Investigation of femicide in Turkey: modeling time series of counts

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Abstract

This study aims to reveal the relationship between the number of femicide in Turkey, the female unemployment rate, the male unemployment rate, and inflation. The contribution of the study to the literature is that it estimates the relationship between femicides and macroeconomic variables with a method that incorporates the count data. The dataset was analyzed by using the INGARCH model, one of the most popular approaches for count time series data. This model is particularly attractive for dealing with serial dependence and over-dispersion. The findings revealed that an increase in the female unemployment rate and a decrease in the male unemployment rate increases the number of femicide. In addition, it was observed that the number of femicide in the previous month had a negative effect on the current month's number. Increasing the employment rate of women, and women's economic freedom generally, are essential factors in reducing femicide. To prevent femicides, policymakers should aim to increase women's employment.

Keywords Gender-based violence · Femicide · Count time series model · Female unemployment rate

Abbreviations
ACF   Autocorrelation function
AIC   Akaike information criteria
ARIMA   Autoregressive integrated moving average
ARMA   Autoregressive moving average

The category other includes family council decision, honor killing, suspicious death, making it seem like an accident, resistance to rape/violence, economic reasons, crisis and unemployment, infertility and child arguments, jealousy, rejection, theft-money-substance abuse, and saving the life of another woman.

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GLM	Generalized linear models
INGARCH	Integer-valued generalized autoregressive conditional heteroscedasticity
IPV	Intimate partner violence
PACF	Partial autocorrelation function
PIT	Probability integral transform
SIC	Schwartz information criteria
TurkStat	Turkish Statistical Institute
UNODC	United Nations Office on Drugs and Crime

1 Introduction

The World Health Organization (2012) calls violence against women a worldwide problem and a major challenge to global public health. It has defined violence against women as "physical, sexual or psychological suffering for women, including threats of such acts, coercion or arbitrary deprivation of liberty, whether occurring in public life or in private life" (*The United Nations*). Femicide, or the killing of women, is the most extreme form of violence against women. The term "femicide" was first used at the beginning of the nineteenth century by Corry (1801) and was legally recognized by Russell (1982).

The phenomenon of femicide refers to the killing of women, through masculine violence, because they are women. The ecological approach, first proposed by Heise (1998), conceptualizes violence as four systems: personal, microsystem, exosystem, macrosystem, and the interaction of these systems. In this study, an analysis is made from the perspective of the exosystem, which includes low socioeconomic status/unemployment, isolation of women and families, and criminal peer associations.

The most common form of violence against women is intimate partner violence (IPV). According to the Global Study on Homicide Report prepared by the United Nations Office on Drugs and Crime (UNODC 2019), women were killed in 82% of intimate partner murders in 2017. This is a strong indicator that women are exposed to gender inequality.

The fact that femicide rates are higher in underdeveloped and developing countries than in other country groups necessitates an examination of the level of development and, accordingly, the role of macroeconomic factors on femicide. Countries with high incomes and high female labor force participation rates have lower femicide rates compared to other countries. In Turkey, while the labor force participation rate for men over the age of 25 was 72.5% in 2020, this rate for women was just 31.6% (*TurkStat*). Men participate in the workforce more than women, in other words. This leads to the formation of a patriarchal societal structure. Patriarchal family structure and unemployment increase the number of femicide.

Studies on femicides can be divided into various groups. Agüero (2019), Srebot-Roeder (2021) and Colagrossi et al. (2022) investigated the impact of raising women's awareness through media, campaign announcements, or calls to a helpline on violence against women. Estévez-Soto (2021) and Hoehn-Velasco et al. (2021) investigated whether violence against women has changed due to the COVID-19 pandemic. Durrance et al. (2011), Roberts (2009), Murillo et al. (2018), Zeoli and Webster (2010) and Stamatel (2016) examined the impact of alcohol, drugs, firearms, and the restriction of their use on violence against women, including murder. Silva (2018), Amaral et al. (2021), Lin (2001), Álvarez-Garavito and Acosta-González (2021) and González et al. (2020) examined the effects of

various issues, such as proximity to a police station, using a panic button, and legal regulations on violence against women and femicide. Monteiro et al. (2021) looked into whether being a black or white woman in different age groups has a significant effect on violence against women and femicide.

Dugan (2002), Brown and Mercy (2008), Roman and Reid (2012) and Torrecilla et al. (2019) focused on the issue of IPV. Femicide was investigated in terms of macroeconomic indicators by Koç and Kutlar (2021) and Çiğdem (2021), and with regards to socio-demographic conditions by Burbano (2016), Valdivia & Castro (2013), Peñaloza et al. (2020), Bekaroğlu (2021) and Kavaklı (2020).

