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A spatial semiparametric approach

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What is behind homicide gender gaps in Mexico?

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Juan Armando Torres Munguía*

Abstract

From 1990 to 2016, more than 425,000 homicides have occurred in Mexico. In 2016, the country recorded the world's second largest number of conflict fatalities with more than 24,000 killings. Despite the growing attention for inquiring into specific causes of homicide victimization, research on the matter suffer from three important shortcomings: disregard for introducing a gender perspective, lack of a multilevel approach -use of information both at the victim and community levels- and the exclusive use of traditional linear models -failing to capture nonlinear relationships, as can be expected, in the linkage between age of a person and their likelihood of being victim of crime-. In order to contribute to the analysis of homicides in Mexico, the present study develops a semiparametric approach to investigate the determinants of gender bias in homicide victimization in Mexico. Homicide statistics from 2010 to 2014 and 2010 census data are used to construct a logistic model with sex of the victim as response variable and a set of potential categorical and continuous covariates. The main results suggest that gender differences in victimization can be explained by the mechanism of killing, interaction between age of the victim and the killing mechanism, social deprivation of the municipality of occurrence, share of the population living in female-headed households, share of the population living in indigenous-headed households, random effects and spatial effects.

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1. Introduction

The phenomenon of intentional homicides -defined as the "*unlawful death inflicted upon a person with the intent to cause death or serious injury*" (UNODC, 2015)- is considered one of the most relevant social issues in the world. According to the latest global estimates, there were around 468,000 intentional homicide victims in 2015, being one of the top leading causes of death (WHO, 2016). The effects of these crimes go beyond the loss of human lives, they also gravely touch societies in a myriad of ways, including effects on peoples' everyday life (Spungen, 1998; Alisic, Groot, Snetselaar, Stroeken & van de Putte, 2015; van Wijk, van Leiden & Ferwerda, 2017), affecting the economy (Robles, Calderon & Magaloni, 2013; Waters, Hyder, Rajkotia, Basu & Butchart, 2005; Zhang, Hoddenbagh, McDonald & Scrim, 2012), the state of development (Matzopoulos, Bowman, Butchart & Mercy, 2008; Geneva Declaration Secretariat, 2011) and also governance (Hofmann, 2009; Trelles & Carreras, 2012; Paasilinna, Palmer-Wetherald & Ritchie, 2017).

Over the past ten years, Mexico has been one of the countries receiving most worldwide attention due to the wave of insecurity and crime unleashed by organized groups and gangs, first and foremost by drug cartels. In 2016, Mexico recorded the world's second largest number of conflict fatalities, only surpassed by Syria and above Iraq, Afghanistan, Yemen and Somalia (IISS, 2017). Considering population size to calculate the homicide rate -a much more accurate manner to compare countries-, in 2015 intentional homicide rate in Mexico -17 per 100,000 inhabitants- was more than three times the world rate of 5.3, close to five times the average rate exhibited by the OECD countries and around three times larger than the rate of the least developed countries in the World (INEGI, 2017; UNODC, 2017; World Bank, 2017).

Homicides are unevenly distributed over time and across the country. From 1990 to 2016, more than 425,000 homicides have occurred in Mexico. Between 1990 and 2004, the total number of homicides constantly decreased from 78,094 in the first 5 years, to 50,526 during 2000 to 2004 -a 35% drop-. For the following 5-year period, 2005-2009, a total of 63,049 homicides were recorded, but from 2010 to 2014, this figure moved to more than 122,000 homicides, a 94% increase. Regarding the geographic distribution of homicides, the phenomenon tends to be spatially clustered in the Northern, Northeastern and Southwestern regions of the country (Valdivia & Castro, 2013; González-Pérez, Vega-López, Cabrera-Pivaral, Vega-López & Muñoz de la Torre, 2012; Schmidt, Cervera & Botello, 2017; Flores & Rodriguez-Oreggia, 2015). Furthermore, there are also inequalities in experiences of homicide victimization between females and males. Although most of the homicide victims are males -around 89% since 1990-, there are regional convergence patterns in their homicide growth rates, and the convergence rate for females is stronger than the male convergence rate (Valdivia, 2012; Valdivia & Castro, 2013).

In this light, enhancing knowledge on the determinants of intentional homicides is a key requirement for policy-makers to effectively fight against this crime. However, most of the studies on the matter suffer from three important shortcomings. First, there is too little focus, or at least insufficient, on introducing a gender perspective into the analysis of homicide victimization and consequently, explanations of male victimization are erroneously generalized to females, and *vice versa* (Morash, 2006; Davies, 2011; Miller, 2014; Lauritsen & Carbone-Lopez, 2011; Britton, Jacobsen & Howard, 2017).[1] Second, most of the studies aggregate data into broader units of analysis -province, city or block level- or categories -age groups or sex of the victim-. This grouping may cause a bias[2] by ignoring the distribution of homicide victimization risks across individual factors. Moreover, by overlooking key information on the characteristics of the homicide event -for instance the mechanism of killing, etc.-, studies disregard the heterogeneous nature of this crime (Sampson & Lauritsen, 1994; Flewelling & Williams, 1999; Pizarro & McGloin, 2006). Third, methodologically, existing research is predominantly based on models that assume the traditional linear linkage between a response variable and a set of covariates, failing to capture inherent nonlinear relationships. Nonlinear effects can be expected, for instance, in the linkage between age of a person and their likelihood of being victim of crime (WHO, 2014; UNODC, 2013; Sant'Anna, Scorzafave & Justus, 2016).

