Making Spatial More Spatial: Decomposing Direct, Indirect, and Total Impacts in Neighborhood and Crime Studies

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Abstract

We attempt to enhance both the theories and empirical examination of neighborhood and crime by adapting the direct-indirect-total effect interpretation. We first discuss theoretical and methodological motivations for the current study and show how to decompose the direct, indirect, and total effects in the context of neighborhood and crime study. We empirically demonstrate this using the sample of block groups in Los Angeles County. For our demonstration of the direct-indirect interpretation with real-world data, we adopt the Spatial Durbin Model (SDM). We examined how variations in explanatory variables impact crime rates within a neighborhood and how these effects spill over into adjacent areas. The estimated effects from the SDM models were calculated with 1,000 simulations. For each variable, the indirect and total impacts reflect the cumulative spatial effects across neighboring units. Our findings suggest that crime-reducing or -producing effect of certain structural characteristics in one neighborhood may have broader regional effects potentially enhancing or reducing crime not only locally but also in neighboring communities through significant spatial spillovers. The suggested approach in the current study further highlighted the importance of spatial dependency of social factors across space and advances our understanding of neighborhood and crime by rigorously interpretating the direct-indirect-total effects of structural characteristics on crime beyond individual neighborhoods. We further discuss the methodological implications of our findings.

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Introduction

In recent decades, ecological studies on crime have significantly advanced our understanding that certain neighborhoods experience higher crime rates than others. Moreover, extensive research examining neighborhoods and crime has empirically demonstrated that certain social environmental features greatly influence the spatial patterns of crime (Sampson, Raudenbush, and Earls 1997; Sampson 2012; Hipp 2007). Social disorganization theory underpins many of these studies. The theory posits that certain structural characteristics such as socioeconomic disadvantage, racial composition or heterogeneity, or residential instability undermine social ties and cohesion among local neighborhood residents, which potentially leads to diminished informal social control and collective efficacy.

On the other hand, another body of studies has focused on the spatial distribution of crime opportunities. For example, routine activity theory emphasizes that crime occurs when three ingredients—motivated offenders, suitable targets, and the absence of capable guardians—converge at a given space and time (Felson 1987; Brantingham and Brantingham 1993; Cohen and Felson 1979). Similar to non-criminals, motivated offenders have their mobility patterns across the urban landscape and search for suitable targets through their routine activities. Thus, a crime incident may occur when the activity spaces of potential offenders and those of targets spatially and temporally intersect. Additionally, the offender mobility literature suggests that offenders are more likely to commit crimes in areas where they have enough familiarity within a proximate distance from their homes or places of work—the distance decay effect (Tita and Griffiths 2005; Hipp 2020; Rossmo 2000; Ackerman and Rossmo 2015).

Reflecting the importance of the theoretical points aforementioned, an extensive body of research has provided theoretical justifications and empirical evidence for incorporating the neighboring areas when studying spatial crime patterns (Hipp and Boessen 2013; Kim and Hipp 2020). For example, since the structural characteristics posed in social disorganization theory are expected to affect spatial crime pattern not only in a specific neighborhood but also in nearby areas, they may lead to spatial spillover (or indirect, interchangeably) effects across neighborhoods.[1] Likewise, an important implication from the literature of criminal opportunities is that criminal opportunities are contingent on the spatial mobility patterns of potential offenders and targets at a given time, which is not subject to a focal neighborhood but extends to nearby areas. Thus, scholars highlight that understanding spatial dependency and spillover effects is essential for accurately modeling and predicting crime patterns and thus advancing criminological theory.

Theoretically, a neighborhood is not a physical or social island but is spatially interconnected with adjacent and nearby areas in terms of social and environmental development and change. Moreover, residents often define and perceive their neighborhoods more expansively than predefined spatial boundaries, and their mobility patterns extend beyond the specific area of residence. As such, existing studies have acknowledged the significance of nearby areas and the spatial interdependencies of crime and its determinants when studying the structural characteristics and built physical environment, and their relationships with spatial crime patterns. In essence, this spatial interconnectedness underscores the importance of incorporating spatial dynamics into theoretical frameworks and empirical models to fully comprehend the complexities of crime patterns (Hipp, Kim, and Wo 2021; Hipp 2022).

Theoretical Backgrounds

Accounting for Spatial Dependency

In this section, we briefly review spatial regression analyses and current practices highlighting their utility in estimating direct, indirect, and total effects. Spatial regression allows us to examine how neighborhood factors influence crime not only within specific areas but also across adjacent neighborhoods; thereby providing deeper insights into spatial crime

1. We use the terms spatial *spillover effect* and *indirect effect* interchangeably throughout the manuscript.

patterns. As noted above, a significant body of research has emphasized the importance of spatial dependency when studying neighborhood and crime. Scholars have employed various empirical modeling approaches to capture these spatial dependencies. One common way involves incorporating neighboring areas by introducing a distance decay measures predicting crime in the focal unit, which reflects the reduced impact of distant areas on crime rates in a focal location. Yet an aspatial approach employed in prior work is adjusting the overall estimate of the covariance matrix, such as using the Cluster Covariance Matrix Estimator (CCE), to effectively address spatial dependencies (see Bester, Conley, and Hansen 2011). Despite methodological differences, these studies share a core idea that crime patterns are shaped by spatial dependencies driven by both ecological predictors and/or the diffusion of crime itself. Thus, the essence of a spatial modeling strategy lies in accurately capturing the impacts of variables of interest while accounting for these spatial dependencies. (Anselin et al. 2000; Anselin 2003).

Among the various model specifications, the Spatial Lag of X (SLX) model is one of the most widely used in neighborhood and crime studies. This model incorporates spatially lagged independent variables acknowledging that the factors influencing crime often exhibit spatial dependency. Spatial dependency suggests that factors affecting crime in one neighborhood can also influence crime in nearby areas. For example, concentrated disadvantage in one neighborhood may elevate the risk of crime not only within that area but also in nearby neighborhoods contributing to broader spatial crime patterns. Similarly, protective factors such as residential stability—commonly measured by the proportion of homeowners in a neighborhood—can reduce crime rates within the neighborhood (direct effect) while simultaneously benefiting surrounding areas through spillover (indirect effects). This ability to discern direct and indirect effects makes a spatial model particularly valuable in neighborhood and crime studies offering researchers deeper insights into the intricate dynamics of crime distribution.

Additionally, scholars often incorporate spatially lagged dependent variable when they believe there is spatial dependency in crime itself. It assumes a spatial contagion or diffusion effect of crime as it treats the risk of crime as a contagious disease where crime in one area may directly increase or decrease crime in other adjacent or nearby areas (Cohen and Tita 1999; Loftin 1986; Papachristos, Wildeman, and Roberto 2015; Messner et al. 1999). This leads to models such as the Spatial Autoregressive Model (SAR) including only a lagged spatial-dependent variable, or the Spatial Durbin Model (SDM) with lagged spatial terms for both dependent and independent variables. For example, Morenoff, Sampson, and Raudenbush (2001), focus on a spatial contagious effect of homicide. Specifically, they illustrate that "interpersonal crimes such as homicide are based on social interaction and thus subject to diffusion processes... a homicide in one neighborhood may provide the spark that eventually leads to a retaliatory killing in a nearby neighborhood (p. 523)." Extending this notion, Browning, Feinberg, and Dietz (2004) introduce the concept of "spatial vulnerability" to describe neighborhoods' susceptibility to violence originating from nearby areas. This theoretical framework underpins the use of spatial lag models, which capture spillover effects by integrating spatially lagged dependent variable. As such, their empirical models incorporate spatial dynamics, such that an increase in homicide incidents in one unit may trigger related incidents in nearby areas with a stronger influence on closer units than more distant ones.

