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INTIMATE PARTNER VIOLENCE AND WOMEN´S HEALTH: THE PRIVATE AND SOCIAL BURDEN

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Intimate partner violence and women's health: The private and social burden*

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Abstract

This paper is concerned with the impact of intimate partner violence (IPV) against women on both the victims' health and the healthcare system. We address this issue using Spanish data for 2011. Given the lack of a single data set including complete individual-level information on IPV and healthcare use, we undertake a stepwise procedure using two complementary and compatible data sets: the Violence Against Women Survey and the National Health Survey. To address potential endogeneity issues, we estimate bivariate models of health status, IPV and healthcare use, exploiting exogenous sources of variation in the data. Our results indicate that IPV experience makes it 18 percentage points more likely to be in any of the three worst health states and that it increases the probability of hospitalization, emergency care and sedative and/or antidepressant consumption by 3.7, 7 and 9.8 percentage points, respectively. According to these estimates, the percentage of the total cost of each of these health services for adult women that could be saved in the absence of IPV is around 0.44% of hospitalization expenditure, 0.84% of emergency care expenditure, and 1.18% of the sedative consumption. These results point out that the costs of IPV are borne by the wider economy and society, not only by the victims, as they entail a significant drain on healthcare resources.

JEL classification: I14, J12, J16, D19, C24, C25, C26, C35, C36.

Keywords: intimate-partner violence, health, gender inequality, medical care costs, ordered response, endogeneity.

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1 Introduction

Intimate partner violence (IPV) is one of the most usual types of violence against women, representing a social blot worldwide. According to the Special Eurobarometer conducted by the European Commission (2010), about 25% of European women experience domestic violence at some point in their lives, and between 6-10% suffer from it in a given year. Female-focused violence represents a hidden obstacle to economic and social development and is an extreme form of gender-based discrimination.

In the past decades, IPV has become increasingly recognized by policy makers as deserving international concern and action. Nonetheless, it appears that it has not emerged as a major problem of social concern in most countries. Looking at the Special Eurobarometer conducted by the European Commission (2016), 44% respondents disagree with the idea that acts of gender-based violence (especially non-physical) should be considered criminal actions. Also, though about 71% of those who know a victim of domestic violence have spoken with someone about it, they rarely do so with health or support services or the police, with their main reason being that it was "none of their business". Furthermore, in the Spanish Barometer of December 2017 (CIS, 2017), violence against women was ranked as the 16th problem of concern and less than 2% reported it among the three main problems. Therefore, it seems that in practice IPV is still seen mostly as a private issue that entails mainly private costs. But it might entail substantial public costs and it affects all of society in many ways too, so the popular perceptions from the private domain should shift to the public one.

This paper focuses on the effects of IPV on women's health outcomes and on the excess cost burden to the health system. A relevant body of research, mainly from the medical literature, has provided an accurate description of IPV consequences on health, which continues even long after the abuse has ended. Direct health consequences associated with IPV include cardiovascular diseases, central nervous system disorders and reproductive disorders, among others (Heise et al., 1994; Ellsberg et al., 2008). Physical violence is also typically accompanied by emotional or psychological abuse, with important mental-health consequences such as depression and post-traumatic stress disorders (Roberts et al, 1998). Pregnancy represents a particularly vulnerable period for women subject to high risk of abuse, increasing the risk for multiple poor maternal and infant health outcomes as well (Silverman et al., 2006; Kishor and Johnson, 2006; Aizer, 2011). It is also associated with adult disadvantages for children who witness or suffer from it (Heise, 1998; Ferraro et al., 2016). Women with a history of IPV are also more likely to engage in risky behaviors (substance abuse, alcoholism, suicide attempts) than women without a history of IPV. These adverse effects of abuse on women's health might impact on their economic independence and labor market outcomes such as employment opportunities, productivity, and dependence on welfare (Fuchs, 2004).

The literature has also recognized the burden that IPV places on healthcare systems. On average, abused victims experience more operative surgery, prescriptions, primary and specialty healthcare, and hospital stays than non-victims (Wisner et al., 1999; Kruse et al., 2011). Therefore, it is important to gauge both the costs of IPV for the individual, as well as for government budgets. Assessing the costs of IPV borne by the wider economy and society, beyond the victims' private costs, might contribute to policy development aimed at reducing this violence and justifying government programs to prevent it.

Previous studies have estimated the association of IPV and health status (Campbell, 2002; Rivara et al., 2006; Ellsberg et al., 2008; Brown et al., 2008). Most of them belong to the medical literature and show the link between these variables. Other studies have documented the burden it places on healthcare systems. For instance, Koss et al. (1991), using a multiple regression analysis, found that a history of rape or assault was a stronger predictor of visits and outpatient costs than any other variable, including woman's age or health risks such as smoking.[1] These studies are relevant since they provide an accurate description of the problem and have been used in many policy reports to foster government programs to prevent IPV. Nonetheless, most of them typically use techniques that do not disclose the true causal effect of IPV, but only the correlation between IPV and health outcomes.[2] This correlation would overestimate (underestimate) the causal effect if, for example, bad health outcomes are more likely for women with certain unobserved characteristics associated with an increasing (decreasing) risk of IPV.

In this paper we study the causal impact of women's IPV on the victims' health of the victims and on the healthcare system as well, using Spanish data for 2011. For such purposes, we have to address two challenging issues. First, we lack a data set that includes complete

[1] A different strand of the literature evaluates the causal effect of certain policy changes on women's behavior related to IPV. For instance, Rice and Vall Castelló (2018) exploit a change in the public healthcare entitlement of undocumented migrants in Spain to investigate the causal link between withdrawal of healthcare and changes in help-seeking behavior of women experiencing IPV.

[2] An exception is Agüero (2017), who studies the effect that violence against women has on the health outcomes of their children using a partial identification method to account for the possible bias due to omitted variables.

individual-level information on both IPV and use of healthcare services. Thus, we undertake a stepwise procedure using two complementary and compatible data sets: the Violence Against Women Survey (VAWS), which lacks information on the use of medical services, and the National Health Survey (NHS) which in turn lacks information on IPV episodes. Second, we must account for the endogeneity of IPV on health status in the first step and for the endogeneity of health on the use of healthcare services in the second step. We estimate a bivariate model of self-reported health status (modeled as an ordered response model) and IPV incidence (modeled as a binary choice model), using as an exogenous source of variation indicators of a woman's awareness of episodes of IPV in her environment. Likewise, the endogeneity of health status on the use of the healthcare system is accounted for by the joint estimation of a model for the probability of use of certain healthcare services and an ordered health status model, using as excluded instruments variables related to the quality of the tap water at home and to the geographical variation of air pollutants released by industrial complexes.

Our results indicate that the presence of IPV makes it 18 percentage points more likely to be in any of the three worst health states and that it increases the probability of hospitalization, use of emergency care and consumption of sedatives and/or antidepressants by 3.7, 7 and 9.8 percentage points, respectively. Given that according to our VAWS data the percentage of abused women is 12%, the percentage of the total cost of each of these health services that could be saved in the absence of IPV is around 0.44% of hospitalization expenditure, 0.84% of emergency care expenditure, and 1.18% of the total cost of sedative and antidepressant consumption. These results point to the fact that the costs of IPV are also borne by the wider economy and society, not only by the victims, since it represents a significant drain on health resources.

2 Data and descriptive evidence

As there is not a single data set that provides complete individual-level information about IPV and use of healthcare services, we exploit two independent data sources, each providing representative samples for adult women living in Spain in the same year, 2011: the Violence Against Women Survey (VAWS) and the National Health Survey (NHS). Both samples contain common variables about individual and household characteristics, as well as self-reported health status as any of five states: either very good, good, mediocre, bad, or very bad. The definition of this variable is the same for both samples, which is key for our purpose of combining the information from these two data sets. However, while only the VAWS sample contains variables about IPV incidence, it lacks information on the use of healthcare services, which is provided by the NHS.

The 2011 Spanish VAWS is the fourth cross-sectional macro survey undertaken in Spain, following the ones for 1999, 2002 and 2006. This is the only source providing information about IPV incidence for a nationwide representative sample of adult women living in Spain. The 2011 survey, stratified by region and by size of municipality, has been fostered by the Spanish Government Representation Department for Gender-Based Violence, and carried out by the CIS (Centro de Investigaciones Sociológicas, Center for Sociological Research). Unlike the three previous surveys, which were conducted by phone, interviews in 2011 were collected face-to-face by a female interviewer in each interviewee's home; questionnaires were filled out by interviewers.

The original VAWS dataset contains $7,898$ observations. To conduct our analysis, we have required the following selection criteria. We have restricted our sample to women between 25 and 65 years old, who either were cohabiting with a partner at the time of the survey or had cohabited with a male partner in the 12 previous months. We have discarded all respondents with missing information in any of the covariates. Our final VAWS sample size is thus reduced to $4,346$ observations. In addition to information on incidence of abuse and sociodemographic characteristics, the 2011 VAWS is the first one providing information on self-reported women's health status.

The 2011 Spanish NHS is the ninth wave of a series of cross-sectional surveys fostered by the Spanish Ministry of Health and Social Affairs, whose main purpose is to provide information about the health situation of individuals living in Spanish households, representative at national and regional levels, stratified by region and by size of municipality. The original NHS dataset contains $21,007$ individuals aged 15 years or more. After restricting the sample to women using the same selection criteria as with the VAWS, the final NHS sample size turns out to be $3,996$ observations.

Furthermore, we also consider a complementary data set that provides province-level information on air pollutants released by industrial complexes, using registries from the Spanish PRTR (Pollutant Release and Transfer Register) for 2010, fostered by the Ministry of Ecological Transition. We will exploit such information as an exogenous source of variation by province to identify the causal effect of women's health status on the use of healthcare services. PRTR data has been increasingly used in recent years to investigate possible health outcomes and other issues like demographic dynamics around industrial facilities, trends in chemical releases and environmental policies, etc. (see Wine et al., 2014). The reported registries comprise releases into air, water and soil of 105 pollutants from about $8,000$ industrial facilities that exceed the minimum legal pollution thresholds, which obligate them to disclose the amounts of pollutants they released. Given that the most detailed level of information about the individuals' location of residence is the province, the released air emissions of each pollutant by each industrial complex are then aggregated by province, and divided by the province extension to measure its concentration. We have focused on 18 air pollutant types, reported to be among the most harmful, with most of them listed being as potential carcinogens by the IARC (International Agency for Research on Cancer), which we have aggregated into four groups. These are described in Table A1 in Appendix A, using the inverses of the IARC thresholds for releases into air (normalized to add up 1) as weights.[3]

In Table 1, we report the sample marginal distribution of subjective health status for each of the two VAWS and NHS samples. The fraction of women reporting any of the three worst health states is higher for the VAWS than for the NHS sample, and, unconditionally, the equality of distributions across samples is rejected.

The sample means of the main variables by health status for the VAWS and the NHS samples are reported in Tables 2 and 3 respectively. For both samples, the characteristics of women and their environment strongly differ across health states. In particular, health status tends to worsen with age, and tends to be better the higher the education level of the woman and her partner; these patterns are statistically significant. Furthermore, we find significant mean differences in the woman's and her partner's labor market situation by health status. Differences in health status by level of education and by labor market status of both partners might be partially capturing differences in income and in access to medical services. To a lesser extent, we also find statistically significant differences depending on whether the woman lives in a metropolitan area, and her family composition, measured as whether she has non-adult children (younger than 18 years old) living at home.

[3]Other air pollutants, like greenhouse gases and nitrogen and sulphur oxides, and pesticides, nitrogen carbons and hydrocarbons, have been disregarded. Their reported consequences on health are generally less harmful than those from the pollutants that we have considered. Furthermore, in some cases, such as greenhouse gases and nitrogen and sulphur oxides, industrial facilities are not usually the main source of releases, as road vehicles play a major role at a very local level. However, we cannot exploit this information as we would need individual information on the location of residence at a much greater detail than the province.

These differential patterns in health status by individual and environmental characteristics are alike in both samples. However, we observe substantial differences between both samples in the distribution by age, education and labor market status of both partners, municipality size and family composition. On average, women in the VAWS sample are younger, more educated and with a more educated partner than women in the NHS sample. Differences in stratification and weighting criteria between both surveys might be behind these differences. Looking at the sample distribution by province of each sample, in Table B1 in Appendix B, we observe that more populated provinces have higher weights in the VAWS than in the NHS, which is consistent with the higher proportion of women living in large municipalities in the first survey. In addition to differences in the proportion of women by woman's age and education and labor market status of both partners, different province weights might imply differences in the distribution of health states because of common factors at the province level that might affect health status. These differences in the geographical distribution between both samples must be accounted for to ensure that, conditional on the province distribution, the samples are compatible.

We also report in Tables 2 and 3 descriptive information of further variables that are only included in one of two corresponding surveys. Our main variables of interest, IPV and use of healthcare services, are collected from the VAWS and the NHS, respectively.

Our measure of IPV is defined as a binary indicator of abuse inflicted on the woman by her partner. As discussed in Alonso-Borrego and Carrasco (2017), the Spanish VAWS measures of a woman's exposure to violence by her intimate partner rely on the gold standard methods, which consist of asking women direct questions on whether they have experienced in the last 12 months specific acts of violence, instead of asking more generic questions related with abuse or violence that tend to yield less disclosure (World Health Organization, 2013). The questions posed correspond to several types of violent behaviors in the relevant time period, their frequency and the assailant. In Table 4, we present the list of the 13 behaviors (out of the 26 listed behaviors) which entail serious abuse. Three of these behaviors correspond to physical abuse and the remaining ten correspond to non-physical abuse. We consider the binary variable of serious IPV that takes on value one if the respondents reported her partner exhibited against her, sometimes or usually, at least one of the aforementioned listed behaviors. According to Table 2, about 12% of women in the sample reported some situation of frequent serious abuse by her last partner (either physical or non physical or both)[4] in the

[4]Note that physical and non physical abuse are not mutually exclusive.

last year at the time of the survey.[5] We observe a significant negative association between IPV and health status by which the incidence of IPV is higher the worse the health status. In Table 5, we observe that the distribution of health states differs strongly by IPV status. Being in any of the three worst health states is about 16 percentage points more likely for victimized women; in particular, the incidence of very bad or bad health among women suffering from IPV doubles the incidence of these two health states with respect to non-abused women.

To measure healthcare use, we examine three different binary variables on whether the woman was hospitalized, whether she received emergency care, and whether she consumed sedatives and/or antidepressants, at least once in the last 12 months at the time of the survey. Among those respondents who were hospitalized, 86% reported only one hospitalization service in the last 12 months. For those individuals who reported at least one hospitalization in the last 12 months, the motive for the last hospitalization was also reported. Considering women between 25 and 44 years old who were hospitalized, giving birth was the main motive of hospitalization, amounting to 60% of cases within this age interval.[6] Our binary measure of hospitalization takes on value one if the respondent was hospitalized at least once in the last 12 months, provided that the motive of her last hospitalization was not giving birth, and zero otherwise. Not surprisingly, the sample frequency of hospitalization, emergency care and consumption of sedatives and antidepressants is decreasing with health status. We have also chosen an additional individual-level variable from the NHS survey potentially associated with health status: an indicator of bad quality of tap water at home, which shows a significantly negative association with health status.

In Table 6 we report the sample means of characteristics of the woman and her environment by the use of these three different healthcare services. Looking at the association between healthcare use services and women's individual and environment characteristics, we observe significant differences in the marginal probability of hospitalization, emergency care and consumption of sedatives and antidepressants by age. Whereas the probability of emergency care is decreasing with age, the opposite happens for hospitalization and consumption of sedatives and antidepressants: for these two latter healthcare services, the probability is

[5] The Spanish VAWS only considers current abuse, which corresponds to any of the situations involving abuse in the last 12 months at the time of the survey. Such situations might have started long before the survey. However, past experiences of abuse that ended at least 12 months before the time of the survey are not recorded.

[6] In addition to giving birth (40.8% of cases), the remaining motives for an overnight stay at hospital in our sample were surgery (40.1%), diagnostic testing (7.4%), hospital treatment (7.4%), and other (4.3%).

very low for the youngest women and very high for the oldest women. There is not any association between the municipality size and the use of any of the three healthcare services. Interestingly, we do not observe any clear association between the education of any of the partners and the probability of hospitalization or emergencies use. The fact that the Spanish National Health System is aimed at guaranteeing universal access for all people living in the country, so that the use of these healthcare services is not determined by socioeconomic status or place of residence, might be behind this result. However, there is a negative association between the education of the woman and her partner and the consumption of sedatives and antidepressants.

The VAWS survey also reports information on whether the respondent is aware of IPV episodes suffered by the women among her acquaintances. This variable will be used as an instrument to identify the causal effect of IPV on health. In Table 7 we show the incidence of IPV suffered by the respondent depending on whether she has also reported awareness of IPV among her female acquaintances. IPV incidence is 3 percentage points higher for women who acknowledge episodes of IPV among women in their environment than for women who do not.

3 Empirical model

The lack of a single dataset including complete information on IPV and use of healthcare services requires a stepwise procedure using the two main complementary data sets previously described. The first step requires the estimation of the marginal effect of IPV on health status. For that purpose, we estimate a bivariate model that includes an equation for health status as a function of IPV and sociodemographic control variables, and an equation for IPV as a function of sociodemographic variables and at least one instrumental variable, excluded from the health status equation. The second step requires the estimation of the marginal effect of the health status on the use of health services using the NHS. In this latter case, we specify a bivariate model which includes an equation for the use of health services as a function of health status and sociodemographic control variables and an equation for health status with sociodemographic variables and further instrumental variables excluded from the use of health services equations. With these estimates we compute the marginal effect of IPV on the use of health services.

3.1 Effect of IPV on health status

To model the relationship between self-reported woman's health status and the incidence of domestic violence, we use a bivariate normal model. Let HS^* be the latent woman's health index that drives her health status and IPV^* be the latent process that drives intimate partner violence, both characterized by the following underlying behavioral model:

$$HS^* = \mathbf{X}_1'\beta_1 + \gamma IPV + \upsilon_1, \tag{1}$$

$$IPV^* = \mathbf{Z}_1'\delta_1 + \upsilon_2, \tag{2}$$

where IPV is the observed indicator of domestic violence, $\mathbf{X}_1$ and $\mathbf{Z}_1$ are sets of covariates, β_1, δ_1 and γ are the coefficients associated to the set of covariates $\mathbf{X}_1$, $\mathbf{Z}_1$ and to IPV, and υ_1 and υ_2 are the corresponding unobserved random errors for each equation.

The VAWS asks each woman to rate their health as any of 5 states, either very good, good, mediocre, bad, or very bad. If we assume that each woman's self-reported health status reflects her underlying health state, we can estimate the coefficients β_1 and γ using the self-reported data. We use the following threshold mechanism that relates HS^*, the unobservable latent continuous health index, to the discrete health status HS:

$$HS = s \quad \text{if and only if } \pi_{s-1} < HS^* < \pi_s, \;\; s = 1, ..., 5 \tag{3}$$

where $\pi_0 = -\infty$, $\pi_5 = +\infty$, $-\infty < \pi_{j-1} < \pi_j < +\infty$ $(j = 1, \ldots, 4)$.

Assuming that υ_1 is normally distributed and independent from υ_2, equations (1) and (2) can be estimated separately by Maximum Likelihood (ML), the former as an ordered probit model for self-reported health[7] and the latter as a probit model for IPV.

Nonetheless, if υ_1 and υ_2 are not independent, this method does not yield consistent estimates of the parameters for equation (1). If we had an instrument set, $\mathbf{Z}_1$, for IPV such that $IPV|\,\mathbf{X}_1, \mathbf{Z}_1 \sim N\left(\mu_{IPV}\left(\mathbf{X}_1, \mathbf{Z}_1\right), \sigma^2_{IPV}\right)$ the parameters in (1) could be easily estimated by using a two-stage method. However, since IPV is a binary indicator, its distribution cannot be normal, and as a consequence, two-stage methods are not valid alternatives for estimating this type of nonlinear models. Thus, we need to implement the joint ML estimation of the model. We proceed as follows. Denote the probability of the joint event that woman's latent health index HS^* lies in interval s and the woman suffers from IPV as

$$\Pr\left(HS = s, IPV = 1\right) = \Pr\left(\pi_{s-1} < HS^* < \pi_s, IPV^* > 0\right). \tag{4}$$

[7] Cutler and Richardson (1998) also use univariate ordered response models to examine the relationship between different types of disease and self-reported health status. Other examples are Kenkel (1995), Theodossiou (1998) or Chaloupka and Wechsler (1997).

We can rewrite the probability of this event in terms of univariate and bivariate CDFs as follows:

$$\begin{aligned}\Pr(HS = s, IPV = 1) = {} & [\Pr(HS^* < \pi_s) - \Pr(HS^* < \pi_s, IPV^* < 0)] - \\ & [\Pr(HS^* < \pi_{s-1}) - \Pr(HS^* < \pi_{s-1}, IPV^* < 0)],\end{aligned} \tag{5}$$

where we have used the conversion between the probability of $IPV^* > 0$ and its complement, 1 minus the probability that $IPV^* < 0$. Assuming normality of each CDF, standard univariate and standard bivariate normal, and letting ρ be the correlation coefficient between v_1 and v_2, we have:

$$\begin{aligned}\Pr(HS = s, IPV = 1) = {} & [\Phi(\pi_s - \mathbf{X}_1'\beta_1 - \gamma) - \Phi(\pi_s - \mathbf{X}_1'\beta_1 - \gamma, -\mathbf{Z}_1'\delta_1;\rho)] - \\ & [\Phi(\pi_{s-1} - \mathbf{X}_1'\beta_1 - \gamma) - \Phi(\pi_{s-1} - \mathbf{X}_1'\beta_1 - \gamma, -\mathbf{Z}_1'\delta_1;\rho)].\end{aligned} \tag{6}$$

Likewise, the probability that health status lies in interval s and $IPV = 0$ is:

$$\Pr(HS = s, IPV = 0) = [\Phi(\pi_s - \mathbf{X}_1'\beta_1, -\mathbf{Z}_1'\delta_1;\rho) - \Phi(\pi_{s-1} - \mathbf{X}_1'\beta_1, -\mathbf{Z}_1'\delta_1;\rho)]. \tag{7}$$

To obtain the ML estimates of the parameter vectors β_1, γ, and δ_1, the 4 threshold parameters π_j $(j = 1, \ldots, 4)$ and the correlation coefficient ρ, we define $d_s = \mathbf{1}(HS = s)$ as the usual binary indicator taking the value 1 if HS^* falls in category s of health status and 0 otherwise. Thus, for a sample of $i = 1, ..., N$ independent observations, the likelihood function is the product of (6) and (7) across observations:

$$\begin{aligned}L = \prod_{i=1}^{N}\prod_{s=1}^{5} & [\Pr(\pi_{s-1} < HS^* < \pi_s, IPV^* > 0)]^{d_{is}} \times \\ & [\Pr(\pi_{s-1} < HS^* < \pi_s, IPV^* < 0)]^{1-d_{is}}.\end{aligned} \tag{8}$$

As shown by Maddala (1983), we need some exclusion restriction by which there is some relevant regressor in the IPV equation that does not directly affect the health status to identify the model parameters when v_1 and v_2 are not independent. Our instrument for woman's experience of IPV is an indicator on whether the woman is aware of some episode of IPV among her female acquaintances.[8] Our identification strategy relies on the assumption that the instrument is relevant and exogenous. Previous literature has shown that violent environment is a powerful predictor of an individual's violent experiences. For instance,

[8] This instrument is in line with van der Berg et al. (2015), who use shocks during childhood to instrument the effect of childhood conditions on adult outcomes.

Erikson et al. (2016) find that family and community background explain violent events to a large extent. Case and Katz (1991) analyze the link between the behavior of older family members and neighborhood peers and youths in terms of criminal activity, drug use or schooling.

There is also a vast amount of empirical research exploring the intergenerational transmission of violence. For instance, Iverson et al. (2011) find that males and females who witnessed the same-sex parent become victim of IPV reported greater victimization experiences as adults. Although in our dataset we also have information on whether the woman is aware of IPV episodes among her female relatives (mother or sisters), we have discarded it as an additional instrumental variable. The reason is that we want to preclude a possible genetic transmission of mother's experiences of IPV on her daughter's health, which would make this variable have a direct effect on woman's health and, therefore be an invalid instrument.

Finally, we calculate the ceteris paribus effect of IPV on the probability of each different health status. For each individual, this marginal effect is the difference between the probabilities before and after the change, given the values of the other variables:

$$
\begin{aligned}
&\Pr\left(HS = s \middle|\, IPV = 1, \mathbf{X}_1\right) - \Pr\left(HS = s \middle|\, IPV = 0, \mathbf{X}_1\right) \\
&= \left[\Phi\left(\pi_s - \mathbf{X}_1'\beta_1 - \gamma\right) - \Phi\left(\pi_{s-1} - \mathbf{X}_1'\beta_1 - \gamma\right)\right] \\
&\quad - \left[\Phi\left(\pi_s - \mathbf{X}_1'\beta_1\right) - \Phi\left(\pi_{s-1} - \mathbf{X}_1'\beta_1\right)\right].
\end{aligned} \tag{9}
$$

Given that the marginal effects vary across individuals, we report the average marginal effects taking expectations of (9) with respect to the regressors, which is estimated consistently by replacing the population parameters by their corresponding ML estimates and averaging them over the sample.[9]

3.2 Effect of health status on use of healthcare services

Our objective is to measure the effect of the woman's health index (HS^*) on the use of health services (U), measured as a set of binary decisions. In particular, we analyze the use of hospitalization, emergency care, and consumption of sedatives and antidepressant drugs. A possible approach consists of estimating the following binary choice model:

$$
\Pr\left(U = 1 \middle|\, \mathbf{X}_2, HS^*\right) = \Phi\left(\mathbf{X}_2'\beta_2 + \alpha HS^*\right), \tag{10}
$$

[9] The effects could also be evaluated at the sample averages, or at some other interesting values of the covariates.

where U is a binary indicator on whether the woman uses that particular health service or not, $\mathbf{X}_2$ is a set of covariates, and β_2 and α are the coefficients associated to the set of covariates $\mathbf{X}_2$ and to HS^* respectively. One could estimate equation (10) by ML. However, a selection problem could arise again because the health index HS^* might be correlated with the unobserved individual characteristics and random shocks that might increase the probability of healthcare use. If this is the case, one should specify a model for HS^* as a function of a set of variables that affects U only through HS^*:

$$HS^* = \mathbf{Z}_2'\delta_2 + v_3, \tag{11}$$

where the vector $\mathbf{Z}_2$ includes sociodemographic variables and a set of variables that are potential determinants of individual health status but do not directly affect the use of healthcare services. At the individual level, we include a binary variable on whether the respondent reported bad quality of drinkable water at her home. We also consider province-level information on air pollutants released by industrial complexes, using registries from the Spanish PRTR (Pollutant Release and Transfer Register) for 2010. Many studies show strong negative associations between local pollutant releases and health. In particular, using the Spanish PRTR, Fernández-Navarro et al. (2017) find higher relative risks of cancer mortality among residents in areas close to industrial pollutant sources in comparison with those living in more remote areas without highly polluting industrial facilities.

This model, in which the continuous index HS^* enters as an endogenous regressor instead of the endogenous indicators of health status, is similar to the one considered by Mallar (1977). It allows a two-stage estimation procedure to be used, instead of a more complicated joint ML estimation of model (10) and the indicators for health status. Specifically, we first estimate a reduced form ordered probit model using the self-reported health status information:

$$\Pr\left(HS = s \mid \mathbf{Z}_2\right) = \Pr\left(\tau_{s-1} < HS^* < \tau_s\right), \; s = 1, \ldots, 5, \tag{12}$$

and then we use the predicted values

$$\widehat{HS^*} = \mathbf{Z}_2'\widehat{\delta}_2 \tag{13}$$

to estimate

$$\Pr\left(U = 1 \mid \mathbf{X}_2, HS^*\right) = \Phi\left(\mathbf{X}_2'\beta_2 + \alpha\widehat{HS^*}\right) \tag{14}$$

by the probit ML method. Notice that the computation of the standard errors should account for the use of the generated regressor $\widehat{HS^*}$ instead of the actual index HS^*.

Finally, we estimate the average marginal effect of HS^* on the probability of using health services as the average over the sample of

$$\frac{\partial \Pr\left(U=1|\,\mathbf{X}_2,\widehat{HS^*}\right)}{\partial HS^*} = \alpha\phi\left(\mathbf{X}_2'\beta_2+\alpha\widehat{HS^*}\right), \tag{15}$$

where $\phi(\cdot)$ is the density function of the standard normal.

3.3 Effect of IPV on healthcare use

To estimate the impact of IPV on the probability of using health services we use the estimates of the models presented in Sections 3.1 and 3.2. On the one hand, we use the marginal effect of IPV on the health index HS^* estimated from model (1)-(2):

$$E\left(HS^*|\,\mathbf{X},IPV=1\right)-E\left(HS^*|\,\mathbf{X},IPV=0\right)=\gamma. \tag{16}$$

On the other hand, we use the marginal effect of HS^* on the probability of using health services estimated from model (10)-(11) and given in equation (15).

The marginal effect of interest in this case is defined as

$$\begin{aligned}&\Pr\left(U=1|\,\mathbf{X}_2,HS^*\left(IPV=1\right)\right)-\Pr\left(U=1|\,\mathbf{X}_2,HS^*\left(IPV=0\right)\right)\\&=\alpha\phi\left(\mathbf{X}_2'\beta_2+\alpha\widehat{HS^*}\right)\times\gamma.\end{aligned} \tag{17}$$

Finally, a measure of the "excess" healthcare cost due to IPV is given by the previous figure, (17), times the proportion of women affected by IPV.

4 Results

4.1 Compatibility of the two datasets

For the purposes of this paper, it is crucial to provide statistical evidence of the compatibility of the two samples needed to estimate the effect of IPV on healthcare use. Following Arellano and Meghir (1992) we test whether the conditional distribution of the health status variable is the same in both samples. To that end, we have pooled the two data sets and estimated an ordered probit model for health status as a function of a set of conditioning variables which include woman's age, and education levels and the labor force statuses of the woman and her partner. We have allowed for differences in the slopes by including the covariates as well as the interactions of each covariate with a binary variable indicating the survey each observation comes from. We then test for equality of slopes among both surveys by testing that the coefficients of such interactions are jointly equal to zero.

Although the definitions of most variables in the two surveys are alike, one important difference between them is that they use different sampling criteria. As mentioned earlier (see Table B1 in Appendix B), the VAWS gives more weight to more populated provinces than the NHS.[10] This makes it crucial to account for province dummies in the estimation of the conditional distribution of the health status variable. The results (see Table B2 in Appendix B) show that the interactions of the conditioning variables with the survey indicator are statistically insignificant, except for partner's secondary education. But we do not reject either the joint lack of significance of the partner's education coefficients or the joint lack of significance of all the interaction coefficients (the χ^2 statistic has a p-value of 0.4495). Moreover, as expected, we reject the equality of coefficients of the province dummies. These results lead us to conclude that, after controlling for province of residence, the two surveys are compatible.

4.2 Estimates of the effect of IPV on health status using the VAWS

Table 8 presents the estimation results of the model used to analyze the effect of IPV on woman's health status. Our concern with the potential endogeneity of IPV in the health status equation motivates the joint ML estimation of a two-equation model with health status and IPV as endogenous variables.

As mentioned in the previous section, our exclusion restriction consists of an instrumental variable that affects the probability of experiencing IPV but does not have a direct effect on woman's health status. This instrument is the binary variable on woman's awareness of episodes of IPV in her environment, which indicates whether someone among her female acquaintances has been the victim of abuse. To be a valid instrument, the woman's probability of being a victim of IPV should change as the value of this instrument changes.

The joint ML estimation of health status and IPV allows us to analyze the relevance of our instrument conditional on other controls. In particular, the estimation results for the IPV equation in the third column of Table 8 indicates that the instrument is a strong predictor of IPV. The instrument is statistically significant (the p-value of the Wald test is

[10] There are also differences in terms of the classification of the municipalities, which are the ultimate sampling units. In particular, although the number of strata is the same in both cases, there are differences in their size.

0.0088). The average marginal effect on the probability of IPV indicates that being aware that some non-relative female is victim of IPV increases her own probability of IPV by 3.4 percentage points.

The ML estimation results for the health equation that accounts for the endogeneity of IPV are reported in the second column of Table 8. For the sake of comparison, in the first column of this table we report ML ordered probit estimates for the single-equation model for health status that ignores the potential endogeneity of IPV.

The control variables for woman's characteristics include a set of binary variables for woman's completed education (secondary and college, with primary education as reference group), woman's labor market status (unemployed and inactive, with working as reference group) and a binary variable on whether the woman is not working but worked in the past, woman's age (with the younger ones, between 18 and 34 years old, as the reference group). We also control for her partner's completed education and labor force status.[11] Regarding household characteristics, we control for the size of the municipality of residence using a binary variable on living in a highly populated metropolitan area –above $100,000$ inhabitants–, and whether there are non-adult children living in the household. We include province binary variables to control for unobserved province differences.