The aim of this study is to investigate the relationship between the number of femicides committed in Turkey between January 2013 and November 2021 and certain macroeconomic variables. For this purpose, the relationship between the number of femicide, the unemployment rate for men and women, and the inflation rate was examined. The contribution of this study to the literature is to estimate femicides by using the count time series model. The subject studied is of great interest and the INGARCH approach chosen for data analysis is not commonly used in the literature. The advantage of the INGARCH model is to deal with serial dependence and over-dispersion.

The rest of the study is organized as follows. The second section gives information about the problem of femicide in Turkey. The methodology used is explained in the third section. The fourth section explains the dataset and reports the empirical results. Finally, the fifth section provides concluding remarks.

2 The history of Femicide in Turkey

Turkey has one of the highest rates of violence against women, including murder. Between 2013 and 2021, 3035 women were killed (*We Will Stop Femicide Platform* 2022). Studies carried out to predict and prevent murders of women have made more recognizable the extent of violence against women and femicide.

When the causes of femicides committed in Turkey are examined, it is found that most of the murders have no stated motivation. Of the murders with stated motivations, the woman's desire to make decisions about her own life and the decision to divorce/separation are the most common cases. Femicides committed for reasons besides these are expressed by the category "other".[1] Figure 1 illustrates the rates at which women were killed, broken out by reason.
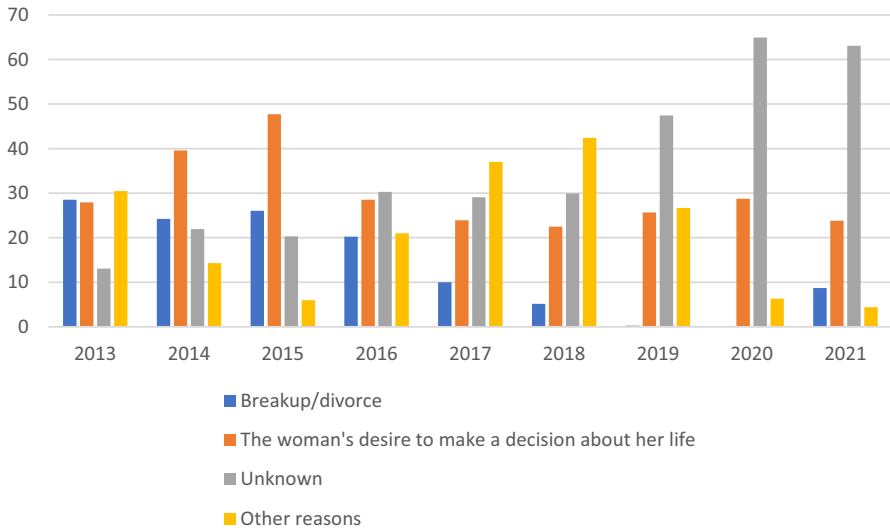
Figure 2 shows the methods by which women were killed. The most used method is firearms and cutting tools. The remaining methods are drowning, using a hard object, battering, crowbar, unknown, suspicious death, and other.

Figure 3 shows by whom the women were killed. As seen in the figure, women were killed mostly by their intimate partners.

Seeing how femicides happen over a 10-year period allows us to see the patterns that repeat, grow, and diminish when it comes to the killing of women. It shows us once again that femicide is not at all unexpected, sudden, or the result of "momentary anger"; on the contrary, it is predictable and preventable. Women are mostly killed at home by their close

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[1] The category "other" includes family council decision, honor killing, suspicious death, making it seem like an accident, resistance to rape/violence, economic reasons, crisis and unemployment, infertility and child arguments, jealousy, rejection, theft-money-substance abuse, and saving the life of another woman.

For What Reasons Are Women Killed?

Fig. 1 The reasons why women were killed (annual average distribution, %)

By Which Method Are Women Killed?
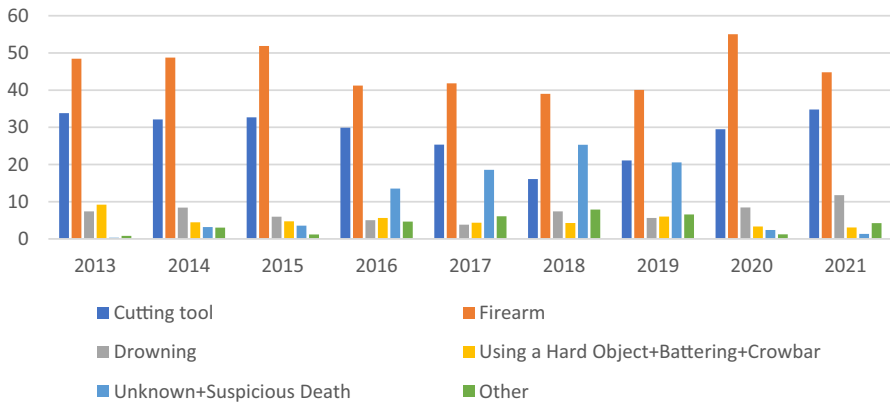
Fig. 2 The methods by which women were killed (annual average distribution, %)

