#### **Appendix A. Data integration process.**

The process of integrating the ENDIREH with the other nine data sources consists of three steps:

- 1. From the ENDIREH microdata we select the information related to the questionnaire applied to married or cohabitation women. The observations in these microdata correspond to individual answers given by the respondents to the ENDIREH questionnaire, and each of these individual answers contains a variable to uniquely identify the municipality (CVE\_MUN) and the state (CVE\_ENT) where the respondent lives. These unique identifiers are assigned by the INEGI (INEGI, 2016).
- 2. Estimations at the municipal level from the Intercensal Population Survey, CONAPO, UNDP, CONEVAL, homicide records, CNGMD, and the geographic information also contain the municipality unique identifier assigned by INEGI, CVE\_MUN. Using this CVE\_MUN as a common variable among the datasets, we first merge all the data at the municipal level from these sources, before merging them with the ENDIREH microdata. This results in a database with a twodimensional tree-like hierarchical structure, in which the individual observations of the ENDIREH microdata (first dimension) are connected to the estimations at the municipal level (second dimension).
- 3. Finally, the estimations at the state level from the ENCIG and the ENVIPE, which contain the state unique identifier assigned by INEGI, CVE\_ENT, are merged with the database resulting from step 2. This results in a database with a threedimensional tree-like hierarchical structure, *i.e.*, the ENDIREH individual observations (first dimension) are connected to the information at the municipal

level (second dimension), and these, in turn, to the state level estimations (third dimension).

The dataset integration was implemented in R. The corresponding code to replicate this process can be provided on request to the authors.

### **Appendix B. Data preparation process.**

After merging the data sources and identifying the available relevant variables, we carry out the following analysis for each of the covariates:

- 1. Plausibility. This process consists of inspecting the data to discover potential incorrect coding or data errors, particularly in new covariates derived from existing variables. The three situations analyzed are:
	- a. Women's age at first sexual intercourse cannot be greater than women's age at the time of being surveyed.
	- b. Women's age at first marriage (or at cohabitation) cannot be greater than women's age at the time of being surveyed.
	- c. Women's age at first childbirth cannot be greater than women's age at the time of being surveyed.

No implausible values were found.

- 2. Outlier detection. To prevent a few unusual observations from influencing the results, we identify the extreme values and exclude them from the final data. To do this, we create boxplots for the continuous variables.
- 3. To ensure we have only complete cases in our dataset, we delete all the observations with at least one missing value in one of the covariates used.

The data preparation process was implemented in R. The corresponding code to replicate this process can be provided on request to the authors.

# **Appendix C. Summary statistics of the final dataset.**



**Table A1.** Summary statistics of categorical variables in the model



# **Table A2.** Summary statistics of continuous variables in the model

authorities







#### **Appendix D. Modelling design.**

We apply an additive probit regression model to identify the correlates of the women's likelihood of emotional IPV victimization. Formally, let the variable  $y_i$ , following a *Bernoulli*( $\pi$ <sub>i</sub>) distribution with probability  $\pi$ <sub>i</sub>  $\in$  [0, 1], indicate whether or not the woman *i*, suffered  $(1 = True)$  from emotional IPV during the previous 12 months (between October 2015 and October 2016), for  $i = 1, ..., 35004$  observations. Consider the vectors  $\mathbf{w}_i := (1, w_{i1}, ..., w_{ip})'$  and  $\mathbf{z}_i := (z_{i1}, ..., z_{iq})'$  of p categorical and q continuous covariates. Then, the binomial model is given by

$$
\eta_i = g^{-1}(\pi_i) = \mathbf{w}_i' \boldsymbol{\beta} + \sum_{k=1}^q f_k(\mathbf{z}_{ik}) + \varepsilon_i
$$
 (1)

For  $g(\eta_i) = \pi_i \in [0, 1]$ , the standard normal cumulative distribution is used.  $\varepsilon_i$  are the standard normal errors. Model (1) corresponds to a generalized additive model as proposed by Friedman et al. (2000) and Hastie & Tibshirani (1999). Introducing covariate effects from Table 2 into Model (1), the model can be formulated as:

$$
\eta_i = \beta_0 + \sum_{j=1}^{13} w'_{ij} \beta_j + \sum_{k=1}^{26} s_k(z_{ik}) + \sum_{l=1}^4 \delta_l(\text{interaction}_l)
$$
  
+ 
$$
\sum_{m=1}^5 \theta_m(\text{interaction}_m) + \sum_{s=1}^2 \vartheta_s(r\mathbf{n}_s) + \varphi(\mathbf{sp}_i) + \varepsilon_i
$$
 (2)

where  $\beta_0$  is the model intercept. The rest of the structure of Model (2) can be divided in the following six components:

1.  $\sum_{j=1}^{13} \mathbf{w}_{ij}' \boldsymbol{\beta}_j$  represent the parametric component for linear effects of the categorical covariates included in Table 2.

