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Chronic high risk of intimate partner violence against women in disadvantaged neighborhoods: An eight-year space-time analysis

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ABSTRACT

We conducted a small-area ecological longitudinal study to analyze neighborhood contextual influences on the spatio-temporal variations in intimate partner violence against women (IPVAW) risk in a southern European city over an eight-year period. We used geocoded data of IPVAW cases with associated protection orders ($n = 5867$) in the city of Valencia, Spain (2011–2018). The city's 552 census block groups were used as the neighborhood units. Neighborhood-level covariates were: income, education, immigrant concentration, residential instability, alcohol outlet density, and criminality. We used a Bayesian autoregressive approach to spatio-temporal disease mapping. Neighborhoods with low levels of income and education and high levels of residential mobility and criminality had higher relative risk of IPVAW. Spatial patterns of high risk of IPVAW persisted over time during the eight-year period analyzed. Areas of stable low risk and with increasing or decreasing risk were also identified. Our findings link neighborhood disadvantage to the existence and persistence over time of spatial inequalities in IPVAW risk, showing that high risk of IPVAW can become chronic in disadvantaged neighborhoods. Our analytic approach provides specific risk estimates at the small-area level that are informative for intervention purposes, and can be useful to assess the effectiveness of prevention efforts in reducing IPVAW.

1. Introduction

Intimate partner violence by current or previous partners is the most common form of violence suffered by women globally, and remains a major social and public health problem, as its severe consequences impact not only the victims and their children but also impose a heavy burden on society (Devries et al., 2013; Ellsberg et al., 2008; World Health Organization, 2013). In the European Union, the context where this study was conducted, lifetime prevalence of intimate partner violence against women (IPVAW) ranges across member states between 13% and 32%, with an average of 22% (European Union Agency for Fundamental Rights, 2014). Geographical differences in IPVAW prevalence can be found not only across countries but also within cities, where differences between residential areas can be larger than those found between countries (Cunradi et al., 2011; Gracia et al., 2015; Heise, 1998; Martín-Fernández et al., 2020; Martín-Fernández et al., 2019). Differences in IPVAW across city areas have been associated with neighborhood risk factors and, therefore, they are important to our understanding of prevalence variations and inequalities in IPVAW risk (Cunradi et al., 2011; Gracia et al., 2015).

There is a broad consensus in the literature that IPVAW risk is determined by the interplay of multiple factors working at individual, relational, community, and macrosocial levels of the social ecology (Hardesty and Ogolsky, 2020; Heise, 1998; Heise, 2011; Heise and Kotsadam, 2015; World Health Organization, 2013; World Health Organization, 2002). IPVAW is thus a complex and multilevel phenomenon, and its likelihood is increased or reduced by the interaction of factors working at different levels, from the most proximal to the most distal (Heise, 2011; Heise and Kotsadam, 2015; Ivert et al., 2020; Kovacs, 2018; World Health Organization, 2002; Yohros, 2020). Scholars, however, have traditionally favored research on individual and relational determinants of IPVAW over contextual explanatory factors (Allsworth, 2018; Hardesty and Ogolsky, 2020; Herrero et al., 2020; Lila et al., 2019; Vanderende et al., 2012). According to a social-ecological model, however, contextual-level factors, including community and macrolevel factors, are also key to understanding IPVAW, and to define the level of risk of IPVAW in a particular setting (Cunradi et al., 2011; Gracia et al., 2015; Heise, 1998; Heise and Kotsadam, 2015;

Abbreviations: IPVAW, Intimate partner violence against women.

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Kovacs, 2018).

At the community level of analysis, neighborhood characteristics are among the distal drivers of IPVAW that have attracted most scholarly attention. Informed mainly from a social disorganization framework, a substantial body of research provides consistent evidence linking a variety of negative neighborhood conditions with an increased risk of IPVAW. This growing scholarly attention to neighborhood-level predictors of IPVAW has produced so far four systematic reviews examining the strength of this body of evidence on neighborhood variables and processes analyzed, and their theoretical significance to understand the link between neighborhood characteristics and IPVAW (Beyer et al., 2015; Pinchevsky and Wright, 2012; Vanderende et al., 2012; Voith, 2019). From this body of research neighborhood concentrated disadvantage, measured in a variety of ways (e.g., poverty, unemployment, education, single-headed families, physical or social disorder) (Pinchevsky and Wright, 2012), emerges as one of the most robust predictors of rates of IPVAW, regardless of other micro- or macro-level factors assessed (Beyer et al., 2015; Pinchevsky and Wright, 2012; Voith, 2019). Rigorous longitudinal research has also shown that long-term exposure to neighborhood-level disadvantage is associated with an increased risk of experiencing IPVAW (Yakubovich et al., 2020). Evidence regarding other neighborhood-level characteristics, such as residential instability, ethnic heterogeneity, or with respect to neighborhood processes or mechanisms such as social ties, collective efficacy (i.e., social cohesion and control), or community norms and attitudes towards IPVAW (e.g., gender norms, acceptability of violence, or intervention norms) is less conclusive, mixed, or still lack further development (Beyer et al., 2015; Pinchevsky and Wright, 2012; Voith, 2019).