partners with firearms, most often due to the woman's desire to make decisions about her life. The reason why this human right cannot be exercised is the dominance of the patriarchal social structure and the lack of gender equality.
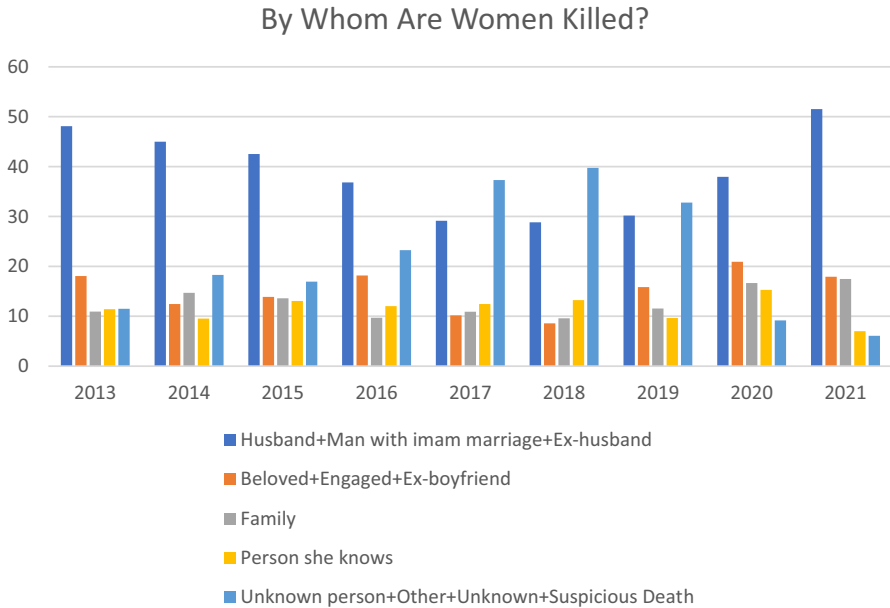
By Whom Are Women Killed?

Fig. 3 By whom the women were killed (annual average distribution, %)

3 Methodology

The non-negative integer-valued data in a time series can be stated as a time series of counts, if the observations are registered by counting the number of events at a specific time instance (Vieira 2019a). The autoregressive moving average (ARMA) model was introduced by Box and Jenkins (1970) by combining the moving average and autoregressive models. We can write the ARMA (p, q) model as

$$y_t = c + \sum_{i=1}^{p} a_i y_{t-i} + \sum_{j=1}^{q} b_j \in_{t-j} + \in_t \tag{1}$$

where $\{\in_t\}$ is zero mean white noise and $\mathrm{cov}(\in_t, y_{t-k}) = 0$ for $k = 1, 2, \cdots, p$. In this formula, p denotes the AR degree and q denotes the MA degree.

If the dependent variable is not stationary in the ARMA model, the autoregressive integrated moving average (ARIMA) model[2] is estimated by taking the difference according to the stationarity degree. The Box-Jenkins approach can be used in the ARIMA models to define, predict, and perform diagnostic tests of a time series. Firstly, the time-series should be stationary or be differentiated to make it stationary. After that, p and q order can be detected by using the autocorrelation function (ACF) or partial ACF (PACF) in a visual manner or by comparing information criteria like Akaike information criteria (AIC) or Schwartz information criteria (SIC). After determining the p and q degrees in the count time series analysis, the link function and the appropriate distribution are decided.

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[2] There are also hands-on studies using versions such as seasonal ARIMA (SARIMA) model (Öncel Çekim 2018) or ARIMA with explanatory variable (ARIMAX) (Öncel Çekim and Koyuncu 2022).

Serial dependence and over-dispersion are common problems in time series of counts data (Vieira 2019b). Generalized linear models (GLM) approaches can deal with these problems through a link function for time series of counts. Let $\{Y_t : t \in \mathbb{N}\}$ and $\{X_t : t \in \mathbb{N}\}$ denote the count time series. X_t is a time-varying r-dimensional covariate vector and $\mathcal{F}_{t-1}$ is the filter containing past observations. The conditional mean of Y_t on $\mathcal{F}_{t-1}$ can be modeled by using a stochastic process with a latent mean process $\{\lambda_t : t \in \mathbb{N}\}$. This model can be written as follows:

$$g(\lambda_t) = \beta_0 + \sum_{k=1}^{p} \beta_k \widetilde{g}(Y_{t-i_k}) + \sum_{l=1}^{q} \alpha_l g(\lambda_{t-jl}) + \eta^T X_t \tag{2}$$

where β_k present AR parameters, $\widetilde{g}$ is a transformation function, g is a link function defined in the set $\mathbb{R}^+ \to \mathbb{R}$, η is the parameter vector corresponding to the effects of the covariates, and $g(\lambda_t)$ represents the linear predictor. For a good model fit, the link and transformation functions must be chosen correctly. When the link function is chosen as identity, the transformation function becomes $g(x) = \widetilde{g}(x) = x$. If the distribution is assumed as the Poisson and the covariates are excluded, the model can be defined as the following equation:

$$\lambda_t = \beta_0 + \sum_{k=1}^{p} \beta_k Y_{t-k} + \sum_{l=1}^{q} \alpha_l \lambda_{t-l} \tag{3}$$

Equation (3) is called the Integer-valued Generalized Autoregressive Conditional Heteroscedasticity (INGARCH) model[3] of order (p, q) when Y_t has the Poisson distribution. If the link function is taken in the logarithmic form, and the dependent variable is expressed as $v_t = \log(\lambda_t)$, the resulting model is:

$$v_t = \beta_0 + \sum_{k=1}^{p} \beta_k \log(Y_{t-k} + 1) + \sum_{l=1}^{q} \alpha_l v_{t-l} \tag{4}$$

The log-linear model in Eq. (4) has a multiplicative effect on the response variable and captures the effects of covariates better than the INGARCH model in Eq. (3). In Eq. (3) having the identity link function, the assumptions $\beta_k \geq 0$, $\alpha_l \geq 0$, $\beta_0 > 0$ and $\left| \sum_l \alpha_l + \sum_k \beta_k \right| < 1$ must be provided (Ferland et al. 2006). In Eq. (4) with the log link function, while it is possible for the coefficients of β_0, β_k and α_l to be negative or positive, the conditions for $|\beta_k| < 1$, $|\alpha_l| < 1$ and $\left| \sum_l \alpha_l + \sum_k \beta_k \right| < 1$ must be met (Manolakis et al. 2019).

As an alternative to the Poisson distribution, the negative binomial distribution can also be used. By assuming a negative binomial distribution, the conditional variance is allowed to be larger than the mean. In fact, the Poisson distribution is a special case of the negative binomial distribution and the conditional variance and mean being the same corresponds to the Poisson distribution.

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[3] See Ferland et al. (2006), Weiss (2018), Zhu (2011), Kim (2020) and Zhu (2012) for further reading.

Table 1 Description and source of the variables

Variable name	Variable description	Source
FEMALE	The number of killed females	We Will Stop Femicide Platform 2022
UNEMP_F	The unemployment rate of females	Turkish Statistical Institute (TurkStat) (2022)
UNEMP_M	The unemployment rate of males	Turkish Statistical Institute (TurkStat)
INFLATION	The rate of inflation (monthly percentage change)	Turkish Statistical Institute (TurkStat)

**Fig. 4** The numbers of femicides
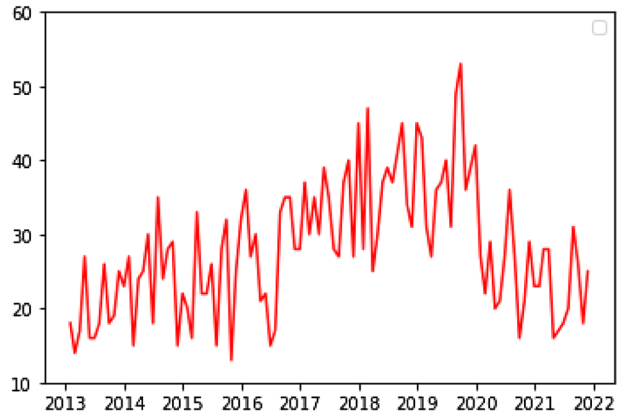
Table 2 Descriptive statistics

Variable	Mean	Median	Maximum	Minimum	Standard Deviation	Skewness	Kurtosis	Jarque-Bera
FEMALE	28.047	27.000	53.000	13.000	8.780	0.430	2.683	3.739
UNEMP_F	14.044	13.800	17.900	10.400	1.850	0.052	1.984	4.654
UNEMP_M	10.248	9.800	14.100	7.900	1.693	0.492	1.937	9.356*
INFLATION	0.983	0.860	6.300	− 1.440	0.947	1.750	11.176	352.658*

*At the 5% significance level, the null hypothesis is rejected

4 Data and empirical results

In this study, which aims to reveal the relationship between the number of femicide in Turkey, the female unemployment rate, the male unemployment rate, and the inflation rate, the monthly frequency series belonging to the 2013.M1–2021.M11 periods has been analyzed. Explanations of the variables are given in Table 1. Since there is no data on demographic variables such as age, education, employment status, and marital status of the murdered women and the murderers, the factors affecting the number of female deaths were examined by taking the variables at the macroeconomic level with monthly frequency.

In the study, since the dependent variable, the number of femicides, was count data, analysis was performed with count time series models by using R, with the tscount package developed by Liboschik et al. (2017) and the Python package programs. The dependent
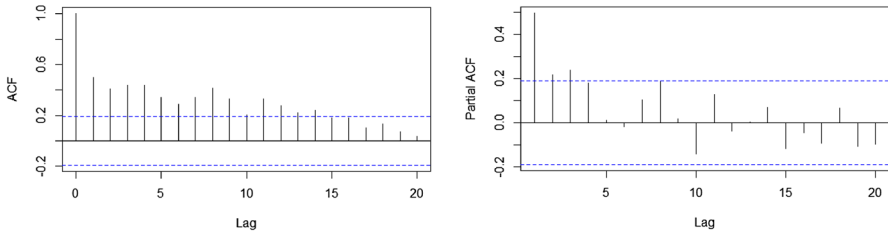
Fig. 5 ACF & PACF for FEMALE

Table 3 The results of unit root for FEMALE

Variable: female	With constant	With constant & trend
PP	− 6.393*	− 6.728*
DF-GLS	− 1.373*	− 2.559*

At the *%1, **%5, ***%10 significance level, the null hypothesis is rejected

Table 4 ARMA model selection

AR	MA	Link	Distribution	AIC	SIC
1	1	Log	Poisson	716.096	724.115
			Negative Binomial	708.479	719.170
		Identity	Poisson	720.051	728.070
			Negative Binomial	711.329	722.021

variable used in the study is illustrated in Fig. 4 and the descriptive statistics belonging to all variables are given in Table 2.

When Fig. 4 is examined, it is seen that the number of murdered women followed a slightly increasing trend until 2020 and reached its highest levels in 2019.

It is seen that the average monthly number of femicides is 28, with a maximum of 53 women in Table 2. When the female and male unemployment rates are analyzed, it is seen that the average female unemployment rate is higher than males. It is observed that all the series of the analyzed variables are right-skewed and all of them are flattened compared to the normal distribution, except for the inflation series. It is seen that the FEMALE and UNEMP_F series are normally distributed, while the UNEMP_M and INFLATION series do not fit the normal distribution.

Analyzing the count time series model, in which the number of killed women is the dependent variable, was done by first determining the degrees of the AR/MA/ARMA or ARIMA model that best represented this series. For this purpose, the autocorrelation and partial autocorrelation functions of the series were examined (see Fig. 5) and the stationarity degree was determined by unit root tests (see Table 3).

The FEMALE series was found to be stationary, and the analysis was continued by estimating the ARMA model. Looking at the ACF and PACF graphs, it was seen that the partial autocorrelation function was cut off after the first lag and the autocorrelation

Table 5 Variable selection

Model	Independent variable	Link	Distribution	AIC	SIC
1	UNEMP_M	Log	Poisson	715.841	726.533
			Negative Binomial	708.775	722.139
		Identity	Poisson	716.998	727.689
			Negative Binomial	709.553	722.917
2	UNEMP_F	Log	Poisson	717.166	727.860
			Negative Binomial	709.724	723.088
		Identity	Poisson	748.786	759.478
			Negative Binomial	728.776	742.140
3	INFLATION	Log	Poisson	721.022	731.713
			Negative Binomial	712.427	725.791
		Identity	Poisson	720.211	730.902
			Negative Binomial	711.899	725.264
4	UNEMP_M UNEMP_F	Log	Poisson	696.096	709.460
			Negative Binomial	**692.809**	**710.940**
		Identity	Poisson	744.111	757.475
			Negative Binomial	727.125	743.162
5	UNEMP_M UNEMP_F INFLATION	Log	Poisson	692.838	708.870
			Negative Binomial	694.904	711.519
		Identity	Poisson	750.584	766.621
			Negative Binomial	731.596	750.306

The bold characters in the table indicate the appropriately selected model

function decreases gradually. However, due to the subjectivity in the Box-Jenkins model selection approach, we estimated alternative ARIMA models, with AR terms ranging from 0 to 14 and MA terms from 0 to 3. The preferred model was selected as ARMA (1, 1) by using the AIC and SIC information criteria. For the most suitable ARMA model, the results of the models with different link functions and distributions are given in Table 4.

