Original Article

Count Regression Model to Predict Spousal Harms in Tamil Nadu

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Abstract

Introduction: Violence against women is becoming more prevalent over the world, particularly in India. Assessing the causes of violence in community will aid in planning supports for victims. This study aimed to compare the performance of various regression models for count data and focused on choosing appropriate count regression model to identify factors related with the number of domestic violence experienced by young married women. **Methods:** Data for this study were retrieved from "The Youth in India: Situation and Needs Study." The current study took the data of 1495 married women in Tamil Nadu. Factors associated with physical violence considered for the study were place of residence, age of husband and wife, education of husband and wife, dowry, miscarriage, abortion, and marriage type. Ordinary least square, Poisson regression, and negative binomial regression models were fitted for the data, and the best fitted model was identified using Akaike information criterion (AIC) and Bayesian information criterion (BIC). **Results:** Proportion of married women who have perpetrated any forms of physical violence was 30.8%. Among the fitted models, negative binomial regression model (AIC = 3020.621, BIC = 3079.030) was found to be the best model to predict violence. Significant factors identified were type of residence, marriage type, education of wife and spouse, miscarriage, and abortion. **Conclusion:** To tackle this public health issue, multisectoral approaches such as boosting literacy, raising awareness about legal assistance, and monitoring victims of violence at primary health facilities should be implemented. Comprehensive model testing is highly suggested for determining the best acceptable analytic model when dependent variable being studied comprises count data.

Keywords: *Count regression model, domestic violence, negative binomial regression, ordinary least square regression, over-dispersion, Poisson regression*

Introduction

Violence against women is a worldwide concern that impacts all aspects of women's health, and the World Health Organization (WHO) has declared domestic violence (DV) as a "public health issue." This global scourge kills, tortures, and maims women on a physical, sexual, psychological, and financial level. It is one of the most widespread breaches of human rights present in every country, regardless of culture, education, money, race, class, or age, depriving women's equality, dignity, security, and self-worth.[1] Based on the WHO estimates from 2000 to 2018 conducted in 161 Countries, one out of every three women around the world has experienced physical and/or sexual intimate partner relationship harm or nonpartner sexual violence or both in their life.[2]

Domestic abuse happens to women of all socioeconomic and cultural backgrounds, and many nations, like India, have socialized women to accept, rationalize, and even endure DV.[3] National Family Health Survey (NFHS)-III, which was conducted in 29 states of India (2005–2006), reported that 37.2% of women experienced abuse after marriage across the country, with 87% of spousal harms. Prevalence of any type of violence (sexual or physical) is higher in Bihar (56%, East India), Madhya Pradesh (47%, Central India), Rajasthan (45%, North India), Tamil Nadu (39%, South India), and Maharashtra (29%, West India).[4]

Nonfatal intimate partner violence was most common among women aged 16–24 years, who were much more likely to be in an active dating relation. The high prevalence of DV and its catastrophic effects on individuals and society development is mirrored in the increased demand for prevention among youth.[5]

DV is now widely regarded as a crucial violation of human rights and an essential public health issue with serious implications

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for women's physical, intellectual, psychological, and reproductive health.[6] It has a negative impact on a country's economy, resulting in increased disability, lost labor hours, and medical costs. Many studies, including NFHS-III, have reported the prevalence of DV in India and various states. As DV differs depending on local social norms and women's literacy levels, it is vital to examine the problem of DV in a given geographic area for implementing supporting measures. Hence, this study mainly focused on identifying the factors responsible for the number of harms perpetrated by the spouse on their wife in Tamil Nadu, South India.

DV has been modeled as a binary or continuous variable in most of the studies.[7-9] The number of harms or violence can be considered neither as a continuous nor as a binary variable and is, in fact, a count variable. Physical violence perpetrated by the spouse included slapped, kicked or dragged or beaten, punched, choked or burnt wife on purpose, twisted the wife's arm or pulled wife's hair, pushed or shaken or had something thrown on her, and threatened or attacked wife with knife or gun. This study models the number of harms as a count variable to explain the appropriateness of count regression models over ordinary least square (OLS) regression in predicting the number of harms perpetrated by the spouse on their wife and identifies the factors responsible for spousal domestic harms on their wife which the other modeling technics could not explain.

Methods

The secondary data for the study are taken from "The Youth in India: Situation and Needs study" also known as "Youth Study" by Indian Institute of Population Science which was conducted in six states – Maharashtra, Andhra Pradesh, Bihar, Rajasthan, Jharkhand, and Tamil Nadu, covering 174,037 households and interviewing 50,848 married and unmarried young men (aged 15–29 years) and women (aged 15–24 years) from all the districts of each selected state. It held data on almost every important aspect of a young life: education, job, family life, sexual activity, marriage, health, and DV within marriage by the state. Since DV differs depending on local social norms, inclusion criteria were set as married women in Tamil Nadu, South India, where divorcees and widows were excluded from the study. Thus, the study has only taken the data of 1495 married young women in Tamil Nadu.

The majority of victims are exposed to multiple forms of assault. Therefore, the dependent variable of interest taken was the number of physical harms experienced from the spouse such as slapped, kicked or dragged or beaten, punched, choked or burnt wife on purpose, twisted the wife's arm or pulled wife's hair, pushed or shaken or had something thrown on her, and threatened or attacked wife with knife or gun. These forms of physical harm were taken based on the NFHS-III measures of violence by the husband. Age of wife, age of spouse, education of wife, education of spouse, type of residents (rural/urban), family type (nuclear/joint), type of marriage (love/arrange), caste, religion, age at marriage, alcohol use, dowry, miscarriage, and abortion were the risk factors associated with physical violence considered for the study. Robust regression models were fitted to study the factors responsible for the number of harms by the spouse on their wife. OLS regression was fitted first, considering the number of harms as a continuous variable. In the second step, count regression models, i.e., Poisson regression and negative binomial (NB) regression, were fitted, considering the number of harms as a count variable. The analysis was carried out using the R programming language version 3.5.2 (R Core Team (2018). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL: https://www.R-project.org/.).

Ordinary least square regression model

The OLS regression also known as linear regression in which the parameters are estimated using least square method of estimation with *P* explanatory variables is written as:

$$y_i = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + \varepsilon_i, i = 1,2,3...n; j = 1,2,3...k \quad (1)$$

where β_0 is the model intercept, y is the response/dependent variable, x is the predictor/independent variable, ε is the random error, β_j, j = 1, 2…k is called the coefficients of regression.

Normality and homoscedasticity assumptions of errors in OLS regression were checked using Breush-Pagan-Godfrey test for homoscedasticity and Shapiro–Wilk test for normality. Test of homoscedasticity in the regression model was established by Trevor Breusch and Adrian Pagan (1979).[10] It tests whether all residual variances are equal, considering hypothesis as:

H_0: There is no heteroscedasticity versus

H_1: There is heteroscedasticity

Martin Wilk and Samuel Sanford Shapiro developed the Shapiro–Wilk test to check the normality assumption (1965). For OLS regression, the hypothesis to be tested is:

H_0: Residuals follow normal distribution versus

H_1: Residuals do not follow normal distribution

Null hypothesis is rejected if the *P* value is lesser than the chosen significance level.[11]

Poisson regression model

The Poisson regression model with *P* independent variables is expressed as:

$$\ln \mu = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p \quad (2)$$

where μ is the mean value of the outcome variable (counts), β_0, β_1, β_2…are the coefficients of Poisson regression model, and x_1, x_2,…are the independent/predictor variables.[12]

As Poisson regression is based on the Poisson distribution, the major assumption for Poisson regression to be checked is that conditional mean and conditional variance of the outcome are equal. Data are said to be over-dispersed if the conditional variance exceeds the conditional mean.[13] Over-dispersion is tested using a regression-based tests (auxiliary regression test in R software) introduced by Cameron and Trivedi in 1990. It can also test for under dispersion in the data.[14] One way to deal with over-dispersion is to use the negative binomial (NB) regression model.[15]

Negative binomial regression model

The NB distribution is quite similar to the Poisson distribution, except the point that the conditional variance of the NB distribution exceeds its conditional mean.[16] The NB regression model is:

$$\ln \mu = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p \quad (3)$$

where β_0, β_1, β_2, β_3…are the coefficients of regression and x_1, x_2, x_3… are the predictor variables.

Akaike information criterion (AIC) and Bayesian information criterion (BIC) are estimated for comparing Poisson and NB regression models and choosing the best-fitted model. Lower BIC value indicates the better model. Lower values of AIC or BIC indicate the better fit of the model.[17]

Ethical consideration

Since this study is a secondary data analysis, acquiring ethical code was not applicable.

Results

Out of the 1495 married women with a mean age of 21.9 ± 1.82 years, 603 (40.3%) were from the rural area and 892 (59.7%) from the urban area. The risk factors for the multivariable regression model were selected by performing the unadjusted Poisson regression for each factor separately at 20% level of significance. The variables found to be significant at 20% level were the place of residence (urban/rural), age of wife, education of wife, age of spouse, type of marriage (love/arrange), dowry, miscarriage, abortion, and education of spouse. Table 1 represents the descriptive statistics of the selected variables.

The number of harms perpetrated by the spouses was count variable ranging from 0 to 7 which include as slapped, kicked or dragged or beaten, punched, choked or burnt wife on purpose, twisted the wife's arm or pulled wife's hair, pushed or shaken or had something thrown on her, and threatened or attacked wife with knife or gun. Out of the total respondents, 461 (30.8%) women have experienced the physical violence and 261 (16.8%) have experienced minimum one type of harms. Table 2 explains the frequency distribution of the number of harms experienced by the wife from their spouse.

OLS regression model was fitted in the data and is exhibited in Table 3. The result from OLS regression model showed that type of residence, type of marriage, dowry, education of wife, education of spouse, and abortion were the factors responsible for the number of harms by the spouse on their wife. The fitness of the OLS regression model was evaluated by checking the normality and homoscedasticity assumptions of error. The normality assumption of OLS regression was assessed using Shapiro–Wilk test. The $P < 0.001$ (test statistic = 0.7273), indicated the violation of normality assumption of errors in OLS regression. Breusch-Pagan-Godfrey test was used to test the homoscedasticity assumption. Breusch-Pagan-Godfrey test with $P < 0.001$ (test statistic = 195.955) showed that the error variances were not equal, i.e., the assumption of homoscedasticity of the residuals was violated.

Considering the discrete count nature of the outcome variable, Poisson and NB regression models were

Table 1: Descriptive statistics of the predictor variables for the number of harms perpetrated by the spouse on their wife

Predictors	*n* (%)
Place of residence	
Rural	603 (40.33)
Urban	892 (59.66)
Type of marriage	
Love	1203 (80.47)
Arranged	292 (19.53)
Dowry	
Yes	1305 (87.29)
No	190 (12.71)
Miscarriage	
Yes	295 (19.73)
No	1200 (80.26)
Abortion	
Yes	81 (5.42)
No	1414 (94.58)
Age of wife (years)*	21.94 (1.82)
Education of wife (years)*	7.45 (3.80)
Age of spouse (years)*	28.68 (4.22)
Education of spouse (years)*	8.06 (5.26)

*Mean (SD). SD: Standard deviation

Table 2: Frequency table for the count of harms perpetrated by the spouse on their wife