Ecological research examining neighborhood effects on IPVAW is still limited, particularly when compared to the body of literature examining more proximal predictors of IPVAW. In this regard, recent reviews have pointed to the need to advance not only our theoretical understanding of neighborhood contextual effects on IPVAW, but also to address some important methodological limitations (Beyer et al., 2015; Voith, 2019). The lack of longitudinal studies, and the need for more advanced measurement and analytic strategies to more accurately evaluate neighborhood effects on IPVAW risk, are important shortcomings that persist in this research area. A 2018 systematic review of all risk and protective factors of this type of violence also noted that no prospective longitudinal study has investigated the association between IPVAW and any community or structural factors outside the US (Yakubovich et al., 2018).

Obtaining reliable estimates of neighborhood effects on IPVAW over time poses significant methodological challenges that are seldom adequately addressed (Cunradi et al., 2011; Gracia et al., 2017; Law et al., 2014; Wodtke et al., 2011). Research aiming to examine the impact of neighborhood disadvantage on the geographical variations of IPVAW risk, and risk persistence over time, needs to acknowledge the spatial and temporal dynamics of neighborhoods and to address them with appropriate analytical strategies. Neighborhood risk factors are not equally distributed geographically and tend to cluster in space. Neither are neighborhoods static: their conditions can change over time, with the result that their influence on IPVAW risk can also change. A spatial and temporal analytical framework is therefore key to understanding the impact of disadvantaged neighborhoods on IPVAW risk. Furthermore, research on neighborhood effects should also adopt a high-resolution approach, as opposed to large boundary areas that do not represent the actual experience of neighborhoods (e.g., census tracts, zip codes). Providing specific risk estimations for small areas clearly increases the potential of this type of research to inform prevention strategies designed for localized high-risk areas (Gracia et al., 2017; Haining et al., 2009; Law et al., 2014).

Small-area ecological studies following a Bayesian spatio-temporal epidemiological approach provide a suitable methodological framework to advance research into the influence of neighborhood disadvantage on IPVAW risk, and risk persistence over time. Bayesian spatio-temporal modeling can effectively address some of the methodological issues raised in this research field, such as spatial and temporal dependence (i.e., accounting for spatial and temporal proximity), small number counts common in crime data, or overdispersion, which would otherwise bias risk estimates. By combining geographical and temporal information, Bayesian spatio-temporal modeling provides more reliable small-area-specific estimates than other frequentist methods (Gracia et al., 2017; Haining et al., 2009; Law et al., 2014). Bayesian spatio-temporal modeling is common in disease risk research, and disease mapping (Bernardinelli et al., 1995; Clayton and Kaldor, 1987; Jonker et al., 2013; Knorr-Held, 2000; Lawson, 2018), and given its clear advantages, there has been an increasing use of this approach in other research fields such as urban crime and violence, including juvenile delinquency or child maltreatment (Freisthler and Weiss, 2008; Gracia et al., 2017; Groff et al., 2009; Grubesic and Mack, 2008; Law et al., 2015; Law et al., 2014; Matthews et al., 2010; Morris et al., 2018; Morris et al., 2019). However, previous research has seldom used this methodological approach to examine the link between neighborhood disadvantage and the spatio-temporal epidemiology of IPVAW risk across city areas. As far as we know, in the US only one study has used Bayesian space-time models to analyze the link between alcohol outlet density and intimate partner violence rates in a Californian city (Cunradi et al., 2011). In Europe only one cross-sectional ecological study has used Bayesian spatial modeling and disease mapping to examine neighborhood influences on small-area variations of IPVAW in a southern European city (Gracia et al., 2015). Therefore, no longitudinal ecological study has yet explored neighborhood influences on the space-time variations of IPVAW risk in cities outside the US (Yakubovich et al., 2018).

This study conducts a small-area ecological longitudinal study to analyze neighborhood contextual influences on the spatio-temporal variations in IPVAW risk in a southern European city over an eight-year period. Drawing from available local administrative data, we use neighborhood-level measures tapping three core constructs of social disorganization theory: (Beyer et al., 2015; Browning, 2002; Cunradi et al., 2011; Gracia et al., 2015; Pinchevsky and Wright, 2012; Sampson et al., 1997; Shaw and McKay, 1942; Vanderende et al., 2012; Voith, 2019) socioeconomic disadvantaged (i.e., income, education), ethnic heterogeneity (i.e., immigration concentration), and residential instability. We also use as indicators of neighborhood disorganization, neighborhood-levels of social disorder and criminality (Voith, 2019), and alcohol outlet density (Cunradi et al., 2011). Concentrated neighborhood disadvantage is not only unequally distributed in our communities but, as Sampson noted (Sampson, 2012), neighborhood inequality is surprisingly stable over time. If negative neighborhood conditions persist over time it is expected that the negative outcomes associated to these conditions will also persist over time (Sampson, 2012). However, ecological longitudinal studies demonstrating the lasting effects of neighborhood disadvantage on IPVAW are almost nonexistent. To this end, the present study uses Bayesian spatio-temporal modeling to examine the influence of neighborhood disadvantage on IPVAW risk, and risk persistence over time. With this analytical approach we also aim to provide an advanced and feasible spatio-temporal analytical framework to detect geographical patterns and trends over time in IPVAW risk across city neighborhoods.