Although the link function was log and the distribution was negative binomial when the AIC and SIC criteria were evaluated together in Table 4, the distribution and link function were also evaluated by considering other criteria in the other analyses of the study.

Model experiments were continued with various independent variables, link functions and distributions to determine which explanatory variables would be more appropriate to include in the model in the estimation of the count time series model of the number of femicides. The results in Table 5 were evaluated by considering the AIC and SIC criteria together, and it was decided that the most appropriate model had the explanatory variables UNEMP_F and UNEMP_M. Moreover, the most appropriate model was also the model with the log link function and the distribution of which was the negative binomial. Due to the negative values in the inflation variable, the models could not be estimated with the identity link function.

The evaluations of the link function and distribution function were continued by examining the probability integral transform (PIT) histograms. Figures 6 and 7 belong
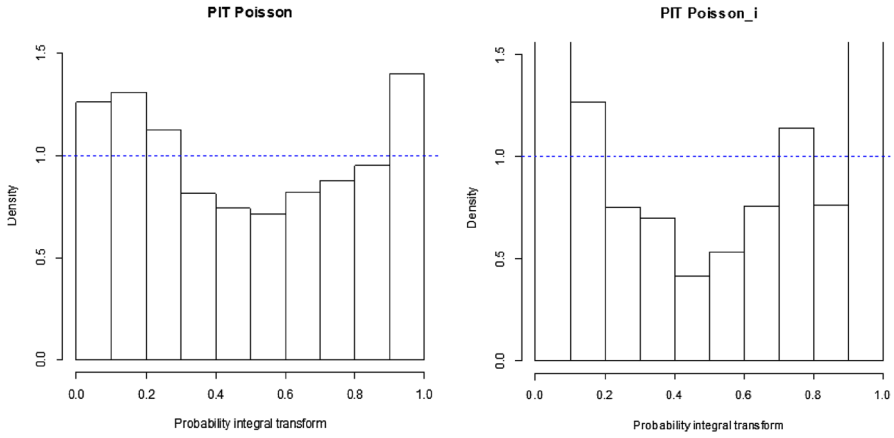
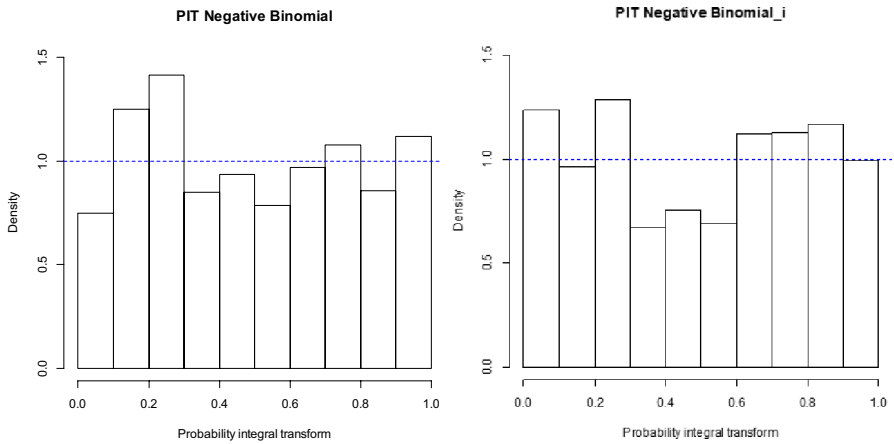**Fig. 6** PIT of Poisson_log & Poisson_identity

Fig. 7 PIT of Negative Binomial_log & Negative Binomial _identity

Table 6 Link function for Poisson distribution

	Logarithmic	Quadratic	Spherical	rankprob	dawseb	normsq	sqerror
Poisson log	3.206	− 0.046	− 0.214	3.401	4.602	1.290	35.765
Poisson identity	3.430	− 0.034	− 0.188	4.055	5.026	1.701	48.177

rankprob: ranked probability score, dawseb: Dawid-Sebastiani score, normsq: normalized squared error score, sqerror: squared error score

to models estimated by using log and identity link functions with Poisson and negative binomial distributions. When the figures were examined, it was concluded that the

**Table 7** Link function for negative binomial distribution

	Logarithmic	Quadratic	Spherical	rankprob	dawseb	normsq	sqerror
NegBin log	3.191	− 0.047	− 0.217	3.382	4.572	0.953	35.765
NegBin identity	3.342	− 0.039	− 0.198	3.956	4.853	0.953	48.177

rankprob: ranked probability score, dawseb: Dawid-Sebastiani score, normsq: normalized squared error score, sqerror: squared error score