A fundamental component of spatial regression strategies is the use of a spatial weight matrix (SWM)—a representation of spatial association between spatial units to quantify how spatial units interact and influence one another. It defines the structure of spatial relationships among units and thus specifying the spatial dependence. The basic intuition follows Tobler's first law of geography, which asserts that "everything is related to everything else, but near things are more related than distant things" (Tobler 1970). Controlling for the interconnectivity between each geographical unit as measured by contiguity or distance, the SWM approach assumes that closer areas exert a stronger influence than those further away. Ecological studies of spatial crime patterns often employ a SWM to define relationships between units within a geographic area. For illustration, Figure 1 depicts a hypothetical region divided into nine sub-units (Unit 1 through Unit 9) and its corresponding Rook contiguity matrix. The SWM is essential in the spatial models as it allows for the inclusion of neighboring influences by assigning weights to either independent or dependent variables; thereby accounting for spatial dependencies in the analysis. By incorporating this matrix into the modeling strategy, empirical models more closely correspond with spatial theories of crime. For example, spatial modeling approaches in neighborhood and crime studies frequently focus on how structural characteristics of adjacent neighborhoods (Bernasco and Block 2011; Haberman and Ratcliffe 2015; Wo, Hipp, and Boessen 2016; Hipp and Kubrin 2017) or spatial diffusion of crime-related behaviors contribute to crime patterns (Browning et al., 2004; Morenoff et al., 2001).

[Figure 1 about here.]

Decomposing Direct, Indirect, and Total Effects

Previous studies have shown theoretical and empirical advantages of spatial modeling approaches with estimator accuracy (For additional technical details, please see LeSage and Pace 2009). Without accounting for spatial dependencies, models risk producing biased and inefficient estimators, as they fail to capture the interconnectivity inherent in spatial data. In other words, regardless of the estimation method—ordinary least squares or maximum likelihood—ignoring spatial dependencies results in inaccuracies. This oversight leads estimators to confuse the direct effects of the independent variables with their spillover effects, ultimately distorting the results (Betz, Cook, and Hollenbach 2021; Anselin et al. 2000; Cook, Hays, and Franzese 2023).

Although many studies have rigorously embraced spatial regression analysis, there remains significant potential to advance the spatial theories of crime further by incorporating recent advancements in spatial regression methods and interpretations. Many ecological crime studies employing spatial regression already estimate direct effects by including terms for focal unit as well as spatially lagged measures. Herein, we suggest that a crucial next step is to estimate and interpret the indirect and total effects as distinct from the direct effects, explicitly and accurately (Whitten, Williams, and Wimpy 2021). This approach has been employed in other areas of social science, particularly in the regional science literature (Ezcurra and Rios 2015; Beer and Riedl 2012). We also acknowledge that a recent body of ecological crime research has adopted this approach. For example, Maksuta, Zhao, and Yang (2024) examine the determinants of police-involved homicides using a Spatial Durbin Model (SDM). Their analysis tests for, and identifies, significant direct and indirect effects of firearm availability on police-involved homicides at the county level.

Nonetheless, we contend that a more rigorous and consistent application of the interpretation of direct, indirect, and total effects is still lacking in the study of ecological determinants of neighborhood crime. While prior ecological studies have adopted spatial modeling approaches, they have often paid limited attention to rigorously interpreting the substantive meaning of spatial direct, indirect, and total effects regardless of types of spatial regression modeling strategies employed (SDM, SLX, SEM, etc.). Our study aims to fill this gap by offering a clearer and more consistent framework for understanding and applying these interpretations in the context of neighborhood crime. This is particularly important given the increasing use of spatial econometric models in criminological research. Therefore, one of the primary contributions of the current study is to address this need by demonstrating how these effects can be meaningfully estimated and interpreted within the context of studying spatial crime pattern. By doing so, we attempt to advance both the methodological precision and substantive understanding of how neighborhood-level factors influence crime.

To further illustrate, we focus on the SDM model. We chose the SDM model as a representative as it provides a simpler structure by focusing on spatially dependent covariates. However, it is important to note that other spatial regression models—such as the Spatially Lagged X Model (SLX), Spatial Autoregressive Model (SAR), and Spatial Error Model (SEM)—can also estimate direct, indirect, and total impacts. Researchers can select the most appropriate model based on their spatial theory of interest and data structure.

Specifically, we estimate the impact of our independent variable using the following SDM specification:

The Spatial Durbin Model (SDM) is formally expressed as:

$$y = \rho W y + X\beta + W X\theta + \epsilon \tag{1}$$

where y is the dependent variable, X represents the independent variables, W is the spatial weights matrix capturing the interconnectivity between units, ρ is the spatial lag coefficient for the dependent variable (capturing spatial feedback/contagion), θ the spillover effect for covariates, β the direct effect, and ϵ is the error term.A distinguishing feature of the SDM is that the effect of a change in an independent variable—whether occurring within a unit or in neighboring units—is not limited to a single, direct transmission. Instead, due to the inclusion of the spatially lagged dependent variable, any initial effect is recursively propagated across the entire spatial network. This recursive process is mathematically represented by the spatial multiplier matrix, $(I - \rho W)^{-1}$, which transforms the relationship between the covariates and the outcome in a fundamental way.

In a standard regression model, the effect of X on y is captured by the estimated coefficients (e.g., β and θ), and direct and indirect effects can be calculated through simple algebra. However, in the SDM, these coefficients no longer represent the marginal effects of X on y in a straightforward manner. Rather, the presence of spatial feedback—encoded by ρ—means that any change in X is distributed throughout the spatial system according to the structure of W and the magnitude of ρ. This property fundamentally alters the interpretation of coefficients and the decomposition of effects. Again, formally, the SDM can be written as:

$$y = \rho W y + X\beta + W X\theta + \epsilon \tag{2}$$

Rearranging terms to isolate y yields:

$$(I - \rho W)y = X\beta + WX\theta + \epsilon \tag{3}$$

$$y = (I - \rho W)^{-1}(X\beta + WX\theta) + (I - \rho W)^{-1}\epsilon \tag{4}$$

Taking the partial derivative of the systematic component of y with respect to a specific covariate X_k results in the following matrix of partial derivatives:

$$S_k = \frac{\partial y}{\partial X_k} = (I - \rho W)^{-1}(\beta_k I + \theta_k W) \tag{5}$$

Here, S_k is the impact matrix for X_k: each element $S_{k,ij}$ quantifies the effect of a marginal change in X_k for unit j on the outcome y_i for unit i, fully accounting for all spatial feedback, spillover, and indirect pathways present in the SDM. The diagonal elements of S_k ($S_{k,ii}$) represent the direct effects, while the off-diagonal elements ($S_{k,ij}, i \neq j$) capture the indirect (spillover) effects across the spatial network.

