Original Contribution

The Spatial Epidemiology of Intimate Partner Violence: Do Neighborhoods Matter?

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We examined whether neighborhood-level characteristics influence spatial variations in the risk of intimate partner violence (IPV). Geocoded data on IPV cases with associated protection orders (n = 1,623) in the city of Valencia, Spain (2011–2013), were used for the analyses. Neighborhood units were 552 census block groups. Drawing from social disorganization theory, we explored 3 types of contextual influences: concentrated disadvantage, concentration of immigrants, and residential instability. A Bayesian spatial random-effects modeling approach was used to analyze influences of neighborhood-level characteristics on small-area variations in IPV risk. Disease mapping methods were also used to visualize areas of excess IPV risk. Results indicated that IPV risk was higher in physically disordered and decaying neighborhoods and in neighborhoods with low educational and economic status levels, high levels of public disorder and crime, and high concentrations of immigrants. Results also revealed spatially structured remaining variability in IPV risk that was not explained by the covariates. In this study, neighborhood concentrated disadvantage and immigrant concentration emerged as significant ecological risk factors explaining IPV. Addressing neighborhood-level risk factors should be considered for better targeting of IPV prevention.

Bayesian spatial modeling; concentrated disadvantage; disease mapping; intimate partner violence; neighborhoods; risk probability; small-area variation; spatial epidemiology

Abbreviations: DIC, Deviance Information Criterion; IPV, intimate partner violence.

A 2013 World Health Organization report defined violence against women as a “public health problem of epidemic proportions, requiring urgent action” (1, p. 3). This report estimated a global lifetime prevalence of intimate partner violence (IPV) of 30% for women. In Europe, where the present study was conducted, a 2014 survey with data from the 28 European Union member states estimated that 22% of women had experienced physical and/or sexual violence since the age of 15 years by actual or former intimate partners (43% when psychological violence was included) (2). The magnitude of this problem and the serious health and social consequences for women, their children, and the wider community make it an urgent public health priority (3–5). A better understanding of the factors explaining the increased risk of IPV is key for better-informed intervention and prevention initiatives.

Recently, a growing body of research, mainly informed by social disorganization theory and ecological approaches (6–9), is recognizing the importance of IPV risk factors beyond the individual and relational levels and has begun to explore the role of contextual factors in explaining IPV (10–28). The recent publication of 2 systematic reviews on the influence of neighborhoods on IPV illustrates this growing interest in contextual explanatory factors (29, 30). Both reviews suggested that, in line with social disorganization predictions, the most common neighborhood-level factors associated with IPV in the available research are those characterizing neighborhood socioeconomic disadvantage.

These systematic reviews, however, also showed that the evidence base regarding the link between other neighborhood-level characteristics and processes (e.g., concentration of immigrants, residential instability, neighborhood disorder and crime, collective efficacy, social ties, and cultural norms) and IPV is either less conclusive or mixed (29, 30). Differences in sample sizes, modeling techniques, study settings, the definition of a neighborhood, the measurements and proxies...
used to analyze neighborhood-level factors, and the measurement, type, and severity of IPV may explain why some results are not consistent and are sometimes conflicting (29, 30).

This is still a relatively new area of study, and clearly more research is needed to build a more consistent evidence base. For example, it is surprising that despite the growing body of research examining neighborhood influences on IPV, there has been practically no use of spatial analysis techniques and disease mapping methods to analyze spatial patterns in IPV risk and their associations with neighborhood-level explanatory variables. However, a spatial epidemiologic approach seems especially appropriate for the study of neighborhood influences on area variations in IPV risk (28). Because neighborhood risk factors are usually clustered in space, spatial epidemiologic methods allow a more detailed examination of their influence on geographical variations in IPV risk. The analysis of spatial patterns of IPV risk with Bayesian spatial models is particularly suitable for small-area data analysis, as it allows us to incorporate geographical information and map the spatial components that reflect area variations in risk (31–33). Important issues that arise when using small-area counts, such as spatial autocorrelation, overdispersion, and the small-numbers problem, can also be addressed with this approach. Another advantage is that it takes into account unobserved spatially structured influences on risk variations (34–39).

We are aware of only 2 instances of the use of this approach to study neighborhood-level influences on IPV risk. One study was conducted in the United States and showed associations between the density of alcohol outlets (liquor stores, etc.) and IPV (26). The other, an exploratory analysis conducted in Europe, found that IPV cases were more likely to be found in areas with higher levels of immigrant concentration, disorder, and crime (28). However, that study was limited by the small number of neighborhood units (only 1 area of the city was explored), the small size of the IPV case sample, and the definitions of covariates used to capture some relevant neighborhood-level factors such as economic disadvantage.

In this study, we aimed to add to this growing body of literature by using spatial data on IPV cases and a Bayesian random-effects modeling approach to analyze the influence of neighborhood-level characteristics on small-area variations in IPV risk. Drawing from social disorganization theory, we analyzed whether any of 3 types of contextual influences explained spatial patterns in IPV risk: concentrated disadvantage, concentration of immigrants, and residential instability. Because concentrated disadvantage has been measured in a variety of ways in the literature (29), we included multiple neighborhood-level indicators, both compositional and structural, to capture the construct (i.e., education, economic status, female-headed families with children, vacant lots, physical disorder, and public disorder and crime). To the best of our knowledge, this is the first study that has used a Bayesian random-effects modeling approach to analyze neighborhood influences on the spatial epidemiology of IPV in a European city.

METHODS

The study was conducted in the city of Valencia, the third largest city in Spain. We used the census block group, which was the smallest administrative unit available, as a proxy for neighborhood. The city of Valencia is divided into 552 census block groups, with a total population of 736,580 (2013 data (40)). The populations of the census block groups range from 630 to 2,845, with an average of 1,334 residents (40).

All IPV cases in this study had an associated legal protection order. We used all protection orders issued in the city of Valencia between January 2011 and March 2013 (n = 1,623). Protection orders are issued by a court of law and enforced by the police. Data were provided by the Valencia Police Department. These IPV cases represent the severe end of the IPV spectrum, as they are issued when the court believes there is an objective risk of harm to the victim. They represent approximately 15% of all reported IPV cases. All protection orders in this study were for male-against-female IPV. To geocode the data, we used the geographical coordinates of the place where the IPV incident leading to the protection order occurred.

Covariates

Data on neighborhood concentrated disadvantage, concentration of immigrants, and residential instability were obtained from 3 different types of sources—the Spanish census, trained raters, and the police department—and corresponded to the year 2013.

Census data. Data on the following variables were provided by the city’s Statistics Office for each census block: education, economic status, percentage of female-headed families with children, percentage of vacant lots, percentage of immigrants in the population, and residential instability. Education was measured on a 4-point scale (1 = less than primary education, 2 = primary education, 3 = secondary education, 4 = college education). Economic status was measured with a scale created through factor analysis which included 4 highly correlated economic indicators (cadastral property values, percentage of high-end cars, percentage of financial businesses, and percentage of commercial businesses). Residential instability was measured as the proportion of the population who had moved into or out of each census block group during the previous year (rate per 1,000 inhabitants).

Observed physical disorder. Trained raters assessed the level of observable physical disorder in each census block group. They used a 13-item scale with a 5-point response (ranging from 0 for not present to 4 for highly present) that included items such as trash in the street, graffiti, vacant or abandoned houses, and vandalized and run-down buildings (28). Observations were made during business hours (α = 0.70).

Policing activity. Senior police officers provided an index of policing activity, indicative of the level of public disorder and crime in each census block. This policing activity index was based on police officers’ perceptions and experience (no recorded objective information was available) and included interventions in violent and drug-related crimes, public drunkenness and fights, vandalism, homeless people, truancy, and other forms of public disorder. The index was based on a 5-item scale with a 5-point response (0 = very low, 4 = very high).

Descriptive statistics for all variables are shown in Table 1. The spatial distribution of all covariates is reported in Web Figure 1, available at http://aje.oxfordjournals.org/.
The dependent variable was number of IPV cases for the 552 census block groups. Therefore, we assumed that the data were conditionally independent Poisson (Po) random variables:

\[ y_i | \eta_i \sim \text{Po}(E_i \exp(\eta_i)), \quad i = 1, \ldots, 552, \]

where \( E_i \) is a quantity which accounts for the expected number of IPV cases (calculated in proportion to the female population aged ≥16 years) in census block group \( i \) and \( \eta_i \) is the log relative risk. The model for \( \eta_i \) takes the form

\[ \eta_i = \mu + X_i \beta + S_i + U_i, \tag{1} \]

where \( \mu \) is the intercept, \( \beta \) is the regression coefficients vector, \( X \) represents the matrix of covariates, \( S \) is a spatially structured term, and \( U \) is the unstructured term, both \( (S \text{ and } U) \) accounting for nonobserved variability.

In a Bayesian approach, all parameters are considered random variables and must be supplemented with appropriate prior assumptions via prior distributions. We assigned vague Gaussian distributions for the fixed effects \( \beta \) and an improper uniform distribution for \( \mu \). The unstructured spatial effect \( U \) was modeled by means of independent identically distributed Gaussian random variables \( N(0, \sigma_U^2) \), and for the structured spatial effect \( S \) we considered a conditional spatial autoregressive model \((41)\), which reflects spatial neighborhood relationships. This model is defined as

\[ S_i | S_{-i} \sim N \left( \frac{1}{n_i} \sum_{j=1}^{n_i} S_j \sigma_S^2 / m_j \right), \]

where \( n_i \) is the number of neighboring areas of census block group \( i \), \( S_{-i} \) indicates the values of the \( S \) vector except for the \( i \)th component, the expression \( j \sim i \) denotes all units \( j \) that are neighbors of census block group \( i \), and \( \sigma_S \) is the standard deviation parameter.

Following the structure of the hierarchical Bayesian models, it was necessary to assign prior distributions (or hyperpriors) to the hyperparameters \( \sigma_U \) and \( \sigma_S \). Specifically, we considered as prior distributions of standard deviations a uniform distribution: \( \sigma_U, \sigma_S \sim U(0, 1) \).

Convergence was inspected by visually examining the plots of the samples for each chain and also using the convergence diagnostic \( R \) (R Foundation for Statistical Computing, Vienna, Austria) \((42)\), which was near 1.0 for all parameters. Finally, as a measure of model fit and identification of the final model, we used the Deviance Information Criterion (DIC) \((43)\). Models with smaller DICs are considered better-fitting.

### RESULTS

Different Bayesian Poisson regression models were examined. In a first step, a model without random variables was fitted \((\text{DIC} = 2,156.4)\) and then both unstructured \((U)\) and structured spatial \((S)\) effects were introduced. Table 2 summarizes the results derived from 2 Bayesian regression models (both were specified with the \( U + S \) components).

Model 1 included all covariates, the unstructured heterogeneity, and the spatial effect. The DIC value obtained was 2,137.6, which improved on the DIC of the initial model \((2,156.4)\). Variables with a less-than-80% posterior probability of being different from zero (single female-headed families and residential instability) were discarded.

Model 2 was specified with both random effects and variables that were considered relevant in model 1 (the Web Appendix shows the WinBUGS code for the final model). When the models’ DICs were compared, model 2 \((\text{DIC} = 2,135.2)\) showed a small improvement in fit. Thus, model 2 was chosen as the final model, following the DIC criteria. As Table 2 shows, model 2 included neighborhood education and economic status, physical disorder, percentage of vacant lots, policing activity, and concentrated immigration as relevant factors.
DISCUSSION

In this study, we used a spatial epidemiologic approach to analyze the influence of neighborhood-level characteristics on small-area variations in IPV risk in Valencia, Spain. Results showed that IPV risk was spatially patterned (i.e., it was not randomly distributed across the city’s areas) and that neighborhood-level characteristics matter in explaining spatial variations in IPV risk. The use of Bayesian spatial modeling to explore this link is a relevant addition to a compelling evidence base documenting neighborhood influences on a wide variety of outcomes, including health and crime (8, 32, 38, 39, 44–48). More importantly, this methodological approach, seldom used in the ecological study of IPV, adds further evidence to the more recent body of research documenting neighborhood influences on IPV (10–30), illustrating that neighborhood influences also extend to a crime that tends to occur “behind closed doors” (25).

The picture that emerges from our study is that IPV risk is particularly high in neighborhoods that are physically disordered and have low educational and economic status levels, a high percentage of vacant lots (also an indicator of physical disorder and decay in neighborhoods (49, 50)), high levels of police activity and crime (as indicated by high policing activity), and high concentrations of immigrants. When we mapped area-specific levels of excess risk, these variables

Table 2. Results From Spatial Bayesian Poisson Regression Models of the Risk of Intimate Partner Violence, Valencia, Spain, 2011–2013

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>PM (SD)</td>
<td>95% CrI</td>
<td>PM (SD)</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.460 (0.570)</td>
<td>−0.641, 1.648</td>
</tr>
<tr>
<td>Educationa</td>
<td>−0.398 (0.172)</td>
<td>−0.746, −0.077</td>
</tr>
<tr>
<td>Economic statusb</td>
<td>−0.089 (0.065)</td>
<td>−0.218, 0.036</td>
</tr>
<tr>
<td>Female-headed families with children, %</td>
<td>0.002 (0.003)</td>
<td>−0.004, 0.009</td>
</tr>
<tr>
<td>Vacant lots, %</td>
<td>0.010 (0.008)</td>
<td>−0.008, 0.026</td>
</tr>
<tr>
<td>Physical disorderc</td>
<td>0.007 (0.005)</td>
<td>−0.003, 0.016</td>
</tr>
<tr>
<td>Policing activityd</td>
<td>0.013 (0.008)</td>
<td>−0.004, 0.029</td>
</tr>
<tr>
<td>Immigrant concentration, %</td>
<td>0.030 (0.009)</td>
<td>−0.004, 0.046</td>
</tr>
<tr>
<td>Residential instabilitye, rate/1,000 inhabitants</td>
<td>0.000 (0.001)</td>
<td>−0.001, 0.002</td>
</tr>
<tr>
<td>$\sigma_s^f$</td>
<td>0.145 (0.081)</td>
<td>0.012, 0.322</td>
</tr>
<tr>
<td>$\sigma_u^g$</td>
<td>0.239 (0.059)</td>
<td>0.096, 0.340</td>
</tr>
<tr>
<td>DIC</td>
<td>2,137.6</td>
<td>2,135.2</td>
</tr>
</tbody>
</table>

Abbreviations: CrI, credible interval; DIC, Deviance Information Criterion; PM, posterior mean; SD, standard deviation.

a 1 = less than primary school, 2 = primary school, 3 = secondary school, 4 = college or more.
b Scale created through factor analysis which included 4 highly correlated economic indicators (cadastral property values, percentage of high-end cars, percentage of financial businesses, and percentage of commercial businesses).
c Score on a 13-item scale with a 5-point response. Higher scores indicate greater physical disorder.
d Policing activity index based on a 5-item scale with a 5-point response. Higher scores indicate more policing activity.
e Proportion of the population who had moved into or out of each census block group during the previous year.
f Standard deviation spatially structured term.
g Standard deviation unstructured term.

explanatory variables (Web Figure 2 shows posterior probabilities). Results indicated that the risk of IPV was higher in areas with lower educational and economic status, greater physical disorder, a higher percentage of vacant lots, higher levels of policing activity (which indicates public disorder and crime), and a higher percentage of immigrants. These results can be interpreted in terms of odds ratios (e.g., a 10% increase in immigrant concentration increases the relative risk of IPV by 65%).

By estimating a structured random effect and an unstructured random effect, we aimed to assess separately the influences of spatial dependency and independent heterogeneity in the data. Figure 1 (which depicts the posterior mean of the spatial random effect) shows a clear north-south gradient. This suggests a spatial effect that can increase or reduce IPV risk by up to 10%. In the southern part of the city, for example, there was a higher relative risk of IPV.

Figure 2 maps the relative IPV risk in each census block group. The risk values were calculated from equation 1 as $\exp(\eta_i)$, where the impacts of both random effects and the explanatory variables are included. By mapping these values, one can visualize where the excess risk among observations lies. Risks greater than 1 indicate an above-average probability. For example, Figure 2 shows some census block groups with relative risks exceeding 1.5, indicating an increase in risk of over 50%. In some areas, this relative increase reaches 100%.

The picture that emerges from our study is that IPV risk is particularly high in neighborhoods that are physically disordered and have low educational and economic status levels, a high percentage of vacant lots (also an indicator of physical disorder and decay in neighborhoods (49, 50)), high levels of police disorder and crime (as indicated by high policing activity), and high concentrations of immigrants. When we mapped area-specific levels of excess risk, these variables
explained substantial spatial variations in IPV risk, identifying some areas with a relative risk 100% above the average. From these results, concentrated disadvantage and immigrant concentration emerge as significant ecological risk factors explaining IPV, illustrating how the unequal spatial distribution of these neighborhood characteristics is linked with the unequal spatial distribution of IPV risk.

Our study used a variety of indicators to reflect concentrated disadvantage, and our results support a possible effect not only of neighborhood socioeconomic indicators (education and economic status)—in line with other studies (29, 30)—but also of other neighborhood characteristics indicative of neighborhood disadvantage that in those studies showed less conclusive evidence of an influence on IPV. Thus, high levels of both physical (high percentage of vacant lots, observed disorder) and social (public disorder and crime) neighborhood disorder are clear influences on increased IPV risk. Interestingly, these results are in line with those of other studies linking perceived neighborhood disorder to residents’ willingness to intervene on behalf of victims of frequently hidden violence (such as IPV and child maltreatment) (19, 51), suggesting that neighborhood disorder and crime are associated with reduced levels of informal social control that may increase rates of violence, including IPV.

Our results regarding immigrant concentration, however, are not in line with those of other studies, which found either no association or a negative one (29, 30). In our study, concentration of immigrants was a clear predictor of higher IPV risk and did not support the so-called “immigrant paradox,” according to which immigrant concentration may protect against IPV (contrary to traditional social disorganization expectations). Although the available body of research on this issue is still small, most studies have used US samples, and some cultural factors may be involved in explaining these differences (21, 28). Official records and surveys show that the prevalence of IPV in Spain is disproportionately higher among immigrants (52–54). Of all officially reported IPV cases in Spain, one-third pertain to immigrants, despite this group’s accounting for only 10% of the total population (52). Risk of death from IPV is also higher among immigrant women (55). The main countries immigrants in Valencia come from are South American countries (34.3%) and European Union countries (34%) (40). Some research suggests attitudes of greater acceptability and tolerance of IPV among Latin-American immigrants as compared with the Spanish population, which may explain a greater incidence in this group (21, 56); however, prevalences of IPV among immigrants in Spain appear to be similar regardless of their country of origin (57). Thus, it is not surprising that in our study IPV risk was higher in neighborhoods with high immigrant concentrations, especially when other risk factors were present at the neighborhood level. Spanish cultural influences

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**Figure 1.** Posterior mean values for the spatial component (census block group) of the relative risk of intimate partner violence, Valencia, Spain, 2011–2013.
might also be relevant to explaining why the “immigrant paradox” may not apply in Spain, since the prevalence of IPV among the Spanish population is the lowest in the European Union (2, 58). Clearly, this is an issue that deserves further cross-cultural research.