The estimated coefficients of most of the variables on the health equation look similar for the single equation and for the two-equation model. The education levels of the woman and her partner have a positive and significant effect on health. We also find a significant negative effect of woman's age on health. Regarding current labor market status, there are no differences in the woman being working with respect to being either unemployed or inactive. However, the fact that the woman is not working but has worked in the past is negatively related with her health. Having non-adult children has a positive relation with health.

Comparing the single equation ordered probit for health status with the joint model for health status and IPV, in both estimations we observe a damaging effect of IPV on health. However, the estimation of this damaging effect is much larger when the endogeneity of IPV is accounted for. This result points out the existence of potential confounders that lead to an underestimation of this damaging effect when the potential endogeneity of IPV is ignored. There could be several explanations for this underestimation. For instance, measurement

[11] As we do not have any measure of household income, we would expect variables for the woman and her partner's education to capture partly both individual and household socioeconomic status.

errors in IPV prevalence. In this case, the effects will be subject to a downward bias if under-reporting of IPV is more serious for women with worse health status.

In Table 9 we report the average marginal effects of IPV on each health state. The marginal effects are positive for the three worst health states and negative for the two best health states. But it is worth mentioning that the magnitudes of the estimated marginal effects of an exogenous increase in IPV prevalence (second column in Table 9) double those from the single equation model. And the magnitude of the effects is substantial.[12]

On average, the exogenous presence of severe abuse makes it 18 percentage points more likely to be in any of the three worst health states (from very bad to mediocre), the probability being 1.7 times higher for abused than for non abused women (taking the unconditional distribution of health status for non abused women as a benchmark). For the two worst health states, the probability of suffering very bad or bad health increases by 2.7 and 4.6 percentage points for abused women. Mediocre health status is, on average, 10.4 percentage points more likely for abused than for non-abused women, so that the probability of reporting mediocre health is 1.5 higher for abused than for non abused women. By the same token, being in any of the two best health states is on average 18 percentage points less likely for abused than for non-abused women. Enjoying good or very good health are 8.6 and 9.3 percentage points less likely for abused than for non abused women, so that the probabilities of enjoying good or very good health are respectively 0.8 and 0.4 times lower for abused than for non abused women. It is particularly noticeable that, on average, the estimated probability of enjoying a very good health state decreases from 16% for non-abused women to less than 7% for abused women.

4.3 Estimates of the effect of health status on use of healthcare services using the NHS

This section presents the estimation results from the model of use of healthcare services as a function of HS^*. We first present empirical evidence regarding the power of the instruments

[12] Recall that the IPV measure used in the estimations considers whether or not the woman has experienced some episode of serious abuse in the last 12 months at the time of the survey, irrespective on when such situation started. In order to assess the sensitivity of the results to the definition of this variable, we have considered an alternative measure, which takes on value one if the woman has experienced some episode of serious abuse in the last 12 months, provided that such situation started more than one year ago, and zero otherwise. With this measure, we aim at the effect of lengthier situations of IPV. Qualitatively, the results are similar with both IPV measures. However, the absolute values of the estimated coefficient and the marginal effects of IPV are smaller in magnitude, and are estimated with lower precision than with our original measure. The fact that, under this alternative measure, IPV is set to zero for women reporting IPV that started less than one year ago, is likely to be behind this loss of precision.

used for health status in the equations of use of health services. The instrumental variables we include in the reduced form specification for HS^* in equation (11) are a binary variable on whether the respondent reported bad quality of drinkable water at her home and province-level information on air pollutants released by industrial complexes, using registries from 2010 the Spanish PRTR (Pollutant Release and Transfer Register). The estimates from the reduced form ordered probit model for woman's health status reported in Table 10 provide strong evidence of the relevance of the set of instruments conditional on further controls.

Using estimates from Table 10 we obtain the predicted values for the health index, $\widehat{HS^*}$. In Table 11 we report its main descriptive statistics, and the sample averages by observed health status. A one-level improvement in health status is represented approximately by an increase in the predicted health index of half a standard deviation.

Table 12 presents the estimated coefficients from the corresponding probit models for our three different measures of healthcare use: the use of hospitalization, the use of emergency care, as well as sedative and antidepressant consumption, in columns (1) to (3) respectively. In addition to the predicted health index, $\widehat{HS^*}$, we include as controls several sets of binary variables for woman's and her partner's education, woman's age, a binary variable on whether the woman lives in a metropolitan area, and province fixed effects. The use of the predicted health index instead of the actual health index introduces an error in the healthcare use equation, so that we have used bootstrap methods to compute the standard errors of the estimated parameters.

We find that there are not significant differences in the propensity to use healthcare services by the education of the woman or her partner. Woman's age has no effect on the probability of hospitalization, and opposite effects on emergency care (negative) and the consumption of sedatives and antidepressante (positive).

Our results indicate that, conditioning on characteristics of the woman and her partner, an exogenous improvement in health significantly decreases the probability of using any of the three healthcare services. Table 13 reports the average marginal effect of $\widehat{HS^*}$. We find that increasing the health index by 1 unit increases the corresponding probabilities of hospitalization, emergency care and consuming sedatives by about 7, 13 and 18 percentage points respectively. To get a more precise flavour of the magnitude of this marginal effect, we must look at the average values of the predicted health index for each discrete health state in Table 11. For the most frequent health states, mediocre and good health, the average change in the predicted health index represents approximately half a standard deviation. A half-standard deviation increase in the health index would reduce the probability of hospitalization by 1.4 percentage points, which is a relevant increase inasmuch as the unconditional probability of hospitalization by then was 6 percent (see Table 3). Likewise, a half-standard deviation increase would increase the probability of using using emergency services by 2.7 percentage points, and the probability of consuming sedatives or antidepressants by 3.7 percentage points. These magnitudes are not only significant but relevant as well, taking into account that the unconditional probabilities of using emergency services or consuming sedatives or antidepressants in the period of reference are, respectively, 28.1 and 12.3 percent.

4.4 Estimates of the effect of IPV on healthcare use

Our previous estimates allow us to first estimate the effect of IPV on the use of healthcare services and second to provide an estimation of the excess cost for the health system due to IPV. Table 14 presents the average marginal effect of IPV on the use of the three different healthcare services that we have considered, as indicated in equation (17).

Our results indicate that IPV increases the probability of hospitalization, use of emergency care and consumption of sedatives by 3.7, 7 and 9.8 percentage points, respectively. In order to give a measure of the costs that IPV imposes on society, we calculate the percentage of the total cost of each of these health services that could be saved in the absence of IPV, that is, a measure of the excess costs due to IPV. To this end, we have to multiply the figures presented in Table 14 by the percentage of abused women, which according to our VAWS data is 12%. Consequently, we obtain that regarding adult women, 0.44% of the hospitalization expenditure, 0.84% of emergency care expenditure, and 1.18% of the total expenditure in sedatives and antidepressants, are due to the existence of IPV.

To put these figures in context, we should relate them to the financial situation of the health system in Spain. Health expenditure and the sustainability of the healthcare system has been an issue of concern in Spain, as in other developed countries. Until the onset of the economic crisis, which translated into budget cutbacks in 2010, the trend in health spending in Spain was in line with other EU countries. But the economic crisis turned into a steady growth of the Spanish public deficit and public debt that led to policies aimed at reducing public expenditure. According to the Health Account System (Sistema de Cuentas de Salud) the total expenditure in the Spanish healthcare system was 99,167 million Euros in 2011, while the expenditure per capita was 2,125 Euros. It represented 9.3% of the GDP.

The reform agenda in the health system in recent years has been strongly influenced by the austerity measures agreed on in the EU stability programmes for Spain, whose chief goal in the health sector was the reduction of the public share of health expenditure. Major reforms have been implemented to address the negative impact of the crisis in public finance, including the exclusion of public coverage for different population groups and the increase of co-payments. According to our results, additional policies aimed at reducing IPV could ameliorate the financial sustainability of the system without detracting from the basic rights associated with healthcare.

5 Conclusions

In this paper, we have addressed the consequences of IPV experienced by Spanish adult women on victims' health and on excess healthcare use. We have stressed that IPV should not only be considered as a private issue because it entails also important public costs that affect the whole society. Given the sustainability problems of the healthcare systems in developed countries, it seems important to determine the extent of the health costs associated to IPV in order to foster policies aimed at reducing them.