It is therefore essential to explicitly decompose the total effect of any variable in the SDM into its direct and indirect (spillover) components. The direct effect of X_k is calculated as the average of the diagonal elements of S_k:

$$\text{Direct Effect} = \frac{1}{n}\sum_{i=1}^{n} S_{k,ii} \tag{6}$$

This quantity summarizes the expected impact of increasing X_k in a unit on its own outcome y_i, after accounting for all spatial feedback and propagation. The indirect effect (or spillover effect) is calculated as the average of the row sums of the off-diagonal elements:

$$\text{Indirect Effect} = \frac{1}{n}\sum_{i=1}^{n}\sum_{j\neq i} S_{k,ij} \tag{7}$$

This measures how, on average, a change in X_k in one unit affects the outcomes in all other units through the spatial network. The total effect is simply the sum of the direct and indirect effects, which can be expressed as the average row sum of S_k:

$$\text{Total Effect} = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n} S_{k,ij} \tag{8}$$

To concretely illustrate the calculation for the structure depicted in Figure 1, suppose we have three spatial units with the following parameter values: $\rho = 0.4, \beta = 0.5$, and $\theta = 0.3$. The spatial weights matrix is given by:

$$W = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix}$$

The spatial multiplier is:

$$I - \rho W = \begin{pmatrix} 1 & -0.4 & 0 \\ -0.4 & 1 & -0.4 \\ 0 & -0.4 & 1 \end{pmatrix}$$

The inverse is:

$$(I - 0.4W)^{-1} \approx \begin{pmatrix} 1.190 & 0.527 & 0.211 \\ 0.527 & 1.351 & 0.527 \\ 0.211 & 0.527 & 1.190 \end{pmatrix}$$

The term $(0.5I + 0.3W)$ is:

$$(0.5I + 0.3W) = \begin{pmatrix} 0.5 & 0.3 & 0 \\ 0.3 & 0.5 & 0.3 \\ 0 & 0.3 & 0.5 \end{pmatrix}$$

Multiplying these gives the matrix of partial derivatives S_k:

$$S_k = (I - 0.4W)^{-1}(0.5I + 0.3W) \approx \begin{pmatrix} 0.893 & 0.691 & 0.165 \\ 0.691 & 1.054 & 0.691 \\ 0.165 & 0.691 & 0.893 \end{pmatrix}$$

The Direct Effect is the average of diagonal elements:

$$\textit{Direct Effect} = \frac{1}{3}(0.893 + 1.054 + 0.893) = 0.947 \tag{9}$$

The Indirect Effect is the average row sum of off-diagonal elements:

$$\textit{Indirect Effect} = \frac{1}{3}[(0.691 + 0.165) + (0.691 + 0.691) + (0.165 + 0.691)] = 1.031 \tag{10}$$

Finally, the Total Effect is the sum of the direct effect and the indirect effect:

$$\textit{Total Effect} = 0.947 + 1.031 = 1.978 \tag{11}$$

This explicit calculation demonstrates how the SDM framework decomposes the overall marginal effect of an independent variable into its direct, indirect, and total effects, accounting for both spatial spillovers and feedback loops across the network. While the calculation above reports average direct and indirect effects, as summarized in the table, it is important to emphasize that the S_k matrix contains the full set of unit-specific marginal effects—that is, for any unit i, the effect of changing the independent variable in unit j on y_i is given by $S_{k,ij}$. For example, if unit 1 represents a block group, $S_{k,1j}$ captures how changes in the independent variable in each block group j affect the outcome in block group 1, allowing us to decompose the direct, indirect, and total impacts at a highly localized level.

We demonstrate that this unit-level calculation enables researchers to move beyond simple summary averages. By leveraging the full S_k matrix, scholars can visualize the spatial distribution of marginal effects across all units—such as mapping unit-specific effects across a city or region. This level of interpretation provides valuable insights into spatial heterogeneity and local dynamics that would otherwise be obscured by aggregated effects.

Additionally, researchers may be interested in the estimator's ability to calculate average effects across the entire study area, which summarize the model's implications across all observations providing a comprehensive perspective on spatial interactions. After estimating the model, we can calculate the average effects through simulations. By generating simulated parameter values across numerous iterations, we can capture the average direct, indirect, and total impacts across the entire sample. This approach offers a robust summary of how spatial dependencies manifest at an aggregate level, going beyond individual units.

This post-estimation process helps in generalizing findings to broader spatial contexts, thereby enhancing our understanding of spatial spillovers and their implications in crime research. Specifically, the average direct effect represents the mean of the direct effects across all observations. Since the direct effect is constant in this example, the average direct effect is:

$$\textit{Average Direct Effect} = \frac{1}{3} \times (0.893 + 1.054 + 0.893) = 0.946 \tag{12}$$

The average indirect effect, representing the spillover effect from neighboring observations, is the sum of the off-diagonal elements of the impact matrix divided by the number of observations:

$$\textit{Average Indirect Effect} = \frac{1}{3} \times (0.856 + 1.382 + 0.856) = 1.031 \tag{13}$$

Finally, the average total effect is the sum of the average direct and average indirect effects:

$$\textit{Average Total Effect} = 0.946 + 1.031 = 1.977 \tag{14}$$

In sum, we decomposed the direct, indirect, and total effects in the SDM model using a simple 3×3 spatial weights matrix. Additionally, we calculated the average direct, indirect, and total effects offering a comprehensive summary of the overall impact of changes in the independent and dependent variables across the spatial structure. In the following section, we demonstrate the advantages of the proposed methodology by leveraging real-world crime data.

Data and Methods

Data

For our empirical demonstration, we utilized two primary data sources at the Census block group level in Los Angeles County. First, we utilized official crime data from the Southern California Crime Study (SCCS) in 2018. This dataset includes the counts of Uniform Crime Reporting (UCR) Part I crime incidents including total crimes, violent crimes, and property crimes. These official crime records were reported by the local police agencies across about 100 cities in the County of Los Angeles. We have geocoded incident-level crime data to corresponding latitude and longitude coordinates and have aggregated the crime points to the block groups. We computed the crime rate by dividing the count of crime incidents by total population in block groups, respectively for each crime type. We then log-transformed them. Therefore, our primary outcomes are the logged crime rates for the three crime types.

We utilized the American Community Survey (ACS) 2016-2020 5-Year Estimates to measure the structural characteristics of neighborhoods at the block group level. Specifically, we included several independent variables to capture neighborhood structural characteristics. First, we constructed an index of concentrated disadvantage. This is a factor score including the percent persons at or below 125% of the poverty level; the percent single-parent households; the average household income; and the percent with at least a bachelor's degree. The last two measures had reversed loadings in the factor score. We also included the measures of racial compositions: the percent Black, the percent Latino, and the percent Asian. We included the percent aged 15 to 29 to capture the proportion of crime-prone age group in neighborhood. We capture the residential stability by including the percent homeowners. These variables are theoretically relevant in understanding the socioeconomic and demographic dimensions influencing neighborhood crime. For our spatial models, we created and included spatially lagged dependent and independent variables in the models. These measures were created based on an inverse distance function with a cutoff at 2.5 mile around each block group (beyond which the areas have a value of zero in the W matrix). Then the spatial weights matrix is row standardized and multiplied by the matrix of values in the block groups for the variables of interests.

Methods

We estimated non-spatial models (OLS) and spatial models for the three dependent variables—total crime rate (logged), violent crime rate (logged), and property crime rate (logged).[2] For our demonstration of the direct-indirect interpretation with real-world data, we adopt the Spatial Durbin Model (SDM). We chose the SDM approach because our diagnostic tests—such as log-likelihood comparisons, the (Robust) Lagrange Multiplier test, and Moran's I indicated significant spatial dependence in both the spatial lag and error terms across all models. While the results suggest that other spatial models could also be considered with this dataset, we selected the SDM due to its flexibility in estimating direct, indirect (spillover), and total effects of predictors for both the focal and nearby units. Additionally, we conducted Moran's I tests on the residuals of the SDM models and found no significant spatial dependencies. This result further supports the sufficiency of the SDM in capturing spatial dependencies without requiring an additional spatial error term.[3] This enables us to explore how variations in explanatory variables impact crime rates within a neighborhood and how these effects spill over into adjacent areas. The estimated effects from the SDM models

2. Our inclusion of the non-spatial model was intended primarily to provide a baseline or point of reference illustrating how coefficient estimates change once spatial dependence is properly accounted for. This contrast is used for interpretive rather than inferential purposes, rather than to claim direct comparability between the OLS and spatial model results.