2. Methods

This study was conducted in the city of Valencia (Spain). Valencia is the third largest city in Spain, with a population in 2019 of 794,288. Census block groups ($n = 552$) were used as a proxy for neighborhoods. These groups are the smallest administrative unit with available aggregated data in the city. The temporal analysis covered a period of eight years, from 2011 to 2018. All variables were collected for each year and census block group. This study was approved by the University of Valencia Ethics Committee (Ref. H1524218214832).

2.1. Outcome variable

IPVAW protection orders: the outcome variable was the count of IPVAW protection orders issued between January 2011 and December 2018 in the city of Valencia ($n = 5867$). IPVAW protection orders represent serious cases of IPVAW, and they are issued by a court when a judge considers that the victim is under an objective risk of harm. Data were geocoded using the geographical coordinates of the place where the incident leading to the protection order occurred, and the number of IPVAW protection orders was counted for each census block group and year. Data were provided by the Spanish National Police Corps.

2.2. Neighborhood-level covariates

Drawing from a social disorganization framework, a set of neighborhood-level variables available from administrative sources were used as covariates indicative of the level of neighborhood disadvantage. Data were provided by the National Institute of Statistics (income), the Valencia Statistics Office (education, immigration, residential instability, and alcohol outlets), and the Valencia Police Department (crime-related police calls).

2.2.1. Income

This variable was measured as the average annual income in each census block.

2.2.2. Education

The average education level in each census block group was measured on a 4-point scale (1 = less than primary education, 2 = primary education, 3 = secondary education, and 4 = college education).

2.2.3. Immigrant concentration

This variable was measured as the percentage of immigrant population in each census block group.

2.2.4. Residential instability

This variable was computed as the proportion of the population that had moved into or out of each census block group during the previous year (rate per 1000 inhabitants).

2.2.5. Criminality

This variable was based on the annual number of crime-related calls (e.g., assaults, fights, robbery, drug dealing, vandalism) to the 092 service (the Spanish police emergency number) in each census block group.

2.2.6. Alcohol outlet density

Based on previous research, three types of alcohol outlet density per square kilometer were coded: off-premise alcohol outlets, restaurants and cafés, and bars (Cunradi et al., 2011; Freisthler et al., 2004; Marco et al., 2017; Marco et al., 2019).

Table 1 shows the descriptive statistics for all variables.

Table 1
Variables (mean, standard deviation, minimum and maximum values) at the census block group level.

Neighborhood-level variables	Mean (SD)	Min	Max
Income (€)	12,284.88 (4031.33)	5170	29,360
Education	3.16 (0.33)	2.39	3.86
Residential instability	183.90 (59.21)	64.07	523.39
Immigrant concentration (%)	13.09 (6.38)	1.54	49.76
Criminality	5.09 (6.88)	0	77.23
Alcohol outlets (off-premise)	58.02 (69.65)	0	1032.32
Alcohol outlets (restaurants-cafés)	48.60 (73.14)	0	650.1
Alcohol outlets (bars)	157.17 (141.94)	0	1329.31
IPVAW protection orders	1.34 (1.41)	0	9

2.3. Statistical analysis

IPVAW protection orders in each census block group and year were modeled as conditionally independent Poisson counts, calculated with the following equation:

$$y_{it}|\eta_{it} \sim Po(E_i exp(\eta_{it})), i = 1, \ldots, 552\ t = 1, \ldots, 8$$

where E_{it} is the expected number of IPVAW protection orders in proportion to the total number of women in the i-census block group and t-year, and η_{it} is the log-relative risk for each area and period.

We followed an autoregressive approach to model both spatial and temporal effects (Martínez-Beneito et al., 2008). The Bayesian autoregressive approach to spatio-temporal disease mapping is a modeling approach that is increasingly used in the field of domestic violence (Gracia et al., 2017; Morris et al., 2018; Morris et al., 2019), and has shown better performance than other models in a variety of outcomes (Gracia et al., 2017; Marco et al., 2019; Marco et al., 2018). To ensure that this was the best analytic approach, we conducted preliminary analyses comparing autoregressive modeling with other less complex competing models. The results for the autoregressive model yielded the best fit to the data (i.e. showed the lowest deviance information criterion). The detailed description of these analyses and results is provided in Supplementary Material 1.

The autoregressive approach combines autoregressive time series and spatial modeling, where the relative risks are considered to be spatially and temporally dependent. The following equation shows the structure of the model:

$$\eta_{i1} = \mu + X_{i1}\beta + \alpha_1 + (1 - \rho^2)^{-1/2} \cdot (\phi_{i1} + \theta_{i1})$$

$$\eta_{it} = \mu + X_{it}\beta + \alpha_t + \rho \cdot (\eta_{i(t-1)} - \mu - \alpha_{t-1}) + \phi_{it} + \theta_{it}$$

The first equation describes the log-relative risk for the first period (2011) and the second equation describes the following years (2012 to 2018); X_{it} is a vector of covariates for census block group i and year t; β represents the vector of regression coefficients; α_t defines the mean deviation of the risk in year t; ρ is the temporal correlation between years; and ϕ and θ refer to structured and unstructured spatial random effects, respectively.