Given the lack of a complete data set with individual information about IPV and health outcomes, we have exploited two independent data sources with corresponding representative samples for Spanish adult women in the same year: the VAWS and the NHS for 2011. While IPV information is only included in the VAWS sample and specific healthcare use variables are only included in the NHS sample, both samples include a comparable set of common conditioning variables and, most importantly, a self-reported measure of health status (with similar definitions). After checking whether both samples are compatible, in the sense that they are representative for the same population, we have combined the estimates obtained from each of them to obtain the effect of IPV on the use of certain healthcare services.

Once endogeneity issues are accounted for through the joint estimation by ML of bivariate models and the use of exclusion restrictions, our estimation results using the VAWS show that the probabilities of suffering from very bad or bad health are about 3 and 2 times, respectively, significantly higher for abused than for non abused women. Combining the previous effect with the marginal effect of health status on healthcare use estimated with the NHS sample, we find that IPV increases the corresponding probabilities of hospitalization, using emergency care and consuming sedatives and antidepressants by 3.7, 7 and 9.8 percentage points, respectively.

The results of this paper suggest that 0.44% of the hospitalization expenditure, 0.84% of the expenditure in emergency care services, and 1.18% of the cost of sedatives and antidepressants for adult women are due to the existence of IPV. Therefore, in addition to affecting women's health, violence also affects the health of society at large –by diverting scarce resources to the treatment of this largely preventable social ill–. The magnitude of the problem is even greater if we consider the well-documented harmful long-lasting consequences for children who grow up in violent homes in terms of their emotional, cognitive and behavioural development and in their odds of being involved in violent relationships as adults.

Considering the prevalence of abuse and the nature of its health effects, it is reasonable to conclude that victimization represents a significant drain on available health resources. Thus, policies aimed at preventing IPV can also contribute to reducing social healthcare costs. Bonomi et al. (2006) propose specific policies for primary and secondary prevention of IPV to be implemented in healthcare settings. Primary prevention programs could include routine interviews of female adult women and adolescents about partner violence, as well as targeted intervention strategies to foster healthy relationships. Secondary prevention would require systematic referral for women reporting IPV in healthcare settings.

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Appendix A: Air pollutants from the Spanish PRTR

Table A1
Air pollutants by group: thresholds for release into air and IARC type

Group	Pollutant	Threshold (kg/year)[a]	IARC type[b]
Chlorides			
	1,2-dicloroethane (EDC)	1,000	2B
	Dichloromethane (DCM)	1,000	2A
	Lindane	1	1
	PCDD + PCDF (dioxines + furans) (as Teq)	0.0001	1
	Polychlorinated biphenyls (PCBs)	0.1	1
	Tetrachloroethylene (PER)	2,000	2A
	Tetrachloromethane (TCM)	100	2B
	Trichloroethylene	2,000	1
	Trichloromethane	500	2B
	Vinyl chloride	1,000	1
Cyanides			
	Hydrogen cyanide (HCN)	200	
Heavy metals			
	Arsenic and compounds (as As)	20	1
	Cadmium and compounds (as Cd)	10	1
	Chromium and compounds (as Cr)	100	1
	Copper and compounds (as Cu)	100	3
	Lead and compounds (as Pb)	200	2A
	Nickel and compounds (as Ni)	50	1
Naphtalenes			
	Naphtalene	100	2B

[a]UN/ECE Protocol on Pollutant Release and Transfer Registers
[b]IARC Monographs on the Identification of Carcinogenic Hazards to Humans. 1: Carcinogenic; 2A: Probably carcinogenic; 2B: Possibly carcinogenic.

Appendix B: Compatibility between VAWS and NHS samples

Table B1
Distribution of the VAWS and NHS by province

Province	Sample		Province	Sample	
	VAWS	NHS		VAWS	NHS
Alava	0.8	0.8	La Rioja	0.7	3.4
Albacete	0.8	1.0	Lugo	0.8	0.6
Alicante	4.0	3.1	Madrid	13.3	10.4
Almeria	1.6	1.0	Malaga	3.2	2.3
Avila	0.4	0.4	Murcia	3.3	4.5
Badajoz	1.3	2.9	Navarra	1.2	3.8
Baleares	2.3	3.4	Ourense	0.9	0.6
Barcelona	10.9	7.3	Asturias	2.7	3.6
Burgos	0.6	0.9	Palencia	0.3	0.5
Caceres	1.0	1.4	Las Palmas	2.0	2.5
Cadiz	2.3	2.5	Pontevedra	2.2	1.7
Castellon	1.3	0.9	Salamanca	0.7	0.7
Ciudad Real	1.1	1.4	S.C. Tenerife	2.0	2.2
Cordoba	1.8	1.6	Cantabria	1.3	3.8
Coruña	2.5	2.8	Segovia	0.4	0.3
Cuenca	0.5	0.4	Sevilla	4.4	3.2
Girona	1.6	1.3	Soria	0.2	0.2
Granada	2.2	1.3	Tarragona	1.9	1.0
Guadalajara	0.6	0.5	Teruel	0.3	0.4
Gipuzkoa	1.4	1.7	Toledo	1.7	1.8
Huelva	1.1	0.6	Valencia	5.6	4.8
Huesca	0.5	0.9	Valladolid	1.1	1.2
Jaen	1.5	0.9	Bizkaia	2.7	2.9
Leon	1.1	1.2	Zamora	0.6	0.4
Lleida	0.9	0.5	Zaragoza	2.3	2.9
χ^2 test for equality of distributions ($p-$ value)				0.00000	

Source: Own calculations from the 2011 Spanish VAWS and NHS.
Percentage values.

Table B2
Equality of slopes between VAWS and NHS samples

Variable	Linear regression	Ordered probit
Woman educ.: Secondary	0.2387***	0.3256***
	(0.0513)	(0.0681)
Woman educ.: College	0.3693***	0.5421***
	(0.0578)	(0.0832)
Partner educ.: Secondary	-0.0059	-0.0074
	(0.0491)	(0.0657)
Partner educ.: College	0.0936	0.1477*
	(0.0578)	(0.0817)
Woman Unemployed	-0.1467***	-0.2085***
	(0.0372)	(0.0509)
Woman Inactive	-0.0860*	-0.1386**
	(0.0448)	(0.0642)
Woman worked past	-0.0579	-0.0771
	(0.0498)	(0.0696)
Woman age: 35-44	-0.0937***	-0.1546***
	(0.0320)	(0.0524)
Woman age: 45-54	-0.2551***	-0.4017***
	(0.0346)	(0.0536)
Woman age: 55-64	-0.4111***	-0.6145***
	(0.0410)	(0.0601)
D × Woman educ.: Secondary	-0.0581	-0.0692
	(0.0627)	(0.0840)
D × Woman educ.: College	-0.0972	-0.1251
	(0.0713)	(0.1017)
D × Partner educ.: Secondary	0.1154**	0.1688**
	(0.0573)	(0.0777)
D × Partner educ.: College	0.1009	0.1523
	(0.0686)	(0.0972)
D × Woman Unemployed	0.1065	0.1544
	(0.0706)	(0.0975)
D × Woman Inactive	0.0273	0.0668
	(0.0634)	(0.0912)
D × Woman worked past	-0.1029	-0.1422
	(0.0726)	(0.1002)
D × Woman age: 35-44	-0.0388	-0.0475
	(0.0432)	(0.0687)
D × Woman age: 45-54	-0.0333	-0.0218
	(0.0477)	(0.0713)
D × Woman age: 55-64	0.0338	0.0716
	(0.0591)	(0.0836)
Obs	8342	8342

Standard errors in parentheses

Source: Own calculations from the 2011 Spanish VAWS and NHS.

D = binary indicator for VAWS.

Province dummies and their interactions with D included in all estimations.