- 2.  $\sum_{k=1}^{26} s_k(\mathbf{z}_{ik})$  is the model component for the effect of the univariate continuous covariates from Table 2. Parameters  $s_k(\mathbf{z}_{ik})$  are smoothing functions and all continuous covariates are zero-centered for convergence reasons (Hofner et al., 2014). Given that no specific functional form is established *a priori* for continuous covariates, every function  $s_k(z_{ik})$  is decomposed into an unpenalized polynomial,  $\alpha_0 + \alpha_1 \mathbf{z}_{ik}$ , and a smooth deviation from this polynomial,  $s_k^{centered}(\mathbf{z}_{ik})$ . Every  $s_k^{centered}(\mathbf{z}_{ik})$  is a smooth P-spline with a second-order difference penalty and 20 equidistant inner knots (Hastie & Tibshirani, 1999; Hofner et al., 2014). Due to the decomposition of  $s_k(\mathbf{z}_{ik})$ , it can encompass four possible results: non-significant effect, linear effect, non-linear effect, or a combination of linear and nonlinear effects.
- 3. Interaction effects between a continuous and a categorical variable are denoted by  $\sum_{l=1}^{4} \delta_l$  (**interaction**<sub>l</sub>). Our aim with these interactions is to estimate age-varying effects on IPV of the categorical variables indigenous origin, education level, consent to first sexual intercourse and consent to marriage (or cohabitation with partner).
- 4. Component  $\sum_{m=1}^{5} \theta_m$  (**interaction**<sub>m</sub>) captures the interaction between two continuous covariates, modeled as bivariate P-spline base-learners (Hofner et al., 2014; Hothorn et al., 2020). Our aim with these interactions is to estimate the following effects: age of the woman by age at first childbirth, age of the woman at her first sexual intercourse by the condition of consent, age of the woman by age at her first sexual intercourse, age in years of the woman at marriage or at cohabitation by the condition of consent, age of the woman by age at marriage or at cohabitation,

age of the woman by age of the husband or partner, and woman's reported monthly earned income by husband's or partner's reported monthly earned income.

- 5. Functions  $\sum_{s=1}^{2} \vartheta_{s\tau}(rn_s)$  represent random effects capturing the unobserved heterogeneity across municipalities and states, respectively.
- 6. Geospatial effects are introduced in  $\varphi_{\tau}(sp_i)$ , and are estimated by bivariate tensor product P-splines (Hofner et al., 2014).

The modelling structure was designed in the R package "mboost" (Hothorn et al., 2020). The corresponding code to replicate this process can be provided on request to the authors.

### **Appendix E. Estimation strategy.**

First, we apply the boosting algorithm to estimate the model. This method is a computerintensive iterative process that combines estimation with automatic identification of significant covariates (variable selection) and determination of the functional form of their linkage with the dependent variable, *i.e.*, model choice (Friedman, 2001). For each of the models estimated in this paper, 5000 initial boosting iterations are performed. Crossvalidation is used to prevent overfitting resulting from running this algorithm until convergence and for finding the finite number of iterations, optimizing the prediction accuracy. By doing so, multicollinearity problems are avoided (Hofner et al., 2014).

Second, once the model is fitted at the optimal number of iterations, complementary pairs stability selection with per family error rate control is applied to avoid falsely selecting covariates. By using subsampling procedures, this method simulates a finite number of random subsets of the data, and then, in each of these subsets, it controls the error rate for the number of falsely selected noise variables while selecting relevant variables in the fitting process of the boosting algorithm. After this finite number of subsets have been fitted, the relative selection frequency per covariate effect is determined by calculating the proportion of subsets for which an effect is selected as relevant. All the effects with a relative selection frequency equal to or greater than a previously specified threshold are declared stable effects. For this paper, we set a cutoff of 0.8, *i.e.*, for an effect to be considered stable, it must be selected in at least 80% of the fitted models. As shown in Meinshausen & Bühlmann (2010) results with a cutoff of between 0.6 and 0.9 do not significantly vary. Given the number of potential predictors and their alternative effects in our model, the cutoff of 0.8 corresponds to a per family error rate with a significance level of 0.0398. See Shah & Samworth (2013) for details.

Lastly, 95% confidence intervals for the subset of effects selected as stable are calculated by drawing 1000 random samples from the empirical distribution of the data using a bootstrap approach based on pointwise quantiles (Hofner et al., 2014).

All computations are implemented in the R package "mboost" (Hothorn et al., 2020). The corresponding code to replicate this process can be provided on request to the authors.

# **Appendix F. Results.**

**Table A3.** Full table of estimation results.

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