Fig. 8 Marginal calibration for Poisson_log & Poisson_identity
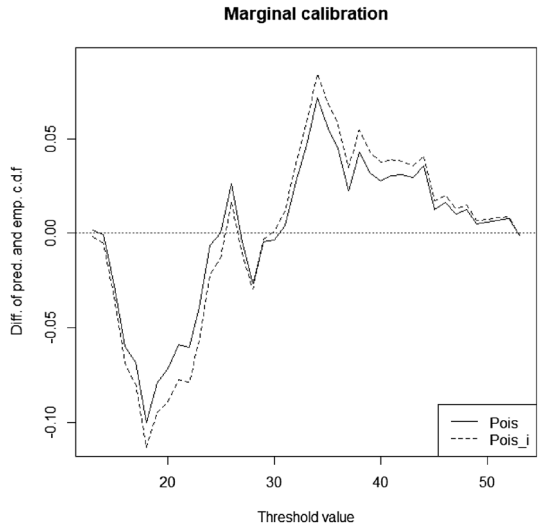
Fig. 9 Marginal calibration for Negative Binomial_log and Negative Binomial _identity
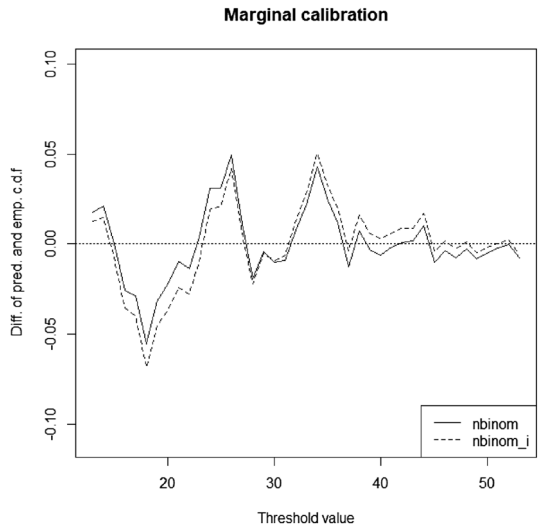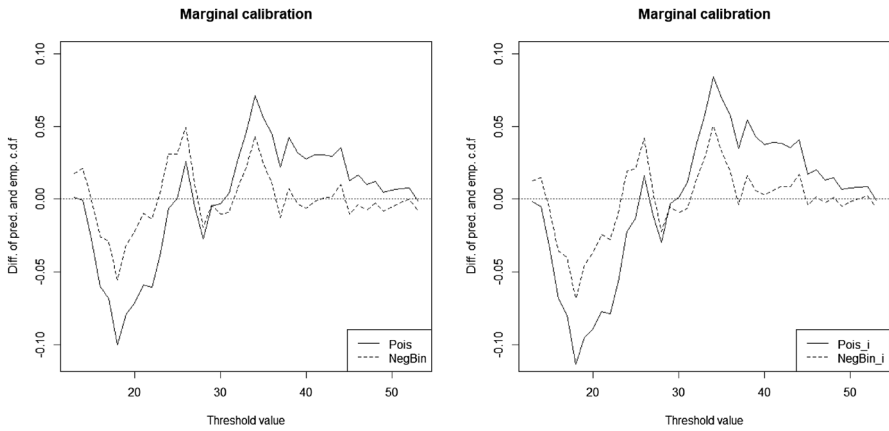
Fig. 10 Marginal calibration for Poisson_log/Negative Binomial_log and Poisson_identity / Negative Binomial_identity

Table 8 Results of the INGARCH model

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Link-Dist	log-nbinom	identity-nbinom	log-nbinom	log-poisson	identity-poisson	log-poisson
Coefficients	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate
Intercept	0.123**	9.530**	0.082**	0.130**	9.530**	0.082**
beta_1	−0.045**	0.372**	−0.029**	−0.045**	0.372**	−0.029**
alpha_1	0.999**	0.262**	0.999**	0.999**	0.262**	0.999**
UNEMP_M	0.019**	0.053**	0.015**	0.019**	0.053**	0.015**
UNEMP_F	−0.024**	7.15e−06**	−0.017**	−0.024**	7.15e−06**	−0.017**
INFLATION	–	–	−8.21e−05	–	–	−8.21e−05
Sigmasq	0.013**	0.028**	0.011**	–	–	–
Log-likelihood	−341.452	−357.562	−339.404	−343.048	−367.055	−340.416
AIC	692.809	727.125	694.904	696.096	744.111	692.833
SIC	710.940	743.162	711.518	709.460	757.475	708.870

**At the 5% significance level, the null hypothesis is rejected

The bold characters in the table indicate the appropriately selected model.

model with negative binomial distribution and log link function was suitable due to the greatest similarity to the uniform distribution.

Another way to determine the link function of the appropriate distribution is to calculate and compare the score values for each distribution/link function. Findings obtained for this purpose are presented in Tables 6 and 7.