Aiming to overcome these shortcomings, the present paper develops a generalized additive model -GAM- with a binary response variable to study the determinants of gender bias in homicide victimization in Mexico from 2010 to 2014. The GAM replaces the linear form of predictors in generalized linear models -GLM- by a sum of smooth functions of covariates, which allow fitting both linear and nonlinear processes (Hastie & Tibshirani, 1986; 1990). Based on previous homicide research, the analysis begins with a full model that incorporates a set of continuous and categorical

[1] One of the reasons behind this is the lack of gender mainstreaming in available crime statistics. According to the Open Data Barometer 2017 only 9 out of 115 countries publish truly open data on crime and only 32% have online sex-disaggregated crime statistics (World Wide Web Foundation, 2017).
[2] See Hammond (1973) on aggregation bias.

potential covariates, including spatial information by states.[3] These variables cover information both on the individual level -including characteristics of the victim and features of the homicide event- and the community context -characteristics of the municipality of occurrence-. In order to achieve both model interpretability and goodness of fit, a variable selection process is applied by pursuing a double penalty approach, as proposed by Marra & Wood (2011).

Rather than solely using city-level data, or aggregated data by sex of the victim, the proposed model utilizes microdata with the victim as recording unit. By doing so, it is also possible to incorporate information on individual level characteristics both from the victim and the homicide event. Since no systematic patterns were found in the missing data, only complete cases were considered. After deleting missing cases, the dataset is composed of 113,878 homicides occurred during the period under study in Mexico.

The remainder of this paper is organized as follows. Section 2 shortly reviews previous work related to gender gaps in homicide victimization. Section 3 describes the framework for GAM and how this semiparametric regression approach is used. A brief description of the variables included in the model is also presented. Section 4 provides information on the data utilized and a discussion of the main results of the model. Finally, section 5 presents the final conclusions and directions for future research.

2. Literature review on gender gaps in homicide victimization

Understanding how homicides are gendered is key for policy purposes to identify causes and social contexts shaping victimization inequalities among sexes (UNSD, 2013). Previous research on victimization disparities has highlighted the need for analyzing crime from both an individual-based perspective along with a community context (see for instance Short (1985); Sampson & Lauritsen (1994) and Smith, Frazee & Davison (2000), among others). Borrowing these concepts and closely following the International Classification of Crime for Statistical Purposes (UNODC, 2015), this paper groups the determinants of victimization gender bias in four broad sets: characteristics of the victim, perpetrator's characteristics, features of the homicide event and characteristics of the community of occurrence.

[3] Administratively Mexico is divided into 32 states.

Most of the work on the characteristics of homicide victims is based on three main demographic factors: age, marital status and socioeconomic status. Overall, general crime victimization is mainly observed against young and single individuals living in socioeconomic disadvantage (Brookman, 2005; Cooper & Smith, 2011; Kingston & Webster, 2015). This can be explained under the umbrella of the lifestyle (Hindelang, Gottfredson, & Garafalo, 1978) and routine activities theories (Cohen & Felson, 1979), that state that victimization risks are determined by the levels of exposition to crime and the frequency of encounters with potential offenders during peoples' daily activities, which correspondingly alter personal victimization levels.

About the age-victimization-risk linkage, it is found to follow an inverted U-shape with a maximum between ages 15 and 29. Even that most of the studies have been merely descriptive, there is a consensus that this inverted U-shape is much more marked in men than in women, since young males are traditionally more exposed to activities outside home, and thus they are in contact with more potential criminals and taking part in more potential conflicts (WHO, 2014; UNODC, 2013). Regarding socioeconomic status, it is expected that people living in socioeconomic disadvantage tend to be involved in more potential conflicts, which has been found to be mainly related to male victimization (Sousa, et. al., 2014; Gartner & Jung, 2014). This same logic can be applied to marital status of the victim, where domestic contexts –role traditionally attributed to females- of married individuals can provide a protective environment from homicide victimization by decreasing their contact with potential offenders and decreasing the time spent in risk situations (Gartner, Baker, & Pampel, 1990; Cohen & Felson, 1979).

The major finding on perpetrator's characteristics in victimization studies is the fact that most incidents involve young men as offenders, but homicides against women are substantially more likely to be committed by intimate partners or by male family members. On the other hand, men are mainly murdered by acquaintances or strange male perpetrators (Campbell, et.al., 2007; Stöckl, et.al., 2013; Laurent, 2004).

Concerning the characteristics of the homicide event, there are two features that play a significant role in addressing homicide victimization: type of location and type of weapon used. Overall, men are more likely to be killed in public spaces -schools, public transport, streets, etc.- than females, who are victimized inside home (UNODC, 2013; Lehti & Kivivuori, 2012; Medina, 2012). Regarding the use of weapon, firearms are the most common mechanism to kill in the world -around 46 out 100 homicides (Geneva Declaration Secretariat, 2011; Geneva Declaration Secretariat, 2015)-. A clear association between the use of firearm and homicide gender bias has not been found (see UNODC (2013: 67)), however, knowledge about the different mechanisms of killing can provide evidence on the nature and motives of homicides against women and men (see WHO (2014); (Chan, Heide & Beauregard (2017) and Fox & Allen (2013)).

Individual factors are not alone in explaining victimization gender gaps. In keeping with the social disorganization theory (Shaw & McKay, 1942; 1969), crime is not evenly distributed across the space, but tend to be geographically concentrated in communities with economic deprivation, ethnic heterogeneity, residential mobility and family disruption. Based on this "ecological" framework of violence, one can consider that these social and cultural structures unequally impact females and males' victimization risks and thus alter gender gaps.

Besides these four variables of social disorganization, a large body of research considering homicide victimization as an urban phenomenon, establishes that crime occurs to a large extend in densely populated cities (see for instance Sampson (1987); and Nolan (2004)). However, some studies have found that once population density has achieved certain threshold, homicide rates start to decline (UNODC, 2013; Browning, et.al, 2010). Finally, since gender gaps -in all aspects of life- are the result of the specific issues and problems faced by women and men, it is reasonable to consider a variable capturing these social inequalities and study their effect on homicides against females and males. By this token, many documents in different social disciplines have incorporated the variable share of female-headed households in a community for analyzing disparities in social roles and lifestyle among sexes (see for instance Klasen, Lechtenfeld & Povel (2010); Newman (2015); Meemken & Qaim (2017); Liu, Esteve & Treviño (2017)). Therefore, one can expect that female headship also influences gender bias in homicide victimization. The process leading to changes in gender gaps can be explained from a feminist perspective (Ganpat, et.al., 2011; Simpson, 1989; Sáenz, 2006; Daly & Chesney-Lind, 1988). Given that males are the major perpetrator of women (UNODC, 2013), it is expected that violence against females would reduce as the social and economic domination of females by males decreases. Thus, communities where women and men are equally empowered tend to show less homicides against females.

In sum, one can hypothesize that at the individual level, characteristics of the victim, perpetrator's characteristics and features of the homicide event differently affect both women and men. One can expect that due to the different levels of exposition to offenders and risk contexts, the effect of victims' age on gender bias varies according to the use of weapon, and that this shows a nonlinear relationship as a result of dissimilar risks through the different stages of life. Regarding the community level, social disorganization variables, population density and share of female-headed households are expected to have an important effect on gender bias. This effect is potentially nonlinear. Moreover, space also shows a significant effect on homicide victimization among sexes.

3. Model

Aiming to study the determinants of gender bias in homicide victimization, consider a GLM as proposed by Nelder & Wedderburn (1972). Let the variable $female_i$, distributed $Bernoulli(\pi_i)$, be the random component of the model. Variable $female_i$, outcome of interest, indicates whether the homicide victim i is women or not $(1 = True)$, for $i = 1, \dots, 113{,}878$ observations. Recall, $Efemale_i = \pi_i = P(female_i = 1)$. The systematic component is $\alpha + \sum_{j=1}^{p} \beta_j x_{ij}$, where p is the number of continuous covariates, x_{ij}. The random and systematic components are then related by the link function $g(\pi_i)$:

$$g(\pi_i) = log\left(\frac{\pi_i}{1 - \pi_i}\right) = \alpha + \sum_{j=1}^{p} \beta_j x_{ij}, \quad i = 1, \dots, 113{,}878 \qquad j = 1, \dots, p \qquad \textbf{[1]}$$

The log-odds ratio, $g(\pi_i)$, measures the probability of a homicide victim being female over the probability of a homicide victim being male. Three general cases arise:

1. If no disparities exist, i.e. $\pi_i = 0.5$, then $g(\pi_i) = 0$;
2. If the probability of a homicide victim being woman is larger than the probability of a homicide victim being a man, i.e. $\pi_i > 0.5$, then $g(\pi_i) > 0$; and,
3. If the probability of a homicide victim being man is larger than the probability of a homicide victim being a woman, i.e. $\pi_i < 0.5$, then $g(\pi_i) < 0$.

Extending the strictly lineal functional form in **[1]** to the GAM context proposed by (Hastie & Tibshirani, 1986), then

$$g(\pi_i) = \alpha + \sum_{j=1}^{p} s_j(x_{ij}), \quad i = 1, \dots, 113{,}878 \qquad j = 1, \dots, p \qquad \textbf{[2]}$$

Where $s_j(x_{ij})$ are smooth functions that allow modelling nonlinear relationships between the response variable and their continuous predictors x_{ij}. However, x_{ij} can also comprise among others, spatial, temporal and random effects. The systematic component of GAM's can include a parametric part, to deal, for instance, with linear effects of categorical covariates (see Wood (2006, 2017); Fahrmeir, Kneib, Lang & Marx (2013: Ch. 8 and 9); Lang, Umlauf, Wechselberger, Harttgen, & Kneib (2012)).

Table 1: Covariates in the model

Variable	**Description**	**Summary statistics**			
		mean	**sd**	**min**	**max**
$\boldsymbol{weapon}$	Type of weapon used (categorical: firearms or explosives, another weapon, no weapon -reference category-, unspecified means, other means).[4]	-	-	-	-
$\boldsymbol{age}$	Age of the victim (continuous).	34.41	14.25	0	117
$\boldsymbol{socdep}$	Social deprivation index in 2010, by municipality of occurrence (continuous). Higher values represent most deprived communities.[5]	-0.908	0.923	-1.89	4.44
$\boldsymbol{marst}$	Number of people who were separated, divorced or widowed as share of the population aged 12 and over in 2010, by municipality of occurrence (continuous).	0.099	0.015	0.039	0.229
$\boldsymbol{mig}$	Number of people who were residing in the same State 5 years earlier as share of the population aged 5 and over in 2010, by municipality of occurrence (continuous).	0.05	0.026	0	0.398
$\boldsymbol{ind}$	Number of people living in indigenous-headed households as share of the total population in 2010, by municipality of occurrence (continuous).	0.067	0.161	0	1
$\boldsymbol{femhd}$	Number of people living in female-headed households as share of the total population in 2010, by municipality of occurrence (continuous).	0.216	0.041	0.056	0.429
$\boldsymbol{den}$	People per square kilometer in 2010, by municipality of occurrence (continuous).	1817	3759	0.144	17656
$\boldsymbol{mun}$	Municipality of occurrence.	-	-	-	-
$\boldsymbol{state}$	Spatial effects considering the State of occurrence.	-	-	-	-