3. Researchers can select their spatial model based on these diagnostics and their interest in the underlying spatial theory. For further details, see, for example, Anselin et al. (2000) and Anselin (2003).

were calculated using 1,000 bootstrap simulations. For each variable, the indirect and total impacts capture the cumulative spatial effects across neighboring units. Reported values are based on the empirical means and standard deviations obtained from the simulations providing robust estimates of spatial spillover effects.

Results

Figure 2 illustrates the estimated impact of concentrated disadvantage on total crime, violent crime, and property crime rates in Los Angeles County using a Spatial Durbin Model (SDM) with 95% confidence intervals overlaid. Each panel represents a specific crime type with four types of estimates: Non-spatial model (OLS), Direct, Indirect, and Total effects. The vertical bands represent 95% confidence intervals indicating the range within which the true effect is likely to fall with a high degree of certainty. Statistical significance at the 95% level is implied when the confidence interval does not cross zero (red dotted line) suggesting that the effect is likely not due to random chance. Please refer to Appendix for the full result table for the non-spatial and SDM models (Table A1), as well as the average direct, indirect, total effects based on the simulation (Table A2). Specifically, the OLS panels in Figures 2, 4, 5, and 6 correspond to the OLS results in Table A1 for each crime type, while the Direct, Indirect, and Total effect panels in Figures 2, 4, 5, and 6 align with the SDM results reported in Table A2.

In the Total Crime panel in Figure 2, the non-spatial model – not accounting for spatial dependencies (named "OLS") suggests a negligible effect of concentrated disadvantage on total crime rate in block groups as the confidence interval crosses zero. When spatial dependencies are considered, the "Direct" estimate shows a slight increase in the effect, but it remains statistically insignificant, which indicate a limited direct influence of concentrated disadvantage on total crime in the focal area. However, the "Indirect" impact is larger and statistically significant (the confidence interval staying above zero). This finding suggests that concentrated disadvantage has a statistically significant spillover effect that increases crime rate in nearby areas, although it has no significant direct impact on crime in the focal area. The "Total" impact (combining both direct and indirect effects) is also statistically insignificant.

Next, in the Violent Crime panel in Figure 2, we observe a different pattern. The OLS estimate of concentrated disadvantage for violent crime is now positive and statistically significant indicating a substantial direct impact even without spatial controls. However, when spatial dependencies are considered, the Direct impact becomes insignificant. Importantly, the Indirect impact is positive and statistically significant, which implies that concentrated disadvantage in adjacent areas is positively associated with violent crime rate in a given focal block group. The statistically significant Total impact further confirms the cumulative influence of concentrated disadvantage on violent crime across spatially connected areas. These findings suggest the importance of considering the effects of concentrated disadvantage in surrounding areas (spillover) for understanding violent crime in the focal area. In contrast, the Property Crime panel shows negative but statistically non-significant effect of concentrated disadvantage on property crime rate. The Direct and Indirect estimates with confidence intervals crossing zero indicate that concentrated disadvantage may have a protective effect for property crime rate, but those effects are not statistically significant. Likewise, the Total impact combining direct and indirect effects shows a cumulative and negative association with property crime but such an effect is statistically not significant.

[Figure 2 about here.]

Another advantage of the proposed method is that we can predict the impact of our independent variable on each geographical unit in a more nuanced way by visually presenting direct, indirect, and total effects. By doing so, we can visualize the localized influence of an independent variable within a specific unit (the direct impact) as well as the spatial spillover influence of neighboring areas (the indirect impact). Such a visualization may provide valuable insights as it enhances our understanding for how structural characteristics in one area can shape spatial crime patterns both in the focal unit as well as the surrounding areas. In our study, we operationalize this idea by creating exploratory intensity scores. Specifically, we multiply each area's values of concentrated disadvantage and its spatial lag by the effects estimated from the SDM. This generates direct, indirect, and total effect maps that highlight areas of greater potential influence under average conditions. It is important to note, however, that these are not true unit-specific impacts of the model. Rather, the values reflect average-effect scaling intended for exploratory purposes and should not be interpreted as the unit-specific effects implied by the full spatial model.

For example, the maps in Figure 3 illustrate the total and spatial spillover effects of concentrated disadvantage on violent crime in the block groups in the entire study area (Panels a and c) as well as near South Los Angeles in our study area (Panels b and d). These maps highlight the spatial heterogeneity in how concentrated disadvantage influences crime, both locally and through its diffusion to neighboring areas. Panel (a) and (b) show the indirect impact (spillover), which represents the extent to which disadvantage in one area influences crime rates in neighboring areas. The shading pattern reveals that areas with higher levels of concentrated disadvantage generate spillover effects that increase crime rates in adjacent neighborhoods, especially those shaded in darker green, which indicate stronger spillover impacts. We did not map the direct impact of concentrated disadvantage as they were proved to be statistically insignificant as Figure 2 shows. Panels (c) and (d) display the total impact (sum of direct and indirect impacts), which combines the effects of disadvantage within each block group and the spillover effects from neighboring block groups. Distinguishing total vs. indirect impacts provides a more comprehensive understanding of how concentrated disadvantage influences crime, both within the area itself and through its effects on surrounding regions. The stronger color intensity in many block groups in Panel (d), compared to Panel (b), emphasizes that the cumulative effect of concentrated disadvantage is substantial when both direct and indirect impacts are considered.

For example, in Figure 3b, we highlight two adjacent Block Groups in South Los Angeles, outlined in red on the map. These Block Groups display differing magnitudes of the estimated indirect effects of concentrated disadvantage on violence, represented by their shading (dark vs. medium green). The darker green area indicates a stronger indirect effect, suggesting that this block group exerts a greater spatial spillover of violence—not only to its immediate neighbor but also to other nearby areas. In contrast, the medium green Block Group exhibits a relatively weaker indirect effect implying that it transmits less violence outward. Conceptually, this spatial pattern suggests that violence tends to "flow downhill" from areas with stronger indirect effects (dark green) to those with weaker ones (light green), rather than in the opposite direction.

[Figure 3 about here.]

Next, Figure 4 illustrates the impact of homeownership on three types of crime incidents. In the Total Crime panel, the OLS estimate shows a negative impact of homeownership on total crime. This indicates that block groups with more homeowners tend to have lower total crime risk. The Direct impact (accounting for spatial dependencies) also shows a negative and statistically significant effect, which suggests that more homeowners in a block group decreases total crime risk in that block group. Both the Indirect and Total effects are also statistically significant indicating that the percent homeowners reduces crime in the focal block group as well as those in nearby. This finding suggests that the crime-reducing effect of homeownership on total crime is substantial so that the crime control benefit from more homeowners in a block group spatially extends beyond the immediate area. We found similar patterns for violent and property crime types (although the indirect effect for violent crime is statistically not significant). In summary, Figure 4 shows that while homeownership is associated with reduced crime risk in block groups, it exhibits significant spillover (indirect) effects on crime in surrounding areas.

[Figure 4 about here.]

Next, Figure 5 focuses on the impact of the Asian American population. We see consistent and statistically significant negative associations between the percent Asian and all types of crime. Specifically, the OLS and Direct estimates suggest that more Asian residents in a block group is negatively associated with crime in that block group. The Total impacts are also negative and statistically significant but the indirect effect (the spillover effects on neighboring areas) is statistically significant only for violent crime. The findings underscore that the crime-reducing effect (especially for violent crime) from the percent Asian spatially extends beyond immediate neighborhoods.