* p<.1, ** p<.05, *** p<.01

Table B2 (cont.)
Equality of slopes between VAWS and NHS samples

	Linear regression	Ordered probit
Wald test for joint significance ($p-$ value)		
All	0.0000	0.0000
Woman education	0.0000	0.0000
Partner education	0.0111	0.0156
Woman labor market variables	0.0000	0.0000
Woman age:	0.0000	0.0000
Province dummies	0.0000	0.0000
$D \times$ Woman educ.	0.3700	0.4632
$D \times$ Partner educ.	0.1276	0.0935
$D \times$ Woman labor market variables	0.3033	0.3409
$D \times$ Woman age	0.5017	0.4743
$D \times$ Province dummies	0.0000	0.0000
$D \times$ All	0.0000	0.0000
$D \times$ All (except Province dummies)	0.4495	0.4295

Table 1
Sample distribution of self-reported health status (%)

Sample	Health status: Very bad	Bad	Mediocre	Good	Very good	N
VAWS	1.6	4.4	22.0	57.0	15.0	$4,346$
NHS	1.0	4.4	19.6	55.8	19.2	$3,996$
Eq. test (p-value)		0.0000§				

Source: Own calculations from 2011 Spanish VAWS and NHS.
Eq. test is a χ^2_4 test for equality of unconditional distributions among samples.
*,†,§ denote significance at 10, 5 and 1 percent, respectively.

Table 2
Sample means of main variables by health status for the VAWS sample

Variable	All	Health status: Very bad	Bad	Mediocre	Good	Very good	Eq. test (p-value)
Woman's age							
25-34	0.27	0.10	0.13	0.17	0.28	0.41	0.0000§
35-44	0.31	0.20	0.25	0.25	0.33	0.34	0.0000§
45-54	0.26	0.42	0.33	0.29	0.26	0.17	0.0000§
55-64	0.16	0.28	0.29	0.28	0.13	0.08	0.0000§
Woman's education							
Primary	0.20	0.32	0.37	0.33	0.16	0.07	0.0000§
Secondary	0.46	0.46	0.39	0.45	0.48	0.40	0.0019§
College	0.34	0.21	0.23	0.21	0.36	0.53	0.0000§
Partner's education							
Primary	0.36	0.45	0.47	0.48	0.33	0.22	0.0000§
Secondary	0.38	0.32	0.27	0.32	0.41	0.40	0.0000§
College	0.23	0.17	0.18	0.15	0.23	0.36	0.0000§
Woman's labor market status							
Employed	0.56	0.32	0.29	0.46	0.60	0.67	0.0000§
Unemployed	0.21	0.34	0.28	0.22	0.21	0.18	0.0022§
Inactive	0.23	0.34	0.42	0.31	0.19	0.15	0.0000§
Partner employed	0.76	0.66	0.56	0.66	0.79	0.85	0.0000§
Large municipality	0.49	0.46	0.46	0.49	0.48	0.54	0.0504*
Children under 18	0.49	0.39	0.36	0.41	0.52	0.56	0.0000§
IPV	0.12	0.23	0.22	0.17	0.10	0.07	0.0000§

Source: Own calculations from 2011 Spanish VAWS.
Eq. test: χ^2test for mean equality across health states.
*,†, § denote significance at 10, 5 and 1 percent, respectively.

Table 3
Sample means of main variables by health status for the NHS sample

Variable	All	Health status: Very bad	Bad	Mediocre	Good	Very good	Eq. test (p-value)
Woman's age							
25-34	0.19	0.05	0.05	0.13	0.20	0.26	0.0000§
35-44	0.31	0.17	0.20	0.23	0.33	0.38	0.0000§
45-54	0.28	0.38	0.29	0.31	0.28	0.24	0.0153†
55-64	0.22	0.40	0.46	0.33	0.19	0.12	0.0000§
Woman's education							
Primary	0.13	0.28	0.29	0.21	0.12	0.05	0.0000§
Secondary	0.66	0.65	0.62	0.68	0.66	0.66	0.5766
College	0.21	0.07	0.09	0.10	0.22	0.29	0.0000§
Partner's education							
Primary	0.14	0.28	0.23	0.20	0.13	0.07	0.0000§
Secondary	0.69	0.60	0.69	0.69	0.68	0.70	0.6305
College	0.17	0.13	0.08	0.11	0.18	0.22	0.0000§
Woman's labor market status							
Employed	0.57	0.38	0.35	0.45	0.60	0.65	0.0000§
Unemployed	0.16	0.30	0.21	0.18	0.15	0.15	0.0179§
Inactive	0.27	0.33	0.45	0.38	0.25	0.20	0.0000§
Partner employed	0.70	0.50	0.51	0.60	0.74	0.75	0.0000§
Large municipality	0.38	0.17	0.37	0.34	0.40	0.36	0.0032§
Children under 18	0.51	0.35	0.31	0.41	0.54	0.58	0.0000§
Healthcare use							
Hospitalization	0.06	0.40	0.31	0.10	0.04	0.02	0.0000§
Emergency care	0.28	0.63	0.55	0.39	0.24	0.20	0.0000§
Sedatives/Antidepressants	0.12	0.63	0.42	0.27	0.07	0.03	0.0000§
Bad tap water at home	0.30	0.53	0.35	0.33	0.30	0.28	0.0043§

Source: Own calculations from 2011 Spanish NHS.
Eq. test: χ^2test for mean equality across health states.
*,†, § denote significance at 10, 5 and 1 percent, respectively.

Table 4
Categories of serious abuse in the Spanish VAWS

Behavior	Physical Abuse	Non-Physical Abuse
Stopped from seeing relatives, friends and neighbors		×
Prevented from fair share of household money		×
Insulted or threatened you	×	
Prevented from deciding by yourself		×
Forced to have sexual intercourse	×	
Deprived of your necessities		×
Scared you sometimes		×
Pushed you or hit you	×	
Scorned about your capacity		×
Criticized for the things you do		×
Despised for your beliefs		×
Disregarded for your work		×
Disrespected in front of your children		×

Source: 2011 Spanish VAWS.

Table 5
Self-declared health status by IPV status (%)

	Health status					
IPV status	Very bad	Bad	Mediocre	Good	Very good	Eq. test (p-value)
No	1.4	3.9	20.6	58.2	16.0	
Yes	2.8	7.6	32.1	48.7	8.8	$0.0000^{\S}$

Source: Own calculations from 2011 Spanish VAWS.
Eq. test: χ^2test for equality of distributions.
*,†, § denote significance at 10, 5 and 1 percent, respectively.

Table 6
Sample means of main variables by healthcare use

	All	Hospitalization			Emergency care			Sedatives/Antidep.		
		no	Yes	eq.test	no	Yes	eq.test	no	Yes	eq.test
Woman's age										
25-34	0.19	0.19	0.13	0.0105†	0.15	0.28	0.0000§	0.21	0.05	0.0000§
35-44	0.31	0.31	0.29	0.5095	0.31	0.31	0.8786	0.32	0.22	0.0000§
45-54	0.28	0.28	0.27	0.7242	0.30	0.23	0.0000§	0.28	0.31	0.1993
55-64	0.22	0.22	0.31	0.0004	0.24	0.18	0.0001§	0.19	0.41	0.0000§
Woman's education										
Primary	0.13	0.13	0.18	0.0221†	0.14	0.12	0.1530	0.12	0.23	0.0000§
Secondary	0.66	0.66	0.66	0.7824	0.66	0.67	0.4228	0.66	0.67	0.7326
College	0.21	0.21	0.17	0.1130	0.20	0.21	0.7990	0.22	0.10	0.0000§
Partner's education										
Primary	0.14	0.13	0.19	0.0079§	0.14	0.13	0.7017	0.13	0.21	0.0000§
Secondary	0.69	0.69	0.65	0.1491	0.68	0.71	0.1308	0.69	0.67	0.3470
College	0.17	0.17	0.16	0.5817	0.18	0.16	0.1515	0.18	0.12	0.0014§
Large municipality	0.38	0.37	0.39	0.4315	0.37	0.38	0.5515	0.38	0.38	0.8480

Source: Own calculations from 2011 Spanish NHS.

Eq. test reports the p-value of the χ^2 test for equality of means by each healthcare use status.

*,†, § denote significance at 10, 5 and 1 percent, respectively.

Table 7
IPV by awareness of abuse in woman's environment

	IPV awareness: non relatives	
	No	Yes
IPV risk	11.1	14.1
Eq. test (p-value)	0.0240†	

Source: Own calculations from 2011 Spanish VAWS.

Percentage of sample women suffering from IPV reported in each cell.

Eq. test is a χ^2_1 test for equality of means between columns.

*,†,§ denote significance at 10, 5 and 1 percent, respectively.