In the scores calculated for both distributions, the log function had smaller values. Therefore, it was decided that the appropriate link function was log.

Another criterion used in the evaluation of the appropriate distribution and link function are the marginal calibration graphs. Marginal calibration graphs obtained by using log and identity link functions with both Poisson and negative binomial distributions are included in Figs. 8, 9 and 10.

Fig. 11 Actual and predicted values
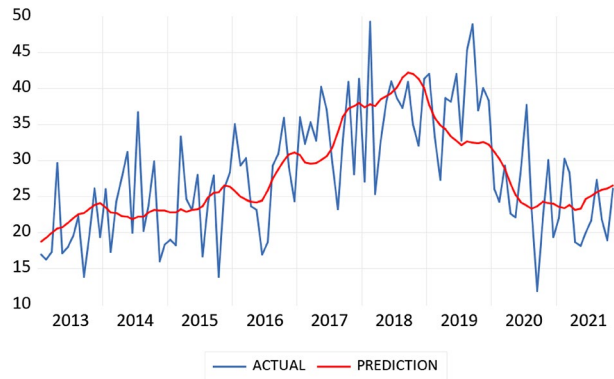
When the link functions of the distributions were examined separately, it seemed that the appropriate link function was log (see Figs. 8 and 9). When we evaluated each function with a different distribution in marginal calibration graphs evaluated according to proximity to the zero line, the appropriate distribution was again negative binomial (see Fig. 10). By evaluating all the findings together, it was concluded that the number of femicides was modeled most conveniently by using the log link function with the negative binomial distribution. The obtained results were also in line with our expectations because the negative binomial distribution allows higher variance (dispersion) than the Poisson distribution.

The findings obtained by using the INGARCH model, one of the count time series models, are given in Table 8. It was determined that the most suitable model was the negative binomial distribution with the log link function and the model contained female and male unemployment rates as the explanatory variables. When the results in Table 8 were examined, the suitability of the model compared to other models was seen once again. All variables in Model 1, which was determined to be the appropriate model, were statistically significant at the 5% significance level. According to the findings obtained from the INGARCH model, the number of femicides increased as the female unemployment rate increased and decreased as the male unemployment rate increased. In addition, it was observed that the number of femicides in the previous month had a negative effect.

The analysis revealed that increasing the employment rate of women is a crucial factor in reducing femicide. A higher unemployment rate for men also reduces femicide. The number of femicides in the previous month leads to a decrease in the number of femicides in the current month.

The real and predicted values for femicides are illustrated in Fig. 11. As seen in the figure, the real and predicted values of the number of femicides follow the same trend. The proximity of the numbers for the real and predicted values indicates the success of using the count time series modelling.

5 Conclusion

Femicide is a social problem that damages the social structure and prevents human development, since it causes avoidable deaths (Murillo et al. 2018). According to *the United Nations*, gender equality and violence against women are one of the major obstacles to succeeding the Sustainable Development Goals for 2030.

The biggest difficulty in analyzing femicides is that the data is not collected properly and shared with transparency. This situation also created limitations for our study, so the analysis was made with independent variables at the macro level. We aimed to reveal the relationship between the number of femicides in Turkey, the female unemployment rate, the male unemployment rate, and the inflation rate in this study. For this purpose, we drew on the data for the period of January 2013 to November 2021 by using the count time series model. The findings revealed that an increase in the female unemployment rate and a decrease in the male unemployment rate both increase the number of femicides. In addition, it was observed that the number of femicides in the previous month had a negative effect on the number in the current month. There was no statistically significant relationship between the inflation rate and the number of femicides. When the obtained findings are interpreted, it becomes clear that increasing the employment rate of women, which ensures women's economic freedom, is a crucial factor in reducing femicide. The fact that men do not have economic freedom devastates the dominance of the patriarchal structure and decreases the probability of femicide. The negative coefficient of the number of femicides in the previous month suggests that drawing attention to cases of femicide through the media brings down the number of femicide in the current month.

Femicide is a violation of human rights and, unfortunately, is one of the least reported forms of crime. Women tend to fear male backlash, economic hardship, and adverse consequences for their children if they attempt to call attention to it. The success of sustainable development policies based on gender equality is possible, first of all, if women are respected within the family. For this reason, the causes of domestic violence and femicide should be examined and optimal solutions should be proposed so that women can take part in society as strong individuals.

Another avenue for preventing femicides is mapping the regions where women are killed the most. In this sense, the map will be a data-based guide that facilitates location-based thinking in studies to be carried out to prevent femicides. As a result, finding effective tools, including collecting data and legislation to avoid femicide, represents a crucial requirement for policymakers.

Declarations

Competing interests The authors declare that they have no competing interests.

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