Counts	Frequency (%)
0	1034 (69.16)
1	251 (16.79)
2	102 (6.82)
3	48 (3.21)
4	19 (1.27)
5	28 (1.87)
6	6 (0.40)
7	7 (0.47)

applied. Table 4 presents the factors associated with the number of harms in Poisson regression model. Type of residence, type of marriage, dowry, education of wife, education of spouse, miscarriage, and abortion were associated with the number of harms by the spouse on their wife. Type of residence (incident rate ratio [IRR] = 1.39, 95% confidence interval [CI]: 1.20–1.60), type of marriage (IRR = 1.41, 95% CI: 1.19–1.67), and dowry (IRR = 1.11, 95% CI: 1.11–1.62) have a positive influence on the number of harms perpetrated by the spouse on their wife. Education of wife (IRR = 0.96, 95% CI: 0.95–0.99), education of spouse (IRR = 0.94, 95% CI: 0.92–0.96), miscarriage (IRR = 0.80, 95% CI: 0.68–0.93), and abortion (IRR = 0.61, 95% CI: 0.48–0.78) have a negative influence on the response variable. Auxiliary regression test was used to check the over-dispersion in the Poisson model. The $P < 0.001$ (test statistic = 8.069) indicated that the data were over dispersed. To account for the over-dispersion, NB regression model was fitted. Table 4 also explains the result from NB regression model fitted to the data. Type of residence, education of wife, education of spouse, type of marriage, miscarriage, and abortion were the factors that influence the number of harms perpetrated by the spouse on their wife. Type of residence (IRR = 1.44, 95% CI: 1.17–1.78) and type of marriage (IRR = 1.46, 95% CI: 1.12–1.92) have a positive significant influence on the number of harms perpetrated by the spouse on their wife. While education of wife (IRR = 0.96, 95% CI: 0.94–0.99), education of spouse (IRR = 0.93, 95% CI: 0.91–0.96), miscarriage (IRR = 0.75, 95% CI: 0.59–0.96), and abortion (IRR = 0.56, 95% CI: 0.37–0.84) have a negative influence on the number of harms perpetrated by the spouse of their wife.

Table 3: Ordinary least square regression model fitted to assess the effect of variables on the number of harms perpetrated by the spouse on their wife

Predictors	Coefficient	SE	*t* statistics	*P*
Type of residence				
Rural	0.167*	0.062	2.693	0.007
Urban	Reference	-	-	-
Age of wife (years)	0.017	0.018	0.973	0.331
Education of wife (years)	−0.028*	0.009	−3.241	0.001
Age of spouse (years)	0.005	0.008	0.666	0.506
Education of spouse (years)	−0.022*	0.006	−3.526	0.004
Type of marriage				
Love	0.213*	0.085	2.492	0.013
Arranged	Reference	-	-	-
Dowry (no)	0.265*	0.100	2.636	0.008
Miscarriage (no)	−0.135	0.076	−1.780	0.075
Abortion (no)	−0.323*	0.134	−2.413	0.016

*Significant at 0.05 level. SE: Standard error

The fit indices AIC and BIC were calculated and compared for Poisson and NB regression models, to fix the most suitable model for the data. Compared to Poisson regression model (AIC = 3432.747, BIC = 3485.846), NB regression model (AIC = 3020.621, BIC = 3079.03) has the smallest AIC and BIC values. The smaller values of AIC and BIC indicate the better fit of NB regression over Poisson regression.

Table 5 shows the IRR and 95% CI for the fitted NB and Poisson regression models. The best fitted NB regression model showed that married women in rural residence were expected to experience 1.44 (95% CI: 1.17–1.78) times more harm than that of urban. Likewise, the number of harms experienced was 1.46 (95% CI: 1.12–1.92) times more in a love marriage compared to an arranged marriage. IRR for miscarriage is 0.75 (95% CI: 0.59–0.96) and abortion is 0.56 (95% CI: 0.37–0.84). The women who never had miscarriages (RR: 0.75, 95% CI: 0.59-0.96) and those who never had abortions (RR: 0.56, 95% CI: 0.37-

Table 4: Poisson regression and negative binomial regression models fitted to assess the effect of variables on the number of harms perpetrated by the spouse on their wife