This model followed a Bayesian approach. Thus, different prior distributions were assigned for each parameter. Specifically, the fixed effects β were specified as vague Gaussian distributions; μ was treated as an improper uniform distribution; unstructured spatial and temporal effects θ and α were modeled as normal distributions $N(0, \sigma^2)$; and finally the structured effect ϕ was defined using a conditional spatial autoregressive (CAR) model:(Besag et al., 1991)

$$\phi_i|\phi_{-i} \sim N\left(\frac{1}{n_i}\sum_{j\sim i}\phi_j\ ,\ \frac{\sigma_\phi^2}{n_i}\right)$$

where n_i indicates the number of neighbors of each census block group i; ϕ_{-i} defines the values of the ϕ vector except the i-component; σ_ϕ is the standard deviation parameter; and $j \sim i$ represents all unit j neighbors of area i. In addition, hyperparameters σ were specified by uniform distributions $U(0, 1)$, following the hierarchical Bayesian model structure. The WinBUGS code for the final model is showed in Supplementary Material 2.

To perform the Bayesian estimations, we used Markov Chain Monte Carlo (MCMC) simulation techniques with the software R and the R2WinBUGS package. We generated 100,000 iterations, including a burn-in period of the first 10,000. The convergence diagnosis $\widehat{R}$ (Gelman et al., 1990) showed good convergence for all parameters (values near to 1.0) in all models. Previously, a sensitivity analysis was performed on prior distributions of hyperparameters, which yielded consistent results.

To assess the relevance of the neighborhood-level covariates in the model, we considered as relevant those variables in which the 95% credible intervals did not include zero.

3. Results

Table 2 shows the results of the autoregressive model. Regarding the neighborhood-level covariates, immigrant concentration and alcohol outlet density (off-premise, restaurants-cafés, and bars) included zero in their credible intervals and were considered not relevant to the model. The neighborhood-level covariates considered relevant to the model were income, education, residential instability, and criminality. The results indicated that IPVAW risk was higher in neighborhoods with lower income and education level, and with high residential instability and criminality.

Autoregressive models allow us to map the relative risks and analyze area-specific differences over the years. The relationships between IPVAW risk and the covariates are provided by the β parameters, whose estimates for each covariate are shown in Table 2. Fig. 1 maps the relative risk for each year of the study. A value of 1 in the maps indicates an average risk, and the maps show areas with higher (>1) or lower (<1) than average risk. Thus, areas with a value of >2 show a relative risk twice as high as the average risk. The relative risk values increase up to 3.9 in some census block groups, indicating very high-risk levels of IPVAW (almost four times higher than the average). When the temporal component is added, we found a strong correlation between IPVAW relative risk in a year and the previous one, represented by the high temporal correlation parameter ρ ($\rho = 0.82$); this correlation can be also observed in the maps, which show common patterns over the years, with higher risks in the eastern and northern parts of the city.

The high spatial resolution also allows us to study specific areas with stable risks over time, as well as areas with changes in risk. Fig. 2 shows the temporal paths of relative risk in areas with stable high or low risk. Some areas, especially those on the outskirts of the city, show stable high risk of IPVAW over the years. In contrast, some city center areas show stable low risk, with values of relative risk <0.4 (2.5 times below the average) over the years. Fig. 1 shows that a large number of census block groups present this low- or high-risk stability. These spatio-temporal patterns are the result of a combination of the contribution of each covariate (fixed effects), and the structured and unstructured random effect terms. In this regard, the stability of relative risks in these neighborhoods indicates that temporal changes in the covariates are low. If covariates that have been found relevant to the model showed important changes over time, those changes would have influenced the relative risks, leading to a lower temporal correlation, and showing more fluctuations in the relative risk maps.

Autoregressive models can also identify local areas with changes in risk over time. Fig. 3 illustrates the temporal paths of relative risk in areas with decreasing and increasing IPVAW risk. In some areas the relative risk doubled over the years while in others, the risk fell substantially across the time series, starting with a relative risk higher than the average in 2011 and ending in 2018 with a risk lower than the average. Although the areas experiencing decreasing risk do not follow a specific geographic pattern, areas with an increasing risk are concentrated in the north of the city, close to other high-risk areas, suggesting a possible spillover effect.

Table 2
Results of the Bayesian autoregressive model for IPVAW risk.

	Mean	SD	95% CrI
Intercept	1.897	0.306	1.365, 2.601
Income (€)*	−0.085	0.013	−0.108, −0.058
Education	−0.397	0.132	−0.698, −0.184
Residential instability	0.0007	0.0003	0.0002, 0.001
Immigrant concentration (%)	0.006	0.003	−0.001, 0.012
Criminality	0.016	0.003	0.014, 0.021
Alcohol outlets (off-premise)*	−0.002	0.03	−0.061, 0.054
Alcohol outlets (restaurants-cafés)*	0.053	0.038	−0.019, 0.127
Alcohol outlets (bars)*	−0.014	0.017	−0.047, 0.017
σ_θ	0.226	0.026	0.175, 0.280
σ_ϕ	0.175	0.033	0.113, 0.231
σ_α	0.016	0.014	0.001, 0.051
ρ	0.822	0.031	0.803, 0.878

σ_θ standard deviation unstructured term.
σ_ϕ standard deviation spatially structured term.
σ_α standard deviation temporally unstructured term.
ρ temporal correlation parameter.
* This variable was divided by 1000 to solve computational problems with the prior distributions assigned to fixed effects.

4. Discussion

In this study we analyzed the association between neighborhood-level risk factors and the unequal spatio-temporal distribution of IPVAW risk in the city of Valencia. Results showed that neighborhoods characterized by low levels of income and education and high levels of residential instability and criminality had higher relative risk of IPVAW (up to almost four times higher than the city average), and that in neighborhoods with these characteristics the high risk of IPVAW persisted over time during the eight-year period analyzed. Neighborhood disadvantage was thus linked to the persistence in time of notable spatial inequalities in IPVAW risk. This stability of spatial patterns of high IPVAW risk associated with these neighborhood-level risk factors illustrates how this high risk can become chronic in disadvantaged neighborhoods. Likewise, we found that in "better-off" neighborhoods (characterized by high income and education levels, and low levels of residential instability and criminality), IPVAW risk was lower (up to 2.5 times below the city average) and that this low risk also persisted over the years.

The methodological framework used in this study provided a more accurate evaluation of neighborhood effects, strongly supporting the idea that neighborhood disadvantage is not only an important determinant of IPVAW risk, but also of risk persistence over time. In this regard, the present study advances research in several ways. First, we used a longitudinal approach. As opposed to a static model with aggregated IPVAW data over the years and short-term or single point measures of neighborhoods covariates, we used temporal series of both IPVAW and neighborhood-level data. To acknowledge the spatial and temporal dimensions of neighborhoods, as well as the spatial and temporal dependency of IPVAW risks, we adopted a Bayesian autoregressive approach to spatio-temporal disease mapping, which overcomes the limitations of frequentist-based approaches in addressing important issues such as spatial and temporal autocorrelation, overdispersion, or small counts (Gracia et al., 2017; Haining et al., 2009; Law et al., 2014; Martínez-Beneito et al., 2008).

As far as we know, this is the first study to take a Bayesian spatio-temporal modeling approach to examine neighborhood influences on IPVAW risk variations in a city outside the US (Yakubovich et al., 2018), thus extending evidence to other urban and cultural contexts. Results on the influence of low income and education, residential instability, and crime on IPVAW risk were, however, mostly in line with previous research conducted in US cities (Beyer et al., 2015; Pinchevsky and Wright, 2012; Vanderende et al., 2012; Voith, 2019). This suggests that the mechanisms by which these neighborhood characteristics influence IPVAW risk are shared across cities in different cultural contexts. According to social disorganization theorizing, these neighborhood characteristics weaken social ties and trust among neighbors (social cohesion), thus reducing the community capacity for collective action and informal social control (collective efficacy) of crime and violence, including IPVAW (Beyer et al., 2015; Browning, 2002; Gracia et al., 2015; Pinchevsky and Wright, 2012; Voith, 2019). Socially disorganized neighborhoods can become isolated from mainstream society and its shared norms and values regarding crime and violence (e.g., disapproval of violence in intimate relationships), leading to the emergence of social