[4] *Another weapon* includes sharp and blunt objects. Category *other means* refers to assaults with fire, chemicals, drugs, etc.

[5] A measure that summarizes 4 indicators of social deprivations on education, health, access to basic services and quality of dwelling. For details see Coneval (2015).

In this paper, the set of covariates explaining $g(\pi_i)$ consists of the categorical covariate $weapon$, and the continuous covariates age, $socdep$, $marst$, mig, ind, $femhd$ and den. Particular emphasis is on the effect of the interaction between the individual variables age and $weapon$, therefore this term is accounted. The model incorporates the variable $state$, which captures spatial effects. Since the model considers multilevel or hierarchical data, i.e., both information at the victim-level and grouped at the municipality level, random effects are also included (see **Table 1** for an overview of these variables).

It is important to remark, that these variables were chosen following existing literature and based on data availability -aiming to keep as much data as possible-. Information related to perpetrator's characteristics could not be incorporated, since this information was not available before 2012 in official homicide data for Mexico. Moreover, recall that these data come from health registries on deaths by cause and do not traditionally contain information from prosecution authorities (see UNODC (2013: 109-110) for a discussion on homicide data sources).

Dropping subscript i for simplicity, the full model can be written as follows:

$$\begin{aligned} log\left(\frac{\pi}{1-\pi}\right) = \alpha + \sum_{h\in W} \beta_h weapon_h + s_1(age) + \sum_{h\in W} s_h(age) weapon_h + s_2(socdep) \\ + s_3(marst) + s_4(mig) + s_5(ind) + s_6(femhd) + s_7(den) + s_{re}(mun) \\ + s_{sp}(state) \end{aligned} \quad \textbf{[3]}$$

Which yields to a semiparametric model, where α and β_h are unknown parameters corresponding to the different levels of the categorical covariate $weapon$, for $h \in W$ according to the mechanism of killing, $W = \{Firearm, Another\ weapon, Other\ means, Unspecified\}$, and $No\ weapon$ as reference category; $s_1(age), \dots, s_7(den)$ and $s_h(age)weapon_h$ for $h \in W$, are modeled by P-splines with second order basis, second order difference penalty and 24 inner knots; $s_h(age)weapon_h$ for $h \in W$, are varying coefficient terms capturing the interaction of covariates $weapon$ and age; $s_{re}(mun)$ are simple independent random effects; and, $s_{sp}(state)$ is a Markov random field with the neighborhood structure as smoothing penalty. Details on the modeling of covariate effects are discussed in the following lines.

3.1 **P-splines**

Every $s_j(x_j)$, for $j = 1, \dots, 12$ in **[3]** can be represented as a linear model by choosing m_j known basis functions, $b_{jk}(x_j)$, with γ_{jk} being unknown parameters to be estimated:

$$s_j(x_j) = \sum_{k=1}^{m_j} \gamma_{jk} b_{jk}(x_j), \quad j = 1, \dots, 12 \qquad \textbf{[4]}$$

Then, flexibility of the smooth functions is determined by m_j. This flexibility can go from the extreme case of a straight line to a function with as many terms as number of observations. One alternative for representing the $j-th$ smooth term, $s_j(x_j)$, is by using B-splines bases (see (Boor, 1978) and (Dierckx, 1995)). The underlying idea of B-splines is that $s_j(x_j)$ can be determined by piecewise polynomials of degree d_j, called splines, that consists of $d_j + 1$ intervals joined at d_j evenly spaced knots within the domain of x_j. Certainly, splines depend significantly on the number and position of the knots. A very large d_j may lead to overfitting, while a small d_j can cause underfitting. To control this trade-off between smoothness and fit, Eilers & Marx (1996) based on O'Sullivan (1986, 1988) proposed using a relative large d_j to achieve enough flexibility and applying difference penalties on the basis coefficients of adjacent B-splines to prevent overfitting, technique that they called penalized splines or simply P-splines. Formally, this penalty is characterized by an integrated square of second derivative. Thus, for the $j-th$ smooth term:

$$\int_{min\, x_j}^{max\, x_j} \left(s_j''(x_j)\right)^2 dx_j \qquad \textbf{[5]}$$

Now, let the $j-th$ smooth term, be expressed in matrix notation as $s_j(x_j) = \boldsymbol{Z_j}\gamma_j$, where:

$$\boldsymbol{Z_j} = \begin{bmatrix} b_1(x_{1j}) & \cdots & b_{m_j}(x_{1j}) \\ \vdots & \ddots & \vdots \\ b_1(x_{nj}) & \cdots & b_{m_j}(x_{nj}) \end{bmatrix}, \qquad and\ \gamma_j = \left[\gamma_{j1}, \dots, \gamma_{jm_j}\right]^T \qquad \textbf{[6]}$$

then, **[5]** can be written as:

$$\int_{\min x_j}^{\max x_j} \left(\boldsymbol{s_j}''(\boldsymbol{x_j})\right)^2 dx_j = \int_{\min x_j}^{\max x_j} \left(\boldsymbol{Z_j}''\gamma_j\right)^2 dx_j = \int_{\min x_j}^{\max x_j} \left(\sum_{k=1}^{m_j}\left(\gamma_k b_{jk}''(x_j)\right)\right) dx_j$$
$$= \sum_{l=1}^{m_j}\sum_{k=1}^{m_j}\gamma_l\gamma_k \int_{\min x_j}^{\max x_j} b_{jl}''(x_j) b_{jk}''(x_j) dx_j = \gamma_j^T \boldsymbol{S}_j \gamma_j \quad \textbf{[7]}$$

where $\boldsymbol{S_j}$ is a symmetric $m_j \times m_j$ matrix of known coefficients. This yields to the following penalized log-likelihood criterion to be maximized

$$\ell_{pen}(\gamma, \theta) = \ell(\gamma, \theta) - \frac{1}{2}\sum_{j=1}^{12} \lambda_j \gamma_j^T \boldsymbol{S}_j \gamma_j \quad \textbf{[8]}$$

where $\ell(\gamma)$ is the non-penalized log-likelihood for GLM's, θ are parameters not modelled with P-splines and $0 \leq \lambda$ is a smoothing parameter that can be estimated via cross-validation (see Eilers & Marx (1996); Wood (2006); Marra (2010); Eilers & Marx (2010) and Fahrmeir, Kneib, Lang & Marx (2013) for further details).

3.2 Varying coefficient terms

In addition to main effects of the categorical variable $weapon$, captured in α and β_h, model **[3]** also introduces the smooth terms $s_h(age)weapon_h$ for $h \in W$, to obtain the interaction effects of covariate $weapon$ depending on age. This way, the estimated terms should be interpreted as follows:

- $s_1(age)$ is the nonlinear effect of age when $weapon = No\ weapon$ -reference category-; and,
- $\beta_h + s_1(age) + s_h(age)weapon_h$ refers to the nonlinear effect of age when $weapon = h$, for $h \in W$, and $W = \{Firearm, Another\ weapon, Other\ means, Unspecified\}$.

See Wood (2006), Fahrmeir, Kneib, Lang & Marx (2013) and Hastie & Tibshirani (1993) for further details.

3.3 **Random effects**

In **[3]**, data contain observations for 113,878 individuals grouped in 2,135 clusters -municipalities-.[6] Then, a hierarchical -multilevel- structure is modeled assuming different intercepts from municipality to municipality. Based on **[6]**, smooth term $s_{re}(mun)$ can be written as $s_{re}(mun) = \boldsymbol{Z_{re}}\gamma_{re}$, where $\boldsymbol{Z_{re}}\gamma_{re}$ is estimated as a i.i.d. Gaussian random coefficient model. $\boldsymbol{Z_{re}}$ is a matrix $113{,}878 \times 2{,}135$ with $\boldsymbol{Z_{re}}[i,m] = 1$ if victim i was killed in municipality m, otherwise $\boldsymbol{Z_{re}}[i,m] = 0$. And γ_{re} is a vector with $\gamma_{re}^{1}, \dots, \gamma_{re}^{2135}$ coefficients corresponding to each municipality.

From equation **[3]**, the following can be stated regarding the random effects:

- $\alpha + \gamma_{re}^{m}$ represents the random intercept for municipality m, for $m = 1, \dots, 2135$. It accounts for non-included covariates and unobserved heterogeneity;
- Moreover, every $s_j(x_j)$ represents the smooth term for covariate j, common across the 2,135 municipalities.
-

See Lang, Umlauf, Wechselberger, Harttgen & Kneib (2012); Wood (2006: Ch. 6); Fahrmeir, Kneib, Lang & Marx (2013: Ch. 9) for further details on random effects.

3.4 **Spatial effects**

Model **[3]** accounts for discrete spatial information by including the term $s_{sp}(state)$, where $state \in \{1, \dots, 32\}$, depends on the state of occurrence of the homicide event. To this aim, a Markov random field smooth is used. This approach considers a penalty similar to the one established in **[8]**, but based on a matrix $\boldsymbol{K}$, containing information on adjacency of the states -neighborhood structure-. $\boldsymbol{K}$ is a matrix 32×32, where

- $\boldsymbol{K}\,[s_1, s_2] = -1$, if $s_1 \neq s_2$ and s_1 and s_2 are neighbors;
- $\boldsymbol{K}\,[s_1, s_2] = 0$, if $s_1 \neq s_2$ and s_1 and s_2 are not neighbors;
- $\boldsymbol{K}\,[s_1, s_2] = N$, if $s_1 = s_2$ for N being the total number of neighbors.

See Rue & Held (2005) for further details on Markov random fields.

[6] Only municipalities with homicide events, in which the sex of the victim was identified were included. There are in total 2,457 municipalities in Mexico.

3.5 **Variable selection**

Once modelled the set of p smooth functions, $s_j(x_{ij})$, it is now key to proceed to variable selection with the aim of finding a subset of significant covariates that ensures an equilibrium between parsimony and goodness of fit. Some alternatives have been proposed for selecting variables in the GAM context (see for instance Wager, Vaida & Kauermann (2007); Fenske, Kneib & Hothorn (2009); Kneib, Hothorn & Tutz (2009); Guisan, Edwards & Hastie (2002); Zhang & Lin (2006); Wood (2006); Belitz & Lang (2008), among others). In this paper the double penalty approach proposed by Marra & Wood (2011) is followed. This method is a shrinkage approach for smooth component selection and is based on the decomposition of the space of a spline basis in two, one component in the null space of the penalty and the second in the range space of the penalty. Thus, the penalty term becomes:

$$\lambda\gamma'\boldsymbol{S}\gamma + \lambda^{*}\gamma'\boldsymbol{S}^{*}\gamma \qquad \textbf{[9]}$$

By spectral decomposition,

$$\boldsymbol{S} = \boldsymbol{U}\boldsymbol{\Lambda}\boldsymbol{U}' \qquad \textbf{[10]}$$

with $\boldsymbol{U}$ as a $m_j \times m_j$ orthogonal matrix whose columns are the eigenvectors of $\boldsymbol{S}$, and $\boldsymbol{\Lambda}$ is a matrix with the eigenvalues of $\boldsymbol{S}$ as diagonal elements. For $\boldsymbol{S}^{*} = \boldsymbol{U}^{*}\boldsymbol{U}^{*\prime}$, $\boldsymbol{U}^{*}$ is the matrix of eigenvectors that correspond to the zero eigenvalues of $\boldsymbol{\Lambda}$. Both λ and λ^{*} have to be estimated (see Marra & Wood (2011) for further details).

3.6 **Identification problem**

In **[3]** one could add an arbitrary constant, $c \neq 0$, to $s_j(x_j)$ and simultaneously subtract it to $s_t(x_t)$, for $j \neq t$ and $j, t = 1, \ldots, 12$. Thus

$$log\left(\frac{\pi}{1-\pi}\right) = \cdots + s_j(x_j) + c + \cdots + s_t(x_t) - c + \cdots = \cdots + \hat{s}_j(x_j) + \cdots + \hat{s}_t(x_t) + \cdots \qquad \textbf{[11]}$$

Which introduces an identification problem of the level of the smooth functions $s_j(x_j)$ and $s_t(x_t)$. To avoid this, the following centering constraints are added in GAM's:

$$\sum_{i=1}^{113,878} s_j(x_{ij}) = \cdots = \sum_{i=1}^{113,878} s_t(x_{it}) = 0 \qquad \textbf{[12]}$$

See Wood (2006: Ch. 4) and Fahrmeir, Kneib, Lang & Marx (2013: Ch. 9) for further details.

4. Data and results

Mexican homicide statistics are available from 1990 to 2015 at the microdata level, i.e. victim-by-victim. Information is extracted from death certificates produced by forensic medical services and civil registry offices following the International Classification of Diseases (WHO, 2017). Broadly speaking, if the medical-forensic expert determines that the death was not by natural but from external causes, specifically by injuries perpetrated by another person targeting to injure or kill, by any means, then the case is recorded as intentional homicide -codes from X85 to Y09-.[7] The model also includes information on characteristics of the community of occurrence, which comes from the 2010 national census. Original datasets are freely available on http://www.inegi.org.mx. All computations were implemented in the R package "mgcv" (Wood, 2017). Since a large data set is used, implementation followed the proposal in Wood, Goude & Shaw (2015).

After applying the double penalty approach for component selection, variables $marst$, mig and den were removed. Results suggest that gender differences in homicide victimization can be explained by the mechanism of killing, age of the victim, social deprivation of the community of occurrence, share of the population living in indigenous-headed households, share of the population living in female-headed households, random effects and spatial effects.

Table 2 shows the parametric estimates for covariate $weapon$, the largest effects on gender bias are evident in the use of firearms. During the period of study, when a homicide was committed with firearms, the odds ratio of a homicide victim being female increased by 0.136 ($\alpha = -0.980$ and $\beta_{Firearm} = -1.017$), i.e., a victim of a firearm killing is almost 7.4 times more likely to be a man than

[7] See INEGI (2017: 9) for further details on the methodology for producing homicide data.

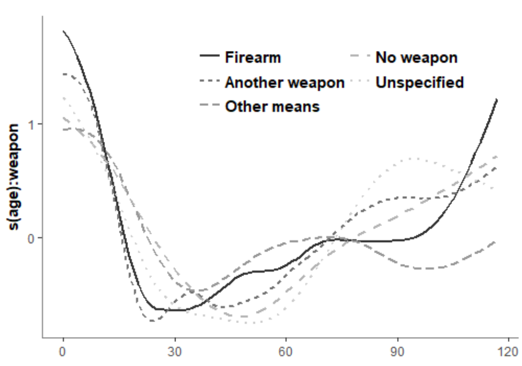
a woman. This result is particularly relevant since firearms are the most common mechanism to kill in the world, representing around 46 out of 100 homicides (Geneva Declaration Secretariat, 2011; 2015). Arranging the effects of the mechanism of killing on gender gaps in descending order, $Firearms$ are followed by $Unspecified$ and $Another\ weapon$. Coefficients of homicides perpetrated with other means -fire, chemicals, drugs, etc.- and without weapon did not show statistical differences between them, and their effects on gender bias are considerable lower than the rest of mechanisms. As found in WHO (2014: 12), this could be the result of lethal intimate partner violence against women, however more research should be done to reach this conclusion in the case of Mexico.

Table 2: Parametric coefficients

	Estimated coefficient	Estimated odds ratio	p-value
$\boldsymbol{Intercept\ (No\ weapon)}$	-0.980	0.375	< 2e-16 ***
$\boldsymbol{Firearm}$	-1.017	0.136	< 2e-16 ***
$\boldsymbol{Another\ weapon}$	-0.382	0.256	1.75E-08 ***
$\boldsymbol{Other\ means}$	-0.167	0.317	0.118
$\boldsymbol{Unspecified}$	-0.434	0.243	9.57E-14 ***
Signif. codes: 0'*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1**			

Figure 1 shows the estimated zero-centered smooth terms for the interaction effects of age and $weapon$ on gender bias in homicide victimization. The different mechanisms of killing depending on age are statistically significant and, overall, their relationship is described by a somewhat U-shape, i.e., the ratio of the probability of homicide victimization for females relative to males is higher in the youngest and oldest ends of the age spectrum. However, despite these similarities, there are important differences to highlight.

Figure 1: Smooth terms



Interaction of use of weapon and nonlinear effects of age of the victim

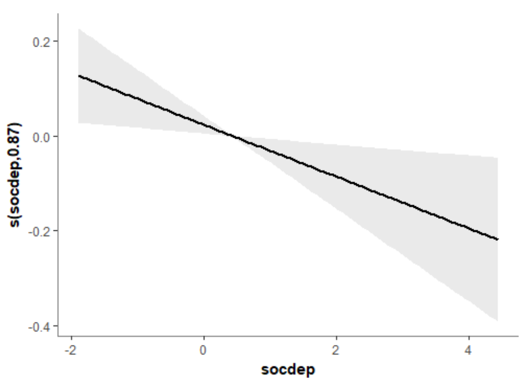
Regarding the use of firearms, the curve descents to its lowest when the victim is aged between 16 and 50 years old. Considering the varying coefficient terms as previously defined, when a homicide is perpetrated with a firearm and the victim is aged around 30 years old, it is almost 13.5 times more likely to be a man than a woman. The smooth term for homicides committed with another weapon -sharp or blunt objects- follows a very similar pattern than firearm homicides, however the increase at the rightmost side of the curve is less pronounced and the largest effect on gender bias is reached when the victim is approximately 25 years old. As suggested by literature on homicides, this may be explained by the fact that young men tend to be more involved in high-risk activities such as gangs and violent conflict resolution (UNODC, 2013; WHO, 2006).

When the crime is committed without weapon or with other means, the curves seem to behave differently than the curves corresponding to homicides with firearms or another weapon. Considering the model intercept, none of the smooths seem to exhibit important gender differences for homicide victims against children younger than 10 years old. The smooth for $No\, weapon$ reaches a minimum for victims aged around 48, while for killings with other means the lowest value of the curve is found approximately in victims of 33 years old. Finally, for homicide victims with means no specified, the smooth curve of the log-odds ratio seems to stabilize around its minimum between ages 30 and 55. After this, the curve has a marked increase. These findings reinforce the idea that the mechanism of killing varies according to the sex and age of the victim, reflecting the different types of violence faced by women and men in their different life-stages.

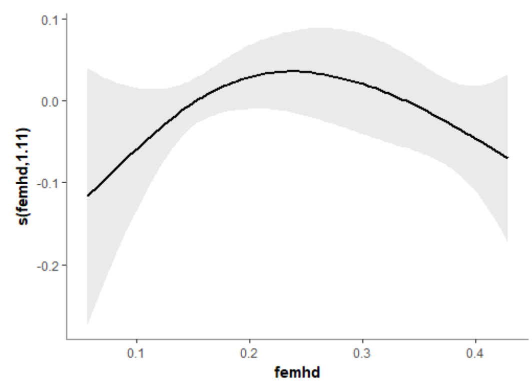
Gender differences in homicide victimization are also shaped by social and demographic structures within communities. The effect of social deprivations on the log-odds ratio is found to be described by a linear decay relationship. When a homicide occurs in a low-deprived community, higher log-odds ratios are observed. As deprivation increases, the smooth decreases (see **Figure 2**). It is important to bear in mind that the lowering tendency in the curve may be the result of a worsening in the number of homicides against men, a decrease in the number of female killings or both.

Concerning the female headship, variable $femhd$, results suggest the existence of an inverted U-shape relationship. In the leftmost side of the curve in **Figure 2** -less egalitarian societies in terms of gender-, as the share of people living in female-headed households increases, the log-odds ratio also grows. In the rightmost portion of the shape, as the percentage of people living in female-headed households goes from approximately 25 to 45, the log-odds ratio declines. The inverted U-shape is much more marked in the ascending side than in the descending segment. One potential explanation for these findings could be clarified by the idea that in less egalitarian societies, where women are more circumscribed to traditional domestic roles with restricted participation in the labor force, females are less vulnerable to some of the main homicide-high-risk situations, such as interpersonal conflicts or assaults in public spaces. When the share of female-headed households is around its median -21%- and 35%, the proportion of female victims increases as a consequence of more similar socialization patterns and roles among sexes. The right-end of the curve can be explained by feminist perspectives which state that, since males are the major perpetrators of females, more equal social conditions would reduce domination roles of women by men and thus violence against women also diminishes (see Gartner, Baker & Pampel (1990) for a discussion about theories on gender differences in homicide).

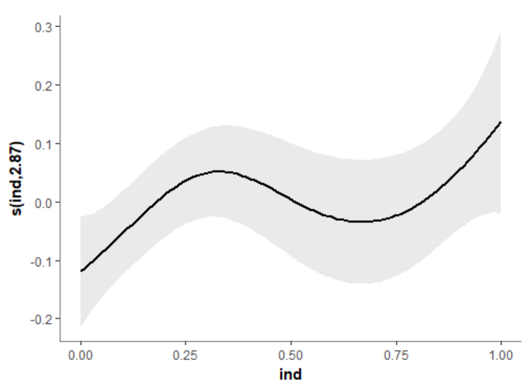
Figure 2: Smooth terms



Nonlinear effects of social deprivation



Nonlinear effects of female-headed households



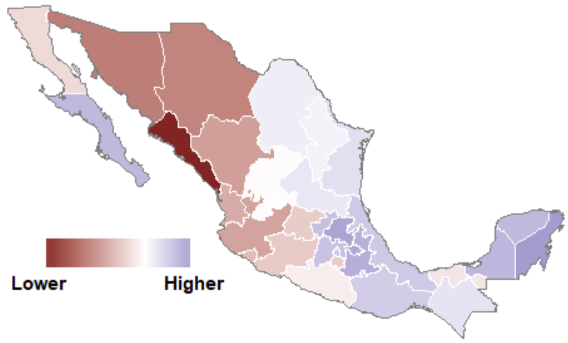
Nonlinear effects of indigenous-headed households

Regarding the relationship between the share of people living in indigenous-headed households and the log-odds ratio, it is observed a kind of double effect (see **Figure 2**). Municipalities where less than half of their population lives in indigenous-headed households show an inverted U-shape relationship, while communities with most of their population living in indigenous-headed households exhibit a U-shape curve. Differences become more apparent when comparing communities with the lowest and highest shares of population in households with indigenous headship. A potential explanation on this difference may be the traditional gender roles played by women and men in indigenous communities. This result highlights the importance of designing public policies to face violence against women in indigenous communities.

Random effects are also statistically significant (p-value < 2e-16), which remark the importance of considering a multilevel approach with random intercept models. Although more complex hierarchies can be introduced, they make computations reasonable slower and may be out of the scope of this paper (see Lang, Umlauf, Wechselberger, Harttgen & Kneib (2012); Heinzl, Fahrmeir & Kneib (2012); Park & Casella (2008)).

Variations in homicide victimization gender gaps cannot be accounted for entirely by these factors. Space also plays a significant role. As seen in **Figure 3**, lower log-odds ratios are found in northwestern Mexico -states of Baja California, Sonora, Sinaloa, Chihuahua, Durango, Nayarit, Jalisco and Colima-. These regions have traditionally exhibited high drug cartel activity levels, mainly related to male homicides (UNODC, 2013: 13). This finding is fairly consistent with existing research on the matter (Valdivia & Castro, 2013; González-Pérez, et.al., 2012; Schmidt, Cervera & Botello, 2017; and Flores & Rodriguez-Oreggia, 2015). Moreover, larger values of the log-odds ratio are shown in central and south Mexico -states of Querétaro, Hidalgo, Mexico, Mexico City, Puebla, Tlaxcala, Veracruz, Oaxaca and Chiapas-, which imply a worsening in the homicide risk of female relative to men, compared to another regions in Mexico.

Figure 3: Nonlinear spatial effects



In sum, gender gaps in homicide victimization can be explained by characteristics of the victim, features of the homicide event and characteristics of the community of occurrence. Furthermore, covariates included in the analysis can help governments to design specific gender policies to fight against violence in Mexico.

5. Conclusion

Despite the growing attention of governments, international agencies and academia for inquiring into specific gender differences in homicide victimization, most of the existing research on homicides do not introduce a gender perspective into the analysis. In the case of Mexico, notwithstanding that microdata with detailed and significant information are available, most of the studies are characterized by exclusively utilizing aggregated data -at province, city or block level-, grouping all the individuals in one category or different types of homicides as the same one and sacrificing key and valuable individual-level information for enhancing knowledge on the matter.

In this paper, aiming to investigate the determinants of gender gaps in homicide victimization in Mexico, a semi-parametric approach is proposed to examine the effect of a set of categorical and continuous covariates on the log-odds ratio for the proportion of female victims compared to male victims. On the methodological aspect of this study, it is important to highlight three key contributions. First, dataset utilized considers information from homicide statistics and census with the victim as unit of analysis, which allow to undertake a more detailed analysis of this phenomenon. Second, covariates cover three broad aspects of analysis on how homicide victimization is gendered:

characteristics of the victim, features of the homicide event and characteristics of the community of occurrence. Third, by using a semiparametric spatial approach, it was possible to capture inherent nonlinear linkages between the dependent and independent variables.

This paper performed variable selection. Through this, it was possible to detect influential variables and ensure an equilibrium between parsimony and goodness of fit. Results suggest that gender differences in homicide victimization can be explained by the mechanism of killing, the interaction of age of the victim and killing mechanisms, social deprivation of the municipality, share of the population living in female-headed households, share of the population living in indigenous-headed households, random effects and spatial effects. These findings also emphasize the importance of moving out of the traditional linear models and considering nonparametric approaches. It is central to remark that non-significant variables may be key for the study of homicide victimization, but do not contribute significantly to gender disparities. Conclusions achieved are also relevant for public policy purposes.

Further research may consider more detailed spatial information and incorporate the effect of time.

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