With regard to other covariates explored in this study, residential instability did not make a clear contribution to the model, which is in line with available research that also provides inconclusive evidence (29). Although the presence of female-headed families with children has been an indicator of neighborhood socioeconomic disadvantage linked to IPV in a number of studies, in our research this variable was not clearly associated with IPV risk. Again, cultural differences may be involved. Notwithstanding the need for further cross-cultural research, our results suggest that the link between neighborhood and IPV observed in US cities (where most of this type of research has been conducted) also matters in the context of a European city, despite differences in urban structures and culture (59, 60).

Several processes may help to explain why neighborhood concentrated disadvantage and immigrant concentration create a “risk environment” for IPV (29, 30). Reduced collective efficacy and social ties among neighbors may diminish informal social control in IPV cases. Social isolation from mainstream values (such as those disapproving of IPV) may also lead to the emergence in these neighborhoods of social and cultural norms that create a climate of tolerance for and acceptance of violence, including IPV (12, 13, 61–64). Furthermore, these neighborhood conditions may be highly stressful, and they can substantially reduce quality of life and trigger violence among partners (25, 29, 30, 65–67). Unfortunately, the nature of our data did not allow us to test hypotheses regarding these processes.

This study also revealed spatially structured remaining variability in IPV risk that was not explained by our covariates. Although this variability was not particularly large (up to 10% increased or reduced risk), it does suggest that future research should take into account other variables that might explain this geographical pattern. One possibility is that unmeasured neighborhood processes, like neighborhood social norms regarding IPV, may explain this pattern (24, 68). For example, we hypothesize that the presence of 2 universities in the northern part of the city, with a large population of students renting apartments in the area, might have an influence, since they may hold different social norms regarding IPV.

Taken together, the influences of both the explanatory variables and the spatially structured random effects point to areas of excess IPV risk deserving of special attention. Our results suggest that addressing neighborhood-level risk factors is an important avenue for better-targeted intervention.

Figure 2. Relative risk of intimate partner violence by census block group, Valencia, Spain, 2011–2013.
and prevention strategies designed to reduce the high incidence of IPV in our communities.

This study had both strengths and limitations. Among its strengths was the fact that this was the first study to have data from all neighborhood units of a European city. It was also conducted with high spatial resolution using census block groups, which is more appropriate for addressing limitations such as the small-numbers problem and can reduce ecological bias due to aggregation effects. The use of a Bayesian random-effects modeling approach was also a major advance for addressing issues such as overdispersion, spatial autocorrelation, and unobserved spatially structured influences on risk (31–39). In addition, we integrated information of different natures (compositional and structural) and from different sources (census data, trained raters, and police).

The type of IPV we examined adds to the existing body of literature analyzing other types of IPV data. However, it also represents a limitation, since our results applied only to the severe end of the IPV spectrum, and we cannot be sure whether they would also apply to other types of IPV, such as less severe cases, self-reported IPV, police calls, or what has been termed “common couple violence” (69). Moreover, no cases of female-to-male or same-sex IPV were available, and thus we cannot generalize our results to those types of IPV (22, 70). Regarding the covariates, we did not have access to other socioeconomic indicators that are often used in this type of research (e.g., income, people living below the poverty line, or rates of unemployment), the above-mentioned neighborhood processes (e.g., collective efficacy, social ties among neighbors, social isolation from mainstream values, neighborhood social norms), or variables that have been previously linked to IPV, such as density of alcohol outlets (26, 71–73). Finally, the modifiable areal unit problem is always an issue in spatial analysis, since other areas of aggregation could have been used. However, we are confident that using census block groups substantially reduced this potential bias.

Future research should address rural-urban differences in the spatial epidemiology of IPV. It would also benefit from studies including the temporal dimension in the analysis of small-area variations in IPV, which would further our understanding of risk factors and trends resulting from planned or unplanned neighborhood changes (e.g., neighborhood-level intervention strategies).

In conclusion, in this study of a European city, neighborhood concentrated disadvantage and immigrant concentration emerged as significant ecological risk factors explaining IPV. Addressing neighborhood-level risk factors should be considered for better targeting of IPV prevention.

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REFERENCES


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