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Using count regression models to investigate the most important economic factors affecting divorce in Iraq

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Abstract: The two most popular models inwell-known count regression models are Poisson and negative binomial regression models. Poisson regression is a generalized linear model form of regression analysis used to model count data and contingency tables. Poisson regression assumes the response variable Y has a Poisson distribution, and assumes the logarithm of its expected value can be modeled by a linear combination of unknown parameters. Negative binomial regression is similar to regular multiple regression except that the dependent (Y) variables an observed count that follows the negative binomial distribution. This research studies some factors affecting divorce using Poisson and negative binomial regression models. The factors are unemployment rate, inflation and Gini coefficient. The data were taken from the website of the Statistics Center for the years 2002 to 2023.Under the Poisson regression model, each factor has been reported to have an effect on the divorce rate. The two factors of inflation and unemployment had a direct effect and income inequality factors had an inverse effect on the divorce rate. But, under the negative binomial regression model, only inflation has an effect on the number of divorces. It is worth noting that according to the AIC values, the negative binomial regression model has a better fit than the Poisson regression model because its AIC value is lower.
Keywords: *Maximum Likelihood Estimation, Negative binomial regression, Poisson regression.*

1. Introduction

This research studies some factors affecting divorce using count regression models. Divorce and family dissolution are global issues that are related to various socio-economic, demographic and spatial variables. In the past decades, the divorce rate has increased dramatically in different countries, including Iraq. Rapid economic development, social transformation, and modernization have directly led to profound cultural changes in marriage and marital instability (Pamukcu and at all 2014). One of the main problems of the modern age is the dramatic change in the family, especially marital relations. The dissolution of the traditional family composition, the difference between generations, the significant increase in the divorce rate and the expansion of cohabitation have become hard and fast realities today. These reforms are more related to social-based personal motivations, the most important of which are financial disturbances in the family, increasing women's financial independence, and changing the role of women in the family (Soleymanov 2010).

Psychological research in the field of family shows that several factors play a role in the separation of couples and the collapse of the family foundation, among which economic problems such as inflation, unemployment, and class differences are known as the most important factors. Naturally, when a family faces difficulties in providing its most basic needs, it will not be successful in controlling and managing other parts of life and psychological and emotional needs. Financial capabilities meet people's low-level needs, and if people feel financially secure, they will also meet their high-level needs. This is despite the fact that if the basic needs are not even partially met, the next needs will not be formed. In most cases, divorce also happens due to lack of financial stability in life (Aghajanian and Thompson 2013).

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2. Poisson Regression

Poisson regression is similar to regular multiple regression except that the dependent (Y) variable is an observed count that follows the Poisson distribution. Thus, the possible values of Y are the nonnegative integers: 0, 1, 2, 3, …. It is assumed that large counts are rare. Hence, Poisson regression is similar to logistic regression, which also has a discrete response variable. However, the response is not limited to specific values as it is in logistic regression.

An example of the proper application of Poisson regression is the study of how the number of divorces in a year is related to influencing factors, including economic factorsAnother example is the study of how the number of bacterial colonies is related to different environmental conditions and dilutions.Another example is the number of failures for a certain machine at various operating conditions. Still another example is vital statistics concerning infant mortality or cancer incidence among groups with different demographics.

2.1. The Poisson Distribution

The Poisson distribution models the probability of y events (i.e., failure, death, or existence) with the formula

$$\Pr(Y = y|\mu) = \frac{e^{-\mu}\mu^{y}}{y!}; \quad y = 0,1,2,\ldots \qquad (1)$$

Notice that the Poisson distribution is specified with a single parameter μ. This is the mean incidence rate of a rare event per unit of exposure. Exposure may be time, space, distance, area, volume, or population size. Because exposure is often a period of time, we use the symbol t to represent the exposure. When no exposure value is given, it is assumed to be one.

The parameter μ may be interpreted as the risk of a new occurrence of the event during a specified exposure period, t. The probability of y events is then given by

$$\Pr(Y = y|\mu, t) = \frac{e^{-\mu t}(\mu t)^{y}}{y!}; \quad y = 0,1,2,\ldots \qquad (2)$$

The Poisson distribution has the property that its mean and variance are equal.

In Poisson regression, we suppose that the Poisson incidence rate μ is determined by a set of k regressor variables (the X's). The expression relating these quantities is

$$\mu = t\exp(\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k) \qquad (3)$$

Note that often, $X_1 \equiv 1$ and β_1 is called the intercept. The regression coefficients $\beta_1, \beta_2, \cdots, \beta_k$ are unknown parameters that are estimated from a set of data. Their estimates are labeled $b_1, b_2, \cdots, b_k$. Using this notation, the fundamental Poisson regression model for an observation i is written as

$$\Pr(Y = y_i|\mu_i, t_i) = \frac{e^{-\mu_i t_i}(\mu_i t_i)^{y_i}}{y_i!} \qquad (4)$$

Were

$$\mu_i = t_i\mu(x_i'\beta) = t_i\exp(\beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki}) \qquad (5)$$

That is, for a given set of values of the regressor variables, the outcome follows the Poisson distribution. We assume that t=1 (one year).

2.2. Maximum Likelihood Estimation of Parameters

We use the method of maximum likelihood estimation to estimate the parameters of the Poisson regression model. The likelihood function is based on Poisson distribution with parameter μ and then β's are estimated through the link function.

The likelihood function of $y_i, y_2, \ldots, y_n$ is

$$L(y, \beta) = \prod_{i=1}^{n}\Pr(Y = y_i|\mu_i) = \frac{\left(\prod_{i=1}^{n}\mu_i^{y_i}\right)\left(\exp\left(-\sum_{i=1}^{n}\mu_i\right)\right)}{\prod_{i=1}^{n}y_i!} \qquad (6)$$

And the logarithm of likelihood function is

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$$\log[L(y,\beta)] = \sum_{i=1}^{n} y_i \log[\mu_i] - \sum_{i=1}^{n} \mu_i - \sum_{i=1}^{n} \log(y_i!). \qquad (7)$$

The parameter μ_i can be related to β's through the link function

$$\mu_i = g^{-1}(x_i'\beta).$$

After choosing the proper link function, the log-likelihood function can be maximized using some numerical optimization techniques for a given set of data. Let $\hat{\beta}$ be the obtained maximum likelihood estimator of β. Then the fitted Poisson regression model is

$$\hat{y}_i = g^{-1}(x_i'\beta) \qquad (8)$$

In case of identity link,

$$\hat{y}_i = g^{-1}(x_i'\beta) = x_i'\beta \qquad (9)$$

In the case of log-link,

$$\hat{y}_i = g^{-1}(x_i'\beta) = \exp(x_i'\beta) \qquad (10)$$

Of course, the likelihood equations may be formed by taking the derivatives with respect to each regression coefficient and setting the result equal to zero. Doing this leads to a set of nonlinear equations that admits no closