMICK, H. G. Neighborhood-based networks and the control of crime and delinquency. In: BALROW, H. (Ed.). Crime and public policy: Putting theory to work. Boulder, CO. Westview, (1995).

BRAGA, Anthony A.; PAPACHRISTOS, Andrew V.; HUREAU, David M. The effects of hot spots policing on crime: An updated systematic review and meta-analysis. **Justice quarterly**, v. 31, n. 4, p. 633-663, 2014.

BRANTINGHAM, Patricia; BRANTINGHAM, Paul. Criminality of place: Crime generators and crime attractors. **European journal on criminal policy and research**, v. 3, p. 5-26, 1995.

BRANTINGHAM, P. L., & BRANTINGHAM, P. J. (1995). Location quotients and crime hot spots in the city. In Crime Analysis through Computer Mapping. Washington, DC. **Police Executive Research Forum** (pp. 129-149).
CAPLAN, Joel M.; KENNEDY, Leslie W. Risk terrain modeling: Crime prediction and risk reduction. Univ of California Press, 2016.
CHAINEY S, RATCLIFFE JH (2005) GIS and crime mapping. Wiley, London.
CHAINEY, Spencer; TOMPSON, Lisa; UHLIG, Sebastian. The utility of hotspot mapping for predicting spatial patterns of crime. **Security journal**, v. 21, p. 4-28, 2008.
CHAMBERLAIN, A. W., & HIPP, J. R. (2015). It´s all relative: Concentrated Disadvantage Within and Across Neighborhoods and Communities, and the Consequences for Neighborhood Crime.**Journal of Criminal Justice**, 43(6), 431-443.
CHANG, Victor et al. Pima Indians diabetes mellitus classification based on machine learning (ML) algorithms. Neural Computing and Applications, v. 35, n. 22, p. 16157-16173, 2023.
CHUDIK, A., PESARAN, M. H., & TOSETTI, E. (2011). Weak and strong cross-section dependence and estimation of large panels.
CLARKE, Ronald V.; WEISBURD, David. Diffusion of crime control benefits: Observations on the reverse of displacement. **Crime prevention studies**, v. 2, n. 1, p. 165-84, 1994.
COHEN, L.E. and FELSON, M. (1979). Social change and crime rate trends: A routine activity approach. **American Sociological Review**, 44, 588-608.
COZENS, P., HILLIER, D. & PRESCOTT, G. (2002) Community Safety, the British City and the 'Active Citizen': Penetrating the Criminal Mind. **Crime Prev.** Community Saf 4, 7–21.
DANTAS, Régis F. and FAVARIN, Serena. "Concentration of Urban Violence in Fortaleza and Strategies for Crime Prevention." **Criminal Justice Review**. 46 (2021): 466 – 483.
DANTAS, Régis Façanha. Governança na Segurança Pública. Fonte Segura, v. 1, p. 1, 2020.
de MEDEIROS, C. N. et al. Correlações Espaciais Entre Homicídios e Concentração de Aglomerados Subnormais em Fortaleza, CE, Brasil. **Revista GeoUECE**, v. 2, n. 2, p. 92-110, 2013.
de MELO, S., MATIAS, L. & ANDRESEN, M. (2015). Crime concentrations and similarities in spatial crime patterns in a Brazilian context. **Applied Geography**, 62, 314±324.
de OLIVEIRA, Denise Xavier Araújo; SIMONASSI, Andrei Gomes. **O Raio da Criminalidade: Delimitação e Alcance de Clusters Espaciais na Cidade de Fortaleza.** Economia do Ceará em Debate, 2019. Fortaleza, CE: IPECE.
de OLIVEIRA, Victor Hugo; de MEDEIROS, Cleyber Nascimento; CARVALHO, José Raimundo. Violence and local development in Fortaleza, Brazil: a spatial regression analysis. **Applied Spatial Analysis and Policy**, v. 12, n. 1, p. 147-166, 2019.
ECK, John; WEISBURD, David L. Crime Places in Crime Theory. **Crime and place: Crime prevention studies**, v. 4, 2015.
FARIA, J., OGURA, L. & SACHSIDA, A. (2013). Crime in a planned city: The case of Brasília. Cities, 32, 80±87.
GEVERT, Vania Gryczak et al. Modelos de regressão logística, redes neurais e support vector machine (svm s) na análise de crédito a pessoas jurídicas. **RECEN-Revista Ciências Exatas e Naturais**, v. 12, n. 2, p. 269-293, 2010.
GLAESER, E. L. and SACERDOTE B. L. "Why is there more crimes in cities" **Journal of Political Economy** 107 (6, 1999): 225-258.
GROOT, Wim; VAN DEN BRINK, Henriëtte Maassen. The effects of education on

crime. **Applied economics**, v. 42, n. 3, p. 279-289, 2010.
GOMES, Rodrigo Carneiro**.** Prevenir o crime organizado: inteligência policial, democracia e difusão do conhecimento. **Segurança Pública & Cidadania**, v. 2, n. 2, p. 107-137, 2009.
GREEN, L. (1995). "Cleaning Up Drug Hotspots in Oakland, California: The Displacement and Diffusion Effects." **Justice Quarterly** (forthcoming).
HAINING R., LAW J., GRIFFITH D. (2009) Modelling small area counts in the presence of overdispersion and spatial autocorrelation. Comput Stat Data Anal 53(8):2923–2937.
HILLIER, Bill; SAHBAZ, Ozlem. An evidence based approach to crime and urban design, or, can we have vitality, sustainability and security all at once. **Bartlett School of Graduates Studies University College London**, p. 1-28, 2008.
HIPP J. R. (2011) Spreading the wealth: the effect of the distribution of income and race/ethnicity across households and neighborhoods on city crime trajectories*. **Criminology** 49:631–665.
HIPP, John R.; WICKES, Rebecca. Violence in urban neighborhoods: A longitudinal study of collective efficacy and violent crime. **Journal of Quantitative Criminology**, v. 33, p. 783-808, 2017.
HIRSCHFIELD, A., & BOWERS, K. J. (1997). The Effect of Social Cohesion on Levels of Recorded Crime in Disadvantaged Areas. **Urban Studies**, 34, 1275-1295.
JACOBS, J. (1961). The life and death of great American cities. New York: Random House.
KAKAMU, Kazuhiko; POLASEK, Wolfgang; WAGO, Hajime. Spatial interaction of crime incidents in Japan. **Mathematics and Computers in Simulation**, v. 78, n. 2-3, p. 276-282, 2008.
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, 481-516.
LESAGE, James P.; CHIH, Yao-Yu. Interpreting heterogeneous coefficient spatial autoregressive panel models. **Economics Letters**, v. 142, p. 1-5, 2016.
LIESENFELD, Roman; RICHARD, Jean-François; VOGLER, Jan. Likelihood-Based Inference and Prediction in Spatio-Temporal Panel Count Models for Urban Crimes. **Journal of applied econometrics**, v. 32, n. 3, p. 600-620, 2017.
LIN, Z., WANG, C., YANG, X., SUN, J., YUE, M., & SHAHABI, C. (2022). Hagen: Homophily-aware graph convolutional recurrent network for crime forecasting**. In Proceedings of the AAAI Conference on Artificial Intelligence** (Vol. 36, No. 4, pp. 4193-4200).
MENEZES, T., SILVEIRA-NETO, R., MONTEIRO, C. & RATTON, J. (2013). Spatial correlation between homicide rates and inequality: Evidence from urban neighborhoods. **Economic Letters**, 120, 97±99.
NEUMAYER E. and PLÜMPER T (2016) W. Political Science Research and Methods 4, 175–193.
NEWBURN, T. (2016). Social Disadvantage, Crime and Punishment. In Social Advantage and Disadvantage (pp. 322-340). Oxford: Oxford University Press. https://doi.org/10.1093/acprof:oso/9780198737070.003.0016
NGUYEN, H.T.M. (2019). Do more educated neighbourhoods experience less property crime? Evidence from Indonesia. International Journal of Educational Development 64: 27–37.
NOGUEIRA, J. H. M. ; MORAES, S. L. C. . Brazils Big Data Cerebrum 2.0. Innovation Snapshots INTERPOL , v. 2, p. 1-3, 2022
OLIVEIRA, Cristiano Aguiar de. **Análise espacial da criminalidade no Rio Grande do Sul**. 2008.

PARK R. E., and BURGESS E. 1925 [1967]. The City: Suggestions for Investigation of Human Behavior and Urban Environment. Chicago, IL: **University of Chicago Press.**
PAUL-PHILLIPPE P., and FELSON R. (2014). Income inequality, poverty and crime across nations: Income inequality, poverty and crime across nations. **The British Journal of Sociology** 65: 434–58.
PESARAN, M. H. (2004). **General Diagnostic Tests for Cross Section Dependence in Panels.** Working Paper Series No. 1229. Available at SSRN: http://ssrn.com/abstract=572504.
PESARAN, M. H. (2014). **Testing Weak Cross-Sectional Dependence in Large Panels.** Forthcoming in Econometric Reviews.
PESARAN, M. H.; TOSSETI, Elisa (2011) "Large Panels with Common Factors and Spatial Correlation", **Journal of Econometrics**, vol 161, pp. 182-202.
PIZA, E. L.; WELSH, B. C.; FARRINGTON, D. P.; THOMAS, A. L. CCTV surveillance for crime prevention: A 40-year systematic review with meta-analysis. **Criminology & public policy**, 18(1), (2019) 135-159
PRATT T. C., CULLEN F. T. (2005). Assessing macro-level predictors and theories of crime: A meta-analysis. **Crime and Justice**, 32, 373–450. https://doi.org/10.1086/655357.
PEREIRA, Débora VS; MOTA, Caroline MM; ANDRESEN, Martin A. The homicide drop in Recife, Brazil: A study of crime concentrations and spatial patterns. **Homicide studies**, v. 21, n. 1, p. 21-38, 2017.
RAKSHIT, Bijoy; NEOG, Yadawananda. Does higher educational attainment imply less crime? Evidence from the Indian states. **Journal of Economic Studies**, v. 48, n. 1, p. 133-165, 2020.
Ratcliffe, J.H.; Breen, C. Crime diffusion and displacement: Measuring the side effects of police operations. Prof. Geogr. 2011, 63, 230–243.
SHAW, C R and MCKAY, H D (1942) **Juvenile Delinquency and Urban Areas.** University of Chicago Press, Chicago.
SHERMAN, Lawrence W.; GARTIN, Patrick R.; BUERGER, Michael E. Hot spots of predatory crime: Routine activities and the criminology of place. **Criminology**, v. 27, n. 1, p. 27-56, 1989.
WEISBURD, David; ECK, John E. What can police do to reduce crime, disorder, and fear?. **The annals of the American academy of political and social science**, v. 593, n. 1, p. 42-65, 2004.
WARNER, Barbara D.; PIERCE, Glenn L. Reexamining social disorganization theory using calls to the police as a measure of crime. **Criminology**, v. 31, n. 4, p. 493-517, 1993.
WENGER M. R., Separating the influence of inequality on burglary and robbery by level of analysis: A multilevel approach, Social Science Research, 10.1016/j.ssresearch.2019.03.007, 81, (42-60), (2019).
WELSH BC, FARRINGTON DP, DOUGLAS S (2022) The impact and policy relevance of street lighting for crime prevention: a systematic review based on a half-century of evaluation research. **Criminol Public Policy**. https://doi.org/10.1111/1745-9133.12585.
WHITTEN GD, WILLIAMS LK, WIMPY C. Interpretation: the final spatial frontier. **Political Science Research and Methods**. 2021;9(1):140-156. doi:10.1017/psrm.2019.9
WILSON, J. and KELLING, G. (1982) The police and neighborhood safety: Broken windows. The Atlantic Monthly, 127, 29-38.
XU, C., HE, Z., SON, G. et al. Unraveling the influence of income-based ambient population heterogeneity on theft spatial patterns: insights from mobile phone big data analysis. Humanit Soc Sci Commun 11, 108 (2024).

ZHAO, X.; FAN, W.; LIU, H.; and TANG, J. (2022). Multi-type urban crime prediction. In AAAI, 4, 4388–4396.