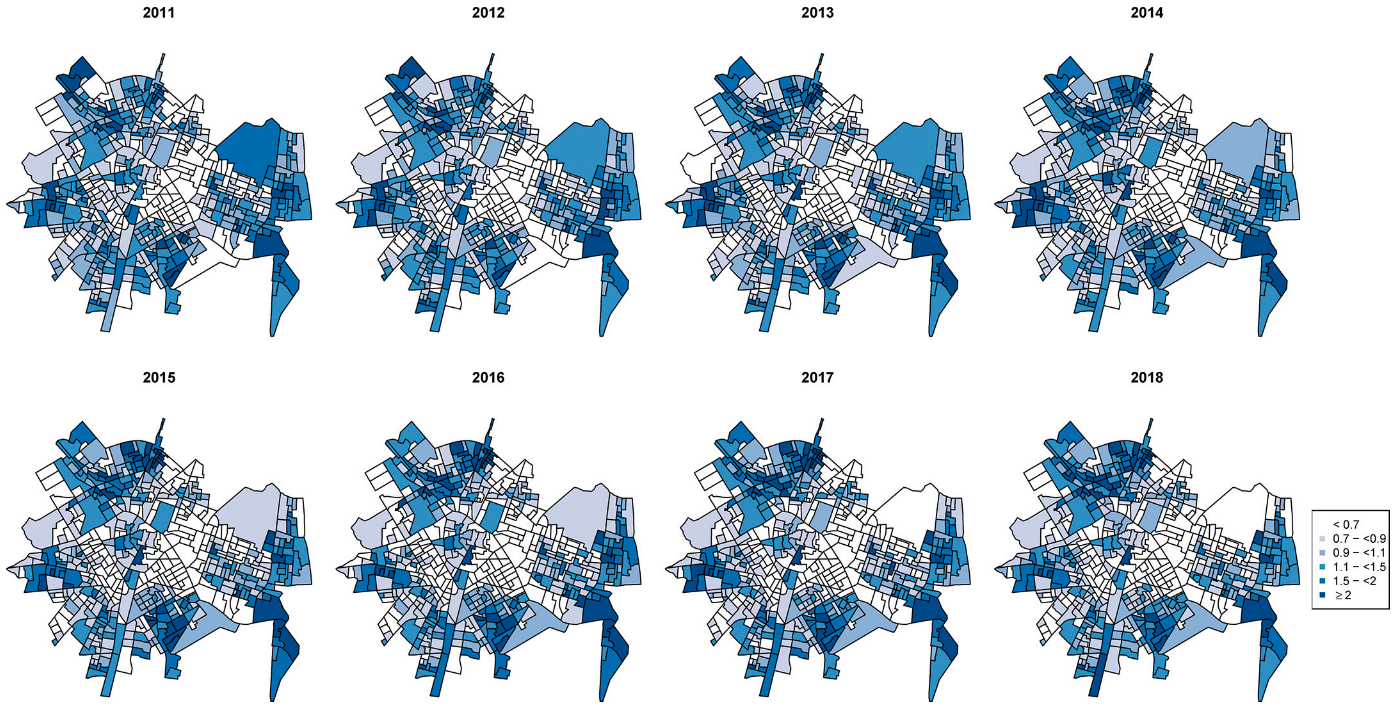

Fig. 1. Maps of relative risk of IPVAW by census block group and year, Valencia, Spain, 2011–2018.

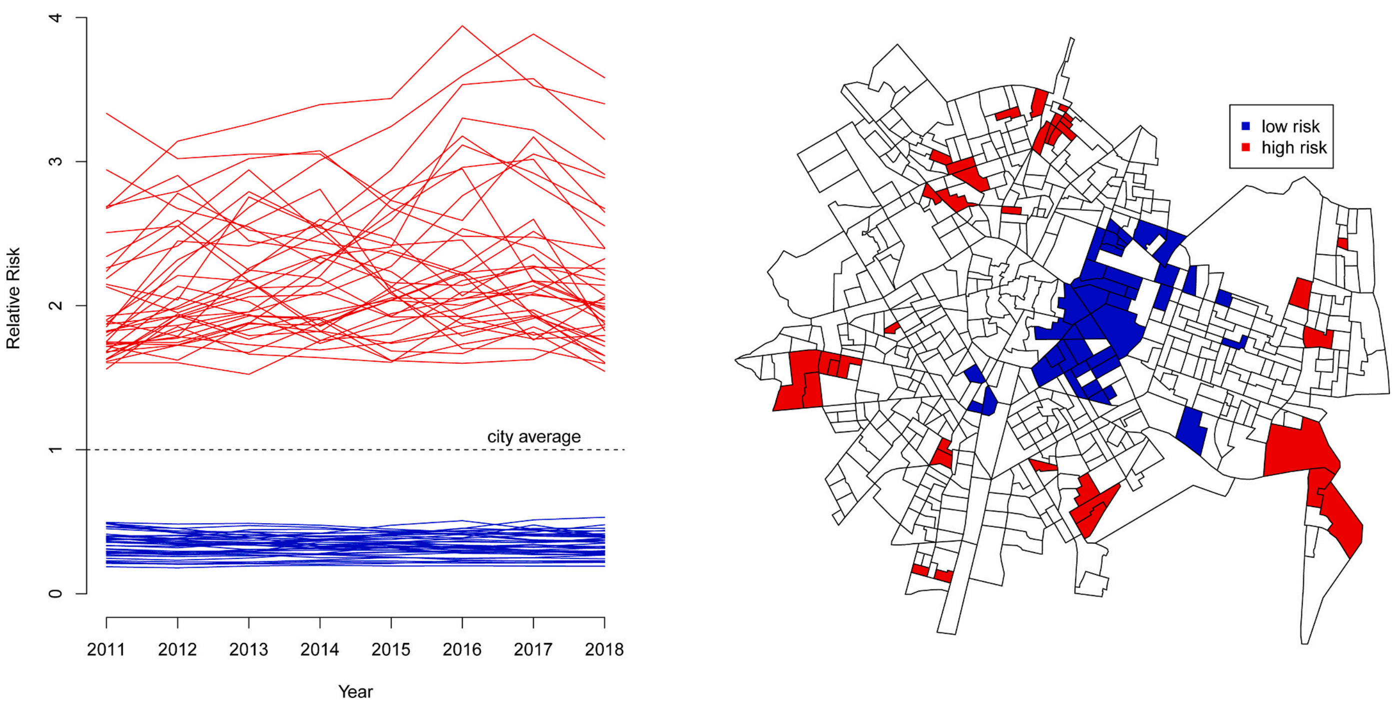

Fig. 2. Temporal paths of relative risk of IPVAW in areas with stable low risk (blue), and stable high risk (red). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

norms and values that facilitates IPVAW (e.g., greater acceptability and tolerance of violence, nonintervention norms, increased legal cynicism) (Gracia and Herrero, 2007; Gracia and Herrero, 2006; National Academies of Sciences, Engineering, and Medicine, 2018; Sampson and Lauritsen, 1994; Taylor and Sorenson, 2005; World Health Organization, 2009). Although more cross-cultural research is needed to replicate our results, and to further explore these explanatory mechanisms, our study suggests that the clustering in space and time of neighborhood disadvantage appears to influence IPVAW regardless of the city cultural context. In this regard, Sampson noted that "there is something fundamental about place stratification and violence that cuts across international boundaries and yet is locally manifested" (Sampson, 2012, p. 19–20).