Table 8
ML estimates of woman health status and IPV

	Single eq. (I)	Two-equation (II)	
	Health	Health	IPV
IPV	$-0.3327^{\S}$	$-0.5369^{\dagger}$	
	(0.0532)	(0.2203)	
Woman: Secondary	$0.2232^{\S}$	$0.2180^{\S}$	-0.0777
	(0.0512)	(0.0515)	(0.0755)
Woman: College	$0.3776^{\S}$	$0.3650^{\S}$	$-0.3038^{\S}$
	(0.0608)	(0.0624)	(0.0947)
Partner: Secondary	$0.1324^{\S}$	$0.1224^{\S}$	$-0.2542^{\S}$
	(0.0423)	(0.0436)	(0.0654)
Partner: College	$0.2704^{\S}$	$0.2595^{\S}$	$-0.2604^{\S}$
	(0.0535)	(0.0548)	(0.0863)
Woman: Unemployed	-0.0283	-0.0202	0.2437^{*}
	(0.0838)	(0.0842)	(0.1280)
Woman: Inactive	-0.0519	-0.0471	0.1549
	(0.0654)	(0.0656)	(0.1008)
Woman: Worked in the past	$-0.2371^{\S}$	$-0.2398^{\S}$	-0.1038
	(0.0726)	(0.0726)	(0.1107)
Partner employed	$0.1633^{\S}$	$0.1569^{\S}$	$-0.1516^{\dagger}$
	(0.0435)	(0.0441)	(0.0651)
Has children under 18	$0.0861^{\dagger}$	$0.0949^{\dagger}$	$0.2562^{\S}$
	(0.0394)	(0.0404)	(0.0647)
Metro area	0.0381	0.0389	0.0126
	(0.0388)	(0.0387)	(0.0606)
Woman age 35-44	$-0.2396^{\S}$	$-0.2374^{\S}$	0.0774
	(0.0465)	(0.0465)	(0.0732)
Woman age 45-54	$-0.4436^{\S}$	$-0.4447^{\S}$	-0.0089
	(0.0490)	(0.0490)	(0.0796)
Woman age: 55-64	$-0.4732^{\S}$	$-0.4654^{\S}$	$0.2390^{\dagger}$
	(0.0644)	(0.0650)	(0.1006)
IPV awareness: non relatives			$0.1821^{\S}$
			(0.0696)
No. observations	4346	4346	
log-likelihood	-4631.5	-6023.2	
Wald tests of joint significance ($p-$ value)			
All	$0.0000^{\S}$	$0.0000^{\S}$	$0.0000^{\S}$
Woman education	$0.0000^{\S}$	$0.0000^{\S}$	$0.0020^{\S}$
Partner education	$0.0000^{\S}$	$0.0000^{\S}$	$0.0002^{\S}$
Wm lab. mkt. status	$0.0000^{\S}$	$0.0000^{\S}$	0.1227
Woman age	$0.0000^{\S}$	$0.0000^{\S}$	$0.0309\dagger$
Province dummies	$0.0009^{\S}$	$0.0006^{\S}$	$0.0000^{\S}$
IPV instruments			$0.0088^{\S}$

Source: Own calculations from the 2011 Spanish VAWS.
Standard errors in parentheses. Province dummies included.
*,†,§ denote significance at 10, 5 and 1 percent, respectively.

Table 9
Average Marginal Effects of IPV on health status

Health status	Single eq.	Two-equation
	(I)	(II)
Very bad	$0.0158^{\S}$	0.0299^{*}
	(0.0034)	(0.0178)
Bad	$0.0264^{\S}$	$0.0459^{\dagger}$
	(0.0050)	(0.0227)
Mediocre	$0.0661^{\S}$	$0.1040^{\S}$
	(0.0105)	(0.0388)
Good	$-0.0456^{\S}$	-0.0864^{*}
	(0.0098)	(0.0486)
Very good	$-0.0627^{\S}$	$-0.0934^{\S}$
	(0.0088)	(0.0304)

Source: Own calculations from 2011 Spanish VAWS.

Average of individual marginal effects. Standard errors in parentheses.

*,†, § denote significance at 10, 5 and 1 percent, respectively.

Table 10
Reduced-form ordered probit for woman's health status

Variable		Variable	
Woman: Secondary	0.3258§	Woman age: 35-44	−0.1580§
	(0.0681)		(0.0536)
Woman: College	0.5222§	Woman age: 45-54	−0.3800§
	(0.0831)		(0.0540)
Partner: Secondary	0.0236	Woman age: 55-64	−0.5686§
	(0.0653)		(0.0644)
Partner: College	0.1708†	Bad drinking water at home	−0.1778§
	(0.0813)		(0.0419)
Woman: Unemployed	−0.2058§	Emissions heavy metals	−0.3908†
	(0.0508)		(0.1910)
Woman: Inactive	−0.1230*	Emissions chlorides ($\times 10^{-4}$)	0.2900†
	(0.0635)		(0.1200)
Woman: Past emp.	−0.0851	Emissions cyanides	0.2732†
	(0.0691)		(0.1285)
Metro area	0.0258	Emissions naphtalenes	−4.2096†
	(0.0385)		(1.9009)
Children under 18	0.0518		
	(0.0425)		
log-likelihood	−4291.8		
Wald tests of joint significance ($p-$ value)			
All	0.0000§		
Woman education	0.0000§		
Partner education	0.0197†		
Wm lab mkt status	0.0000§		
Woman age	0.0000§		
Regional dummies	0.0000§		
Emissions	0.0011§		

Source: Own calculations from the 2011 Spanish NHS.
Standard errors in parentheses. Regional dummies included
*,†,§ denote significance at 10, 5 and 1 percent, respectively.

Table 11
Descriptive statistics of predicted health index $\widehat{HS}^*$

Mean	−0.2046	
Std. dev.	0.4029	
Median	−0.1795	
Interquartile range	0.5533	
Maximum	1.1239	
Minimum	−1.3847	
By health status	Mean	Std.dev.
Very bad	−0.5541	0.3689
Bad	−0.4890	0.4105
Mediocre	−0.3795	0.3879
Good	−0.1876	0.3772
Very good	0.0044	0.3651

Source: Own calculations from the 2011 Spanish NHS.

Table 12
Probit estimates for healthcare use

Variable	(1) Hospitalization	(2) Emergency care	(3) Sedatives and/or antidepressants
Woman: Secondary	0.1878	0.1981*	0.1756
	(0.1469)	(0.1053)	(0.1416)
Woman: College	0.2437	0.2776*	0.1105
	(0.2043)	(0.1450)	(0.1859)
Partner: Secondary	−0.1097	−0.0727	−0.0203
	(0.1604)	(0.0825)	(0.1401)
Partner: College	0.0137	−0.0759	0.0807
	(0.1448)	(0.1089)	(0.1777)
Metro area	0.0133	0.0670	0.0755
	(0.0399)	(0.0514)	(0.0790)
Woman age: 35-44	0.0794	−0.3901§	0.3835§
	(0.1494)	(0.0700)	(0.1080)
Woman age: 45-54	−0.0842	−0.6635§	0.3338§
	(0.2156)	(0.0980)	(0.1254)
Woman age: 55-64	−0.0032	−0.7773§	0.4369†
	(0.2563)	(0.1351)	(0.1842)
$\widehat{HS}^*$	−0.5618†	−0.4047†	−0.9962§
	(0.2380)	(0.1775)	(0.1683)
N	3,800	3,969	3,969
log-likelihood	−875.3	−2258.3	−1333.1
Wald tests of joint significance ($p-$ value)			
All	0.0000§	0.0000§	0.0000§
Woman education	0.4304	0.1437	0.1733
Partner education	0.6616	0.6769	0.6717
Woman age	0.1990	0.0000§	0.0053§
Province dummies	0.1690	0.0102†	0.0000§

Source: Own calculations from the 2011 Spanish NHS.

Bootstrap standard errors (500 replications) in parentheses. Province dummies included.

*,†,§ denote significance at 10, 5 and 1 percent, respectively.

Table 13
Probit estimates for healthcare use: Average Marginal Effects

Variable	(1) Hospitalization	(2) Emergency care	(3) Sedatives and/or Antidepressants
$\widehat{HS}^{*}$	$-0.0684^{\dagger}$	$-0.1304^{\dagger}$	$-0.1835^{\S}$
	(0.0297)	(0.0571)	(0.0330)

Source: Own calculations from the 2011 Spanish NHS.
Standard errors in parentheses.
*,†,§ denote significance at 10, 5 and 1 percent, respectively.

Table 14
Average Marginal Effects of IPV on use of healthcare services

Variable	(1) Hospitalization	(2) Emergency care	(3) Sedatives/ Antidepressants
IPV	0.0367	0.0700	0.0985

Source: Own calculations from the 2011 Spanish VAWS and NHS.