Predictors	Poisson regression model			NB regression model		
	Coefficient	SE	*Z* statistics	Coefficient	SE	*Z* statistics
Type of residence						
Rural	0.327*	0.072	4.519	0.364*	0.107	3.386
Urban	Reference	-	-	-	-	-
Age of wife (years)	0.025	0.019	1.300	0.033	0.030	1.095
Education of wife (years)	−0.034*	0.009	−3.478	−0.036*	0.015	−2.365
Age of spouse (years)	0.009	0.007	1.161	0.007	0.012	0.547
Education of spouse (years)	−0.061*	0.009	−6.601	−0.069*	0.014	−4.837
Type of marriage						
Love	0.347*	0.086	4.032	0.381*	0.137	2.782
Arranged	Reference	-	-	-	-	-
Dowry (no)	0.296*	0.095	3.124	0.285	0.157	1.815
Miscarriage (no)	−0.226*	0.079	−2.846	−0.285*	0.124	−2.296
Abortion (no)	−0.502*	0.124	−4.063	−0.580*	0.205	−2.827

*significant at 0.05 level. NB: Negative binomial, SE: Standard error

Table 5: Incident rate ratio and 95% confidence interval of Poisson and negative binomial regression models

Predictors	Poisson regression model		NB regression model	
	IRR	95% CI	IRR	95% CI
Type of residence				
Rural	1.39	1.20-1.60	1.44	1.17-1.78
Urban	Reference	-	-	-
Age of wife (years)	1.03	0.99-1.07	1.03	0.97-1.10
Education of wife (years)	0.96	0.95-0.99	0.96	0.94-0.99
Age of spouse (years)	1.01	0.99-1.02	1.01	0.98-1.03
Education of spouse (years)	0.94	0.92-0.96	0.93	0.91-0.96
Type of marriage				
Love	1.41	1.19-1.67	1.46	1.12-1.92
Arranged	Reference	-	-	-
Dowry (no)	1.11	1.11-1.62	1.33	0.98-1.81
Miscarriage (no)	0.80	0.68-0.93	0.75	0.59-0.96
Abortion (no)	0.61	0.48-0.78	0.56	0.37-0.84

NB: Negative binomial, IRR: Incident rate ratio, CI: Confidence interval

0.84) had lower risk to experience the events compared to those who had. IRR for the education of wife indicated that the number of harms got decreased by 4% for every one-unit increase in the education of wife. Similarly, the number of harms gets decreased by 7% for every one-unit increase in the education of spouse.

Discussion

In the present study, the proportion of married women who experienced any form of physical violence was 30.8%. The other researches in India have also given the estimates between 26% and 40%, that is in accordance with the various locations, interviewing methods, inclusion criteria, and sociodemographic aspects that exist in the local populations.[18-21]

Regression models that are used to predict the factors responsible for the outcome variable of interest vary according to the data which we are handling. In many contexts, the dependent variables we come across are count variables and it has certain properties such as they are integers/ whole numbers with lowest possible value as zero (i.e., no negative values) and often positively skewed.[14] The number of physical harms is a count variable that can be thought of as neither a continuous nor a binary variable. OLS regression cannot be used in this condition assuming the number of violence as continuous as in the study by Tauchen *et al*.[8] As count data often infringes normality and constant variance assumptions of OLS regression, it leads to erroneous standard error estimates, P values, and CIs.[22] Many studies have converted the number of types of violence (count) experienced by women to binary (experienced violence – yes/no) categories.[23] The use of logistic regression after converting the variable into binary will result in a loss of information.[24] In comparison to logistic regression models, count regression models provide better interpretations for regression coefficients. Therefore, this study used count regression models by considering the discrete count nature of outcome variable and explained the consequences of using OLS regression in count data.