Next, Figure 6 examines the effect of Latino residents on crime incidents. The result reveals a similar but slightly more nuanced pattern. The Direct impacts indicate significant reductions in total and property crime in areas with higher Latino populations. This suggests that Latino communities may help reduce crime within their immediate neighborhoods. However, the spillover effects, captured by the Indirect and Total impacts, are less consistent and insignificant for all crime types. This indicates that Latino communities may exert a more localized effect on crime reduction particularly with respect to total and property crime. Taken together, Figures 5 and 6 demonstrate that both Asian and Latino residents in neighborhood are negatively associated with crime in the study area, although the effects vary by crime type and the extent of spillover influence. Note that we do not report the results for percent African American as none of the associated spatial effects were statistically significant.

[Figure 5 about here.]

[Figure 6 about here.]

Discussion

Although an extensive body of neighborhood and crime studies has recognized the importance of spatial dependency when examining the spatial crime patterns in neighborhood, relatively less attention has been paid to potential meanings of spatial spillover between structural characteristics and neighborhood crime. Moreover, although numerous neighborhood and crime studies have employed various spatial modeling strategies by including spatially lagged independent and/or dependent variables or spatially lagged error term, they have not rigorously interpreted the empirical meanings of the spatially lagged terms in the models but treated them as mere controls. In the current study, we suggest a more explicit interpretation of spatial estimates by disentangling the direct, indirect, and total effects. We provided our theoretical and methodological motivations to the current study and demonstrated its usefulness using the real-world empirical data for a neighborhood and crime study.

The approach proposed in this study enables researchers to estimate the effects of any crime determinant both within a given spatial unit as well as in the surrounding areas. We believe this capability enhances empirical testing and theory-building in neighborhood crime studies. By adopting this method, researchers can directly and separately estimate both direct and indirect impacts in spatial regression models, which enables greater precision and deeper insights into the spatial dynamics of crime. Note that this process can be implemented using Stata and the opensource programming language R, two widely used tools in criminological research that support geographic data formats such as shapefiles. In Stata, spatial analysis is enabled through libraries like spatreg and spwmatrix, which support constructing spatial weight matrices and estimating spatial lag models. Similarly, in R, packages such as spdep, sf, and spatialreg offer robust tools for handling spatial data, creating spatial weights matrices, and performing spatial econometric modeling. These tools provide researchers with flexible and comprehensive frameworks for conducting spatial analyses.

Besides methodological benefits, we note key theoretical takeaways from our empirical findings. First, our results and the direct-indirect-total interpretation make it possible to discern local vs. broader effects of each measures of structural characteristics on neighborhood crime, more nuanced patterns that may be unobservable otherwise. That is, we found that some measures exhibit more pronounced crime-reducing (or producing) spatial spillover effect to the nearby areas, while others tend to show more localized spatial effect for neighborhood crime. For example, concentrated disadvantage has a statistically significant spillover crime-enhancing effect in nearby areas (the positive and statistically significant indirect effect). Yet it has no significant direct impact on crime in the focal area. Moreover, Figure 3 visually illustrates that such an indirect effect seems somewhat distinct from the total effect, a combination of the direct and indirect effects.

It is interesting that concentrated disadvantage is a significant predictor of violent crime in surrounding neighborhoods, but not necessarily within the focal neighborhood itself. Why this might be the case is not clear as we did not directly test specific theoretical mechanisms. However, some plausible explanations can be drawn. First, we can speculate on a possible explanation based on the specific context of the study area. As illustrated in Figure 3, the areas exhibiting the most pronounced indirect effects of concentrated disadvantage spatially overlap with neighborhoods known for high levels of gang-related violence in Los Angeles (Gravel et al. 2018; Valasik et al. 2023). Violent crime in such contexts is often rooted in cycles of retaliation and interpersonal conflict embedded within social networks—such as gang affiliations and territorial rivalries—rather than being confined to the administrative boundaries of neighborhoods. In this sense, a highly disadvantaged focal neighborhood may act as the origin point for conflict, given its historical ties to interpersonal violence and gang activity, while the actual incidents of violence may occur in adjacent neighborhoods. This pattern is especially evident when social ties—particularly among gangs—span across neighborhood boundaries, reflecting the mobility of both offenders and targets, as well as the inherently relational, spatial yet network-based nature of gang-related violent crime.

Also, social disorganization theory posits that concentrated disadvantage weakens informal social control, thereby increasing the likelihood of violence. However, in highly disadvantaged neighborhoods, violence may be displaced to nearby areas so far as residents in focal neighborhood skillfully adopted survival strategies or avoidance behaviors to minimize exposure to local violence. Prior research supports this possibility—for example, Anderson

(2000) notes that savvy residents often carry a small amount of cash to mitigate harm in the event of a robbery as having nothing may lead to more aggressive physical violence. Such behaviors suggest a form of adaptive negotiation with local conditions, or so-called a loyalty strategy according to Hipp (2022), which may reduce the likelihood of violence occurring within the focal neighborhood. At the same time, violent incidents may instead diffuse to nearby neighborhoods where residents are less familiar with or less able to implement such tight-knit strategies.

Additionally, from a routine activity perspective, crime (including violent crime) often occurs in public settings where potential offenders and targets are spatially and temporally convergent. Such environments typically include commercial corridors, retail areas, transit hubs, and other activity nodes (Brantingham and Brantingham 1995). Disadvantaged neighborhoods, however, may lack these types of physical features due to prolonged economic decline and disinvestment. As a result, residents in highly disadvantaged areas may travel to nearby neighborhoods for employment, goods, services, or transit access—contexts where the likelihood of offender–target convergence is greater. This dynamic may help explain the absence of a significant direct effect of concentrated disadvantages on violent crime within the focal neighborhood, while still producing significant indirect effects in adjacent areas. Although our explanations remain speculative, these findings highlight a promising line for future research to more explicitly theorizing and empirically testing the spatial relationship between socioeconomic disadvantage and neighborhood crime.

Also, our findings provide implications for a spatially nuanced relationship between racial/ethnic composition and neighborhood crime patterns, especially in our study area context, the Southern California region. Specifically, the percent Asian population exhibits a stronger and more robust crime-reducing effect (especially for violent crime) in nearby areas evident in significant indirect effects than in the focal area (direct effect). This suggests that Asian communities may exhibit broader neighborhood-level or regional influence on violent crime reduction, potentially via extended co-ethnic social networks or institutional completeness that cover a wider geographic area with ethnic centers and businesses in the region (Kubrin, Kim, and Hipp 2019; Breton 1964). In contrast, our findings suggests that Latino communities may have a more localized influence on crime reduction. For example, the direct effect of the percent Latino exhibits a significant crime-reducing effect but not significant indirect and total effects.

These different findings by racial groups may reflect variations in social cohesion, immigrant density, or the structure of ethnic enclaves across racial/ethnic groups. For example, while both Asian and Latino populations represent substantial portions of the population in Southern California, the nature and organization of their ethnic enclaves may differ significantly. Asian ethnic enclaves, particularly those associated with East and Southeast Asian communities (e.g., Koreatown, Chinatown, Little Tokyo, Little Saigon), often feature relatively higher levels of socioeconomic status, residential stability, and institutional completeness; and thus host a range of ethnic businesses, services, and organizations that serve co-ethnic residents. Such characteristics may foster stronger informal social control and community efficacy, which could contribute to lower levels of neighborhood crime (Kim, Hipp, and Kubrin 2019). Additionally, there may be differences across racial groups in terms of interactions with law enforcement, willingness to report crime (Baumer 2002), or even patterns of victimization (Hipp, Tita, and Boggess 2009). These differences could also help explain the observed variation in crime patterns across neighborhoods with different racial and ethnic compositions.

In sum, these findings generally contribute to a comprehensive theory of neighborhood and crime by explicitly illustrating how structural characteristics in one area can influence crime rates in adjacent areas. By focusing on the statistically significant spillover effects, the current study highlights the need for theoretical frameworks that account for both direct and indirect effects of social structural characteristics on crime. That is, the findings suggest that crime-reducing or -producing effect of certain structural characteristics in one neighborhood may have broader regional effects potentially enhancing or reducing crime not only locally but also in neighboring communities through significant spatial spillovers. Thus, the suggested approach in the current study further highlighted the importance of spatial dependency of social factors across space and advanced our understanding of neighborhood and crime by rigorously interpretating the direct-indirect-total effects of structural characteristics on crime beyond individual neighborhoods.

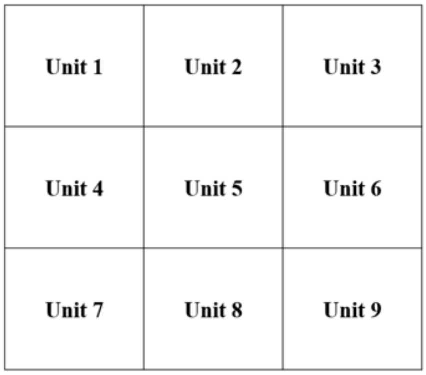
On a similar note, our findings also carry important methodological implications, particularly with regard to spatial scale considerations in the study of neighborhood crime. A significant indirect and total effect alongside a non-significant direct effect suggests that certain neighborhood structural characteristics such as concentrated disadvantage exert influence beyond the local context affecting surrounding areas as well. At the same time, some covariates appear to have more localized effects on crime reduction (i.e., % Latino) given the less consistent and generally insignificant indirect and total effects observed. Such variation in spatial influence across different covariates would likely be missed using traditional approaches. The current study provides an implication for addressing this challenge by explicitly interpreting spatial direct, indirect, and total effects, thereby capturing the complex geographic dynamics that shape neighborhood crime patterns.

A common baseline in the traditional approach is that it assumes the effects of structural characteristics do not spatially vary within the study area (e.g., LA county for the current study) so that the effect of covariate x may be identical across all units (e.g., block groups for the current study). However, in some situations, a change in x could lead to a greater increase in crime in some block groups, or even a decrease in other block groups. Or it is also possible that some ecological factors may have more localized effect on crime (i.e., concentrated disadvantage, percent homeowners, and percent Asian from our findings) while others have broader regional influences, which previous ecological studies of crime have paid relatively less attention to. This limitation yet applies to nearly all ecological studies of crime as it is virtually impossible to employ different spatial unit for each measure included in the models at the same time. One way to circumvent this is to estimate a model that incorporate geographical context of each spatial unit by allowing the flexibility of parameters in the model varying across all spatial units employed (see Fotheringham and Li 2023; Fotheringham, Li, and Wolf 2021). However, such an approach requires additional methodological techniques and computing power. An alternative is to empirically employ a classical spatial regression model while incorporating the interpretational approach suggested in the current study by incorporating local (direct), broader (indirect), and comprehensive (total) spatial impact at the same time.

One remaining question concerns the generalizability of our findings across different spatial units as our analysis was conducted at the block group level. Varying spatial scales—from micro-level units to more aggregated ones—may provide different implications for understanding spatial crime patterns. We encourage future research to examine the direct, indirect, and total effects using other spatial units commonly employed in prior studies, such as street segments, blocks, or larger units like census tracts. Also, we utilized a Spatial Durbin Model (SDM) as it is one commonly and widely employed modeling strategies. Yet, another remaining question is whether our findings remain similar when employing other types of spatial models such as the spatial lag model (SLM), Spatially Lagged X Model (SLX), or spatial error model (SEM). Although we selected the Spatial Durbin Model (SDM) based on both theoretical reasoning and empirical evidence discussed in the paper, we recognize that it may not be the best fit in every situation. Researchers can identify the most appropriate spatial specification by conducting diagnostic tests such as the Lagrange Multiplier (LM) or Moran's I-based assessments. Additionally, when theoretical arguments suggest particular forms of spatial dependence, alternative models may be more suitable. Therefore, it is worth testing for future research how other spatial modeling types may produce similar or different results compared to the one tested in the current study and discuss why so.

In conclusion, we highlighted the theoretical and methodological importance of spatial modeling for a neighborhood and crime study. Although previous studies have well recognized and employed spatial modeling strategies by including spatial terms to the models, they tend to treat the spatially lagged terms merely as controls without rigorously interpreting them. We adapted the direct-indirect-total effect interpretation for the estimates of the ecological factors of neighborhood crime at the focal geographic unit as well as their spatial lag terms. We also empirically demonstrated how to decompose the spatial direct, indirect, and total effects and discussed the theoretical and methodological implications for studying neighborhood crime. We hope future research employs the suggested approach to provide crucial insights into the spatial crime patterns and expand our understandings on neighborhood crime.

Figures



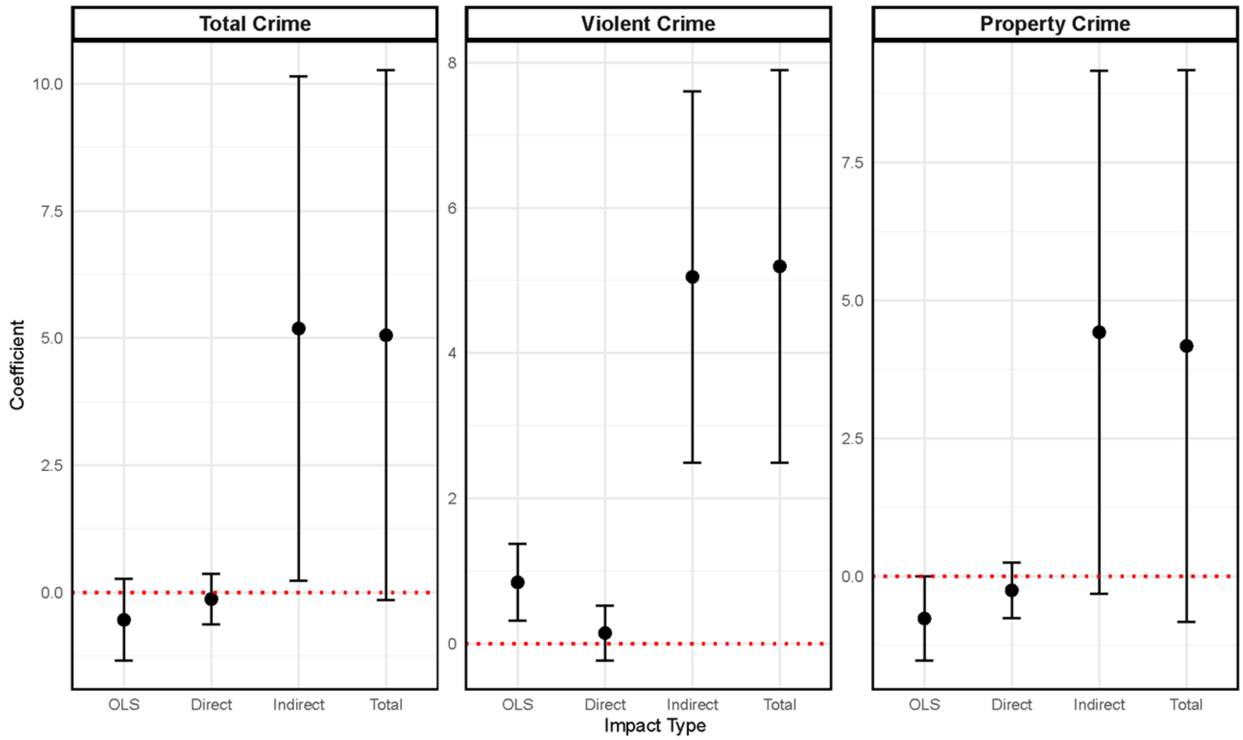
(a) Geographical Region with 9 Sub-units

$$\begin{bmatrix} 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 \end{bmatrix}$$

(b) Spatial Weight Matrix ($\boldsymbol{W}$)

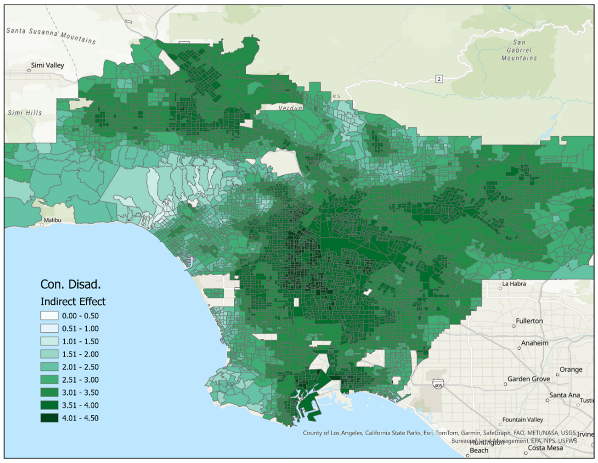
Figure 1: Example of a geographical region with 9 sub-units (panel a) and its corresponding Rook contiguity spatial weight matrix (panel b)

Figure 2: The Effect of Concentrated Disadvantage on Various Crime Types

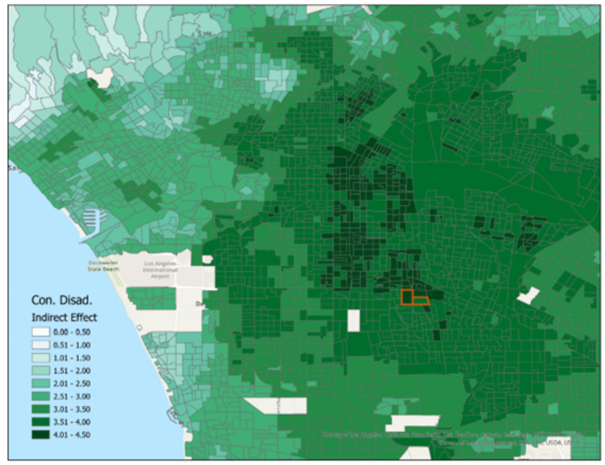


Note: The bands represent 95% confidence intervals. OLS represents the coefficients derived from OLS; Direct, Indirect, and Total indicate estimates from the Spatial Durbin Model.

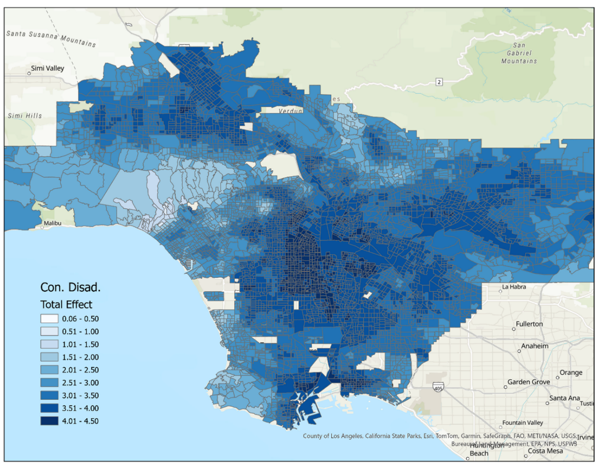
Figure 3: The Indirect Effect of Concentrated Disadvantage on Violent Crime



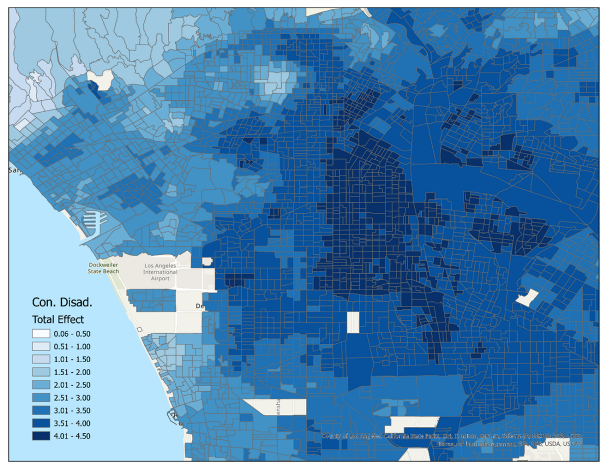
(a) Indirect Effect (Full Study Area Extent)



(b) Indirect effect (South Los Angeles Area)

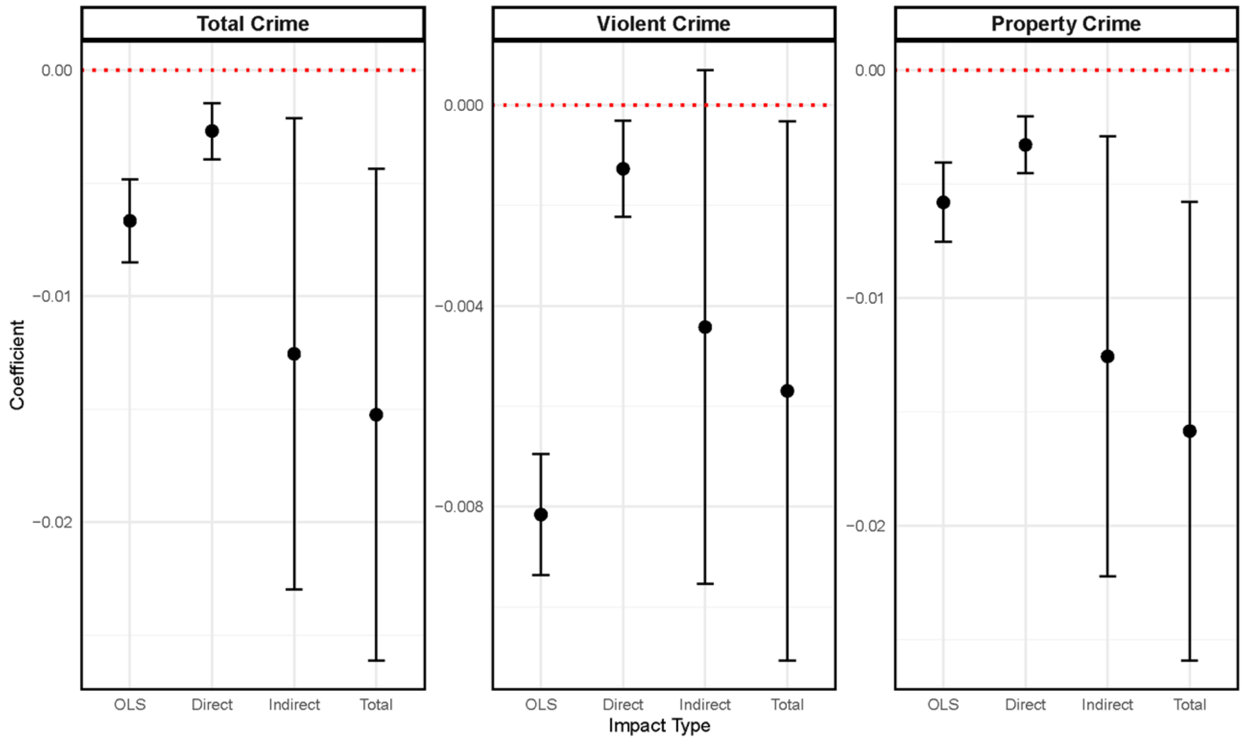


(c) Total Effect (Full Study Area Extent)