Other neighborhood-level covariates that were not considered relevant to the model in our analysis were immigrant concentration, and alcohol outlet density. Regarding immigration, the available research

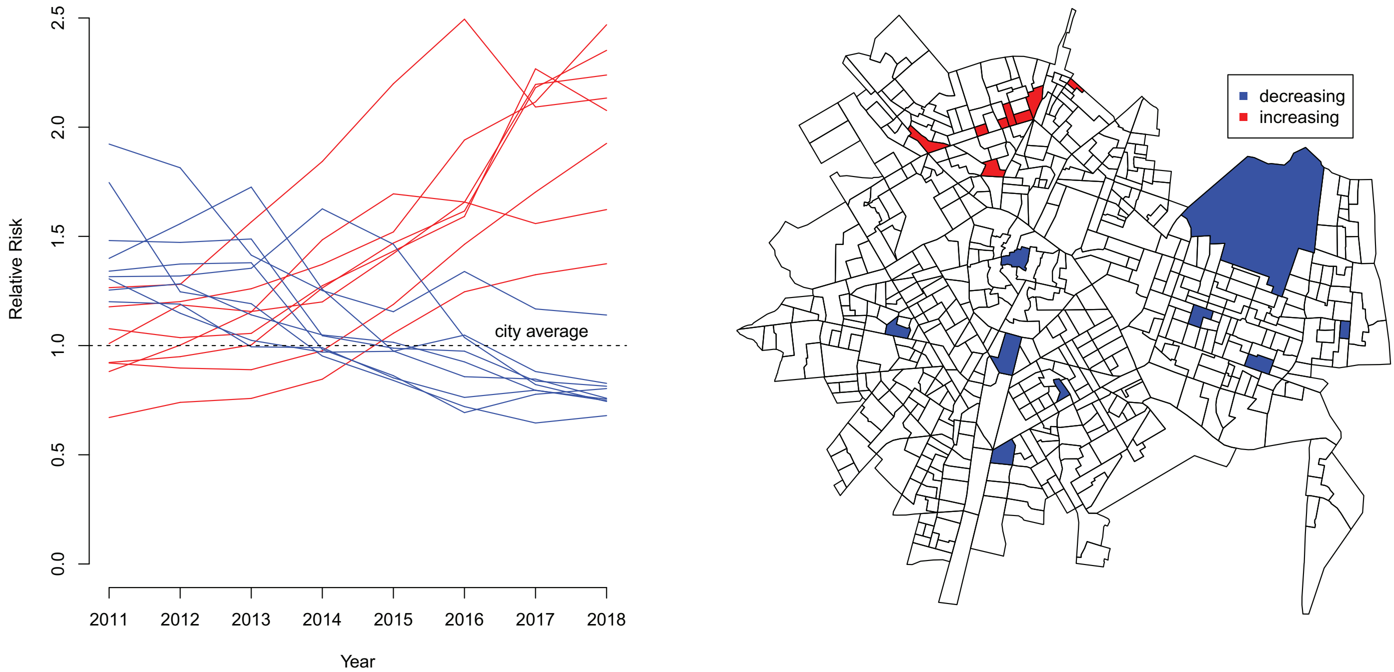

Fig. 3. Temporal paths of relative risk in areas with decreasing (blue) and increasing (red) IPVAW risk. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

provides mixed evidence, with studies finding a positive, negative or no clear relationship (Beyer et al., 2015; Pinchevsky and Wright, 2012; Vanderende et al., 2012; Voith, 2019). Interestingly, in a previous spatial study in Spain (Gracia et al., 2015), immigrant concentration was positively related to IPVAW risk. However, this study was limited by its cross-sectional design that did not take into account variations in immigration rates in the city over the years, thus highlighting the importance of applying a spatio-temporal approach to obtain reliable estimates. Regarding the density of alcohol outlets, research conducted in US cities has found a positive relationship mainly between off-premise outlets and IPVAW (Cunradi et al., 2011). In our study the density of alcohol outlets, in any form, was not relevant to explain IPVAW risk, and this may reflect cultural differences in the alcohol consumption culture in the US and in other cultural contexts such as Spain, differences that have been also observed in other types of domestic violence such as child maltreatment (Marco et al., 2019).

Our study documented the chronic high risk of IPVAW in disadvantaged neighborhoods during the eight-year period analyzed, suggesting that neighborhood disadvantage play an important role in the reproduction of IPVAW over time. This is an important finding with implications for policy; this knowledge should now be incorporated into prevention efforts to detect and reduce IPVAW risk and risk persistence over time in high-risk neighborhoods. IPVAW interventions typically are focused at the individual-level, directed to victims and perpetrators (Arce et al., 2020; Eckhardt et al., 2013; Santirso et al., 2020), or at the macro-level through public education, or the enforcement of new laws. In line with our study, however, a growing body of literature emphasizes the importance of incorporating also community-level interventions targeting high-risk areas, for a more holistic and effective approach to preventing IPVAW (Boggess and Chamberlain, 2020; Gracia et al., 2015; Kim et al., 2013; Kelling et al., 2020; Niolon et al., 2017; Voith, 2019; Wodtke et al., 2011).