Compared to OLS regression model, Poisson regression model and NB model showed that miscarriage was an important significant factor with a negative influence on the count variable. Significant associations that OLS missed are identified by the count data models.[25] The magnitude of regression coefficients was also larger in Poisson and NB regression compared to OLS regression. Modeling a count variable using OLS regression, assuming it as a continuous variable, can lead to inaccuracies in standard error estimates, CIs, and *P* values.[26] The results of OLS regression model are not reliable as it violated the normality and homogeneity assumptions. This shows the appropriateness of count regression models over OLS regression. Thus, to account for the effect of independent variables on the number of harms, count regression models are used. The study has assessed the appropriateness of OLS and count regression models to predict the number of harms perpetrated by the spouse on their wife.

From the Poisson regression model, it has been observed that type of residence, type of marriage, dowry, education of wife, education of spouse, miscarriage, and abortion were associated with the number of harms. To account for the over-dispersion in the Poisson regression model, NB regression model was fitted. The estimated coefficients of Poisson regression were similar to the coefficients obtained from the NB model fit. The major difference was observed in the standard error of Poisson and NB regression models. The standard error for regression coefficients in Poisson regression models was smaller, which resulted in larger test statistics and inflated the significance of the independent variables. Dowry ($P = 0.001$) was found to be a significant factor in Poisson model, whereas it was not significant ($P = 0.069$) in NB regression model. Due to the underestimation of standard errors, the confidence

intervals of IRR obtained from Poisson regression were narrower than that of NB model. This shows that NB regression model could rectify the limits that arise in Poisson regression model when the data are over-dispersed. Compared to Poisson regression model, NB regression model has the smallest AIC and BIC values indicating the superiority of NB model over the Poisson regression model. Hence, for this study, NB regression has been chosen as the suitable regression model to assess the factors predicting the number of spousal harms on their wives. Based on the fitted NB regression model, the significant predictors were the type of residence, type of marriage, education of wife, education of spouse, miscarriage, and abortion.

The majority of studies have identified a link between female, male illiteracy, and DV; this study has also found the exact association.[27,28] Education of men and women protects women from the number of harms perpetrated by the spouse on their wife. Other researches in Goa and throughout the world have backed up this claim. It is essential to adopt a conscious gender lens toward the development of economic stimulus and social assistance packages to develop effective equality, opportunities, and social protection.[29]

The study has also shown that women who had a love marriage were considerably much more likely to be assaulted than those women who had an arranged marriage. A similar relation has been observed in another study from South India. This could be due to the lack of family support during times of dispute among women who had love marriages.

One of the study's most intriguing findings, which has not been reported in any previous studies, was that miscarriage and abortion were found to be the important significant factors associated with the number of physical harms. Women who have never had miscarriages or abortions are predicted to experience fewer events compared to those who had. A study conducted by Avanigadda and Kulasekaran reported that women who had suffered physical or sexual assaults had a higher risk of pregnancy problems, but vice versa is not yet studied or identified.[30] Type of residents was also found to be a major instigating cause for physical harms in the present study. Married women in rural residence were expected to experience 1.44 times more number of harms than that of urban.[31]

Limitations

This research has a few limitations that must be addressed. To begin with, this study used secondary data that are little older. Further research should be committed with primary data to measure the long-term effect of domestic abuses including more socioeconomic aspects. Second, this study looked only at young married women under the age of 24 years; therefore, we were not able to assess the case of married women aged above 24. In this regard, self-administered questionnaire surveys are really a significant achievement in this area of research. Despite its limitations, this study calls for more research into the factors that lead to such acts of violence, the health and social consequences for young women and men and their children, and interventions that enable youth to prevent such acts of violence.

Conclusion

Study reported that physical violence was more in the rural area of residence. Factors such as type of marriage, education of wife, education of spouse, miscarriage and abortion were also found to have a significant association with the number of physical harms by the spouse on their wife.

When the dependent variable being analyzed involves count data, the study concluded that comprehensive model testing is highly recommended for identifying the best suitable analytic model. This strategy leads to more accurate and valid results, especially in DV studies. The study discovered that over-dispersion in count data must be accounted for to avoid spurious significance arising in Poisson model fit.

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Conflicts of interest

There are no conflicts of interest.

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