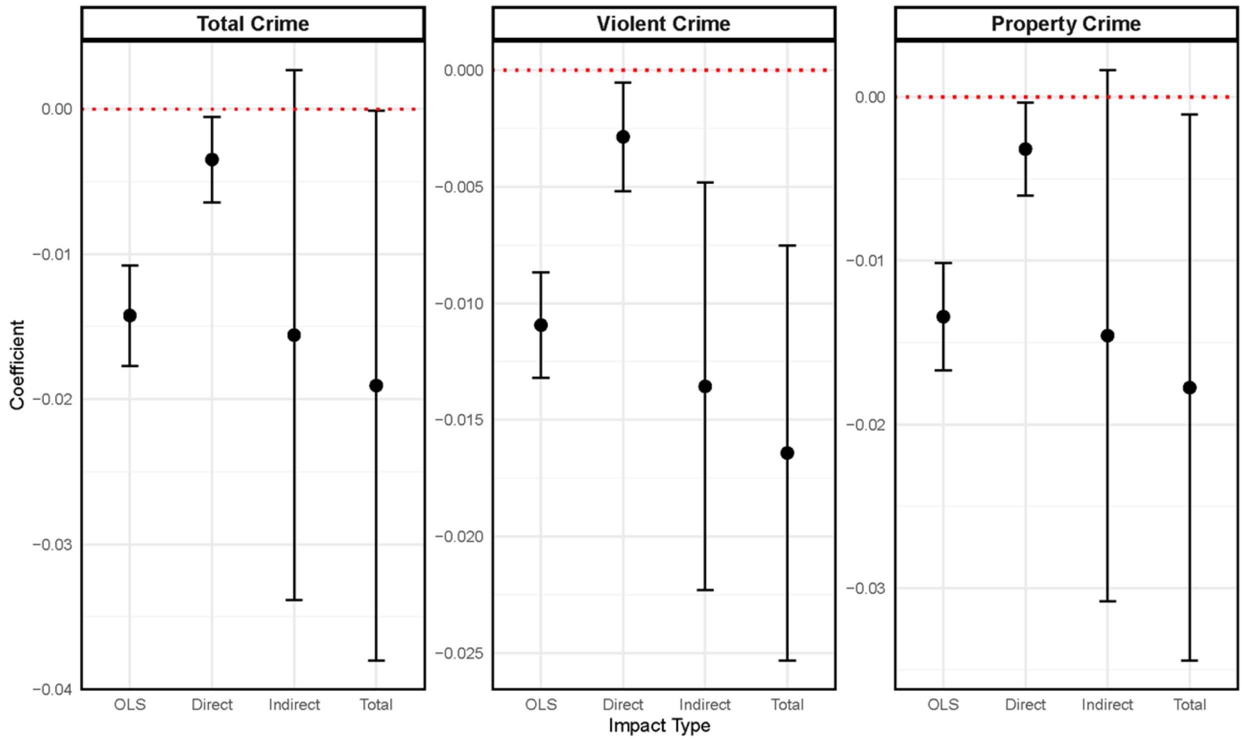
(d) Total effect (South Los Angeles Area)

Figure 4: The Effect of % Homeowners on Various Crime Types



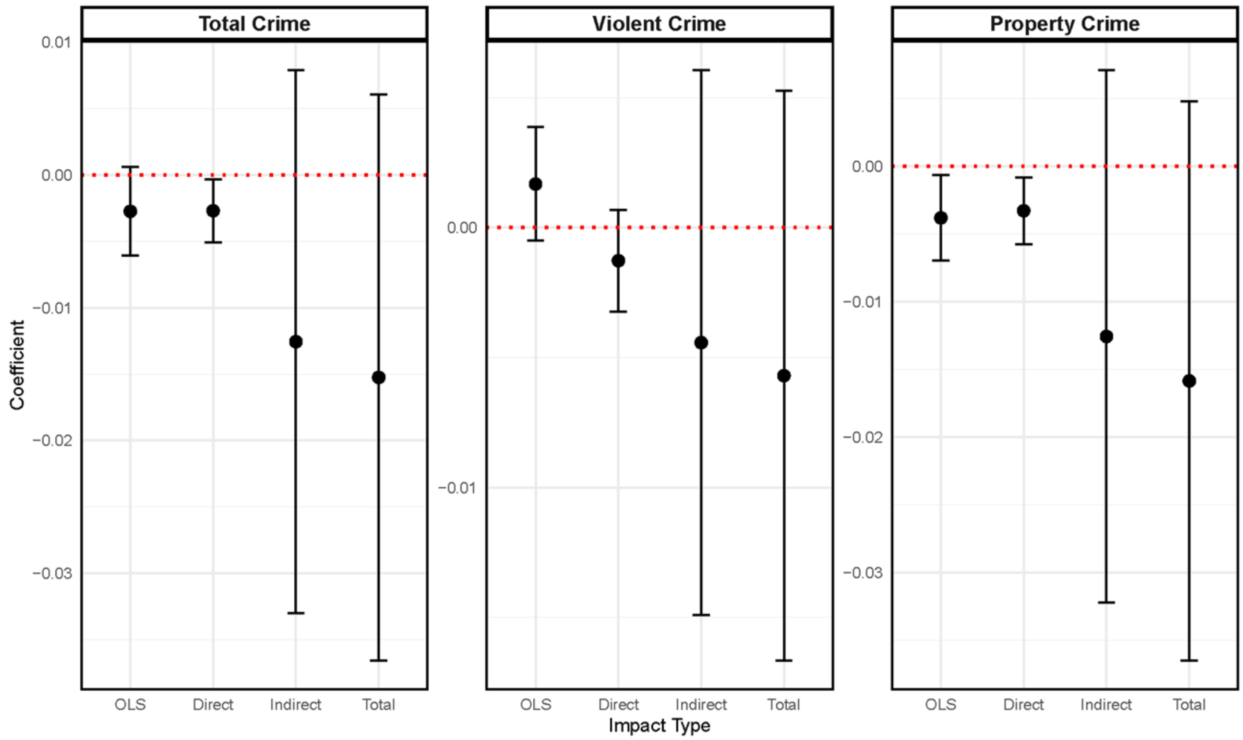
Note: The bands represent 95% confidence intervals. OLS represents the coefficients derived from OLS; Direct, Indirect, and Total indicate estimates from the Spatial Durbin Model.

Figure 5: The Effect of % Asian on Various Crime Types



Note: The bands represent 95% confidence intervals. OLS represents the coefficients derived from OLS; Direct, Indirect, and Total indicate estimates from the Spatial Durbin Model.

Figure 6: The Effect of % Latino on Various Crime Types



Note: The bands represent 95% confidence intervals. OLS represents the coefficients derived from OLS; Direct, Indirect, and Total indicate estimates from the Spatial Durbin Model.