Among these area-specific interventions, for example, a CDC report points to interventions aiming to modify the physical and social environment of high-risk neighborhoods as an effective approach for preventing IPVAW (Niolon et al., 2017). Examples of structural interventions in disadvantaged neighborhoods are community economic investment and development, or neighborhood greening initiatives (Boggess and Chamberlain, 2020; Branas et al., 2011; Garvin et al., 2013; Kuo and Sullivan, 2001; Kondo et al., 2018; Niolon et al., 2017). Examples of strategies targeting the neighborhood social environment are community mobilization for awareness raising, increasing informal social control, collective action, and bystander interventions (Banyard et al., 2020; Cohen et al., 2008; Emery et al., 2017; Hatcher et al., 2020; Holliday et al., 2019). In this regard, evidence from criminological research suggest that place-based policing strategies are particularly effective when trust, informal social control, and collective action among neighbors is also mobilized (Sampson, 2012; Weisburd, 2018; Weisburd et al., 2020). Finally, public policies targeting high-risk neighborhoods for IPVAW would include increasing proximity support and social delivery services for women (Coy et al., 2011; Grogan-Kaylor et al., 2020; Muldoon et al., 2019), and predictive policing including big data and AI algorithms based on risk predictions (Braga et al., 2019; Hunt et al., 2020; Grogan-Kaylor et al., 2020; Weisburd, 2015). Furthermore, these initiatives targeting high-risk neighborhoods for IPVAW may have a positive spillover effect as research has linked concentrated neighborhood disadvantage not only to violence in intimate relationships, such as IPVAW or child maltreatment, but also to street-level crime and violence, and other health-related outcomes (Díez-Roux and Mair, 2010; Gracia et al., 2017; Gracia et al., 2018; Law et al., 2014; Sampson et al., 1997; Wodtke et al., 2011).

One of the advantages of the high-resolution analytical framework we used in this study is that it provides specific IPVAW risk estimates at the small-area level, which are more useful and informative for intervention purposes than other low-resolution approaches using larger boundary areas. This analytical tool not only detects spatial patterns of high IPVAW risk and their stability over time, but also areas with increasing or decreasing risk. It can therefore be usefully applied to assess the short- and long-term effectiveness of initiatives aiming to reduce excess IPVAW risk in disadvantaged neighborhoods.

Our study also has several limitations. The outcome variable we used to estimate relative risks was officially reported cases of IPVAW with an associated protection order, which represent the severe end of this type of violence. Officially reported IPVAW incidents do not reflect the actual prevalence of IPVAW, as many cases do not come to the attention of the authorities. Notwithstanding the need for further research into the neighborhood effects on less severe cases of IPVAW or other types of partner violence, we believe that preventive efforts addressing neighborhood-level risk factors associated with the most severe end of IPVAW may also have a positive effect on unreported or less severe cases. The generalizability of our results beyond the context of a medium-sized southern European city, or to rural areas, is also uncertain and requires replication, and further comparative and cross-cultural research. Neighborhood-level covariates tapping some of the above-mentioned mechanisms to explain the link between neighborhood disadvantage and IPVAW, such as gender norms, collective efficacy, attitudes of acceptance and tolerance of violence, or intervention norms, were not available in the administrative data set we used and, therefore, testing relationships with our outcome measure was not possible. Our study, however, also aimed to provide a feasible analytical tool to detect spatio-temporal patterns of IPVAW risk across city neighborhoods based on available administrative data. Thus, whereas administrative data on variables such as income, education, immigration or crime are usually available at the small-area level, other potentially relevant variables such as those mentioned above are not typically gathered as part of the administrative data set, and have to be developed and measured for specific research needs. The variables used in this study are common in most local administrations and, within a social disorganization framework, cover some of the most important variables that have traditionally been linked with violence and crime, both street-level and behind closed doors, as well as other behavioral- and health-related outcomes (Allsworth, 2018; Cunradi et al., 2011; Clayton and Kaldor, 1987; Gracia et al., 2015; Heise, 2011; Heise and Kotsadam, 2015; Haining et al., 2009; Ivert et al., 2020; Lila et al., 2019; Vanderende et al., 2012; Voith, 2019; World Health Organization, 2002). This study therefore provides an adaptable analytic framework that can be applied to administrative data typically collected on a regular basis, and usually available at the small-area scale, for both neighborhood-level covariates and outcomes.

5. Conclusions

The present high-resolution ecological longitudinal study illustrated the link between neighborhood disadvantage and the existence and persistence over time of spatial inequalities in IPVAW risk, showing that high risk of IPVAW can become chronic in disadvantaged neighborhoods. Our study underlines the importance of intervention efforts targeting disadvantaged neighborhoods in IPVAW prevention, and our results can help to better inform and target prevention efforts at the small-area level. The advanced analytical framework we used to identify geographical patterns and trends over time in IPVAW risk across city neighborhoods can also contribute to an epidemiological monitoring system assessing the effectiveness of preventive efforts to reduce IPVAW in disadvantaged neighborhoods over the years.

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Credit author statement

Enrique Gracia conceived the study and drafted the initial manuscript. **Miriam Marco** conducted the data collection, conducted the statistical analysis, and drafted the initial manuscript. **Antonio López-Quílez** designed the analytic strategy, supervised the statistical analysis, and drafted the initial manuscript. **Marisol Lila** designed and coordinated the data collection, and assisted in drafting and critically revising the manuscript. All authors read and approved the final manuscript as submitted.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ypmed.2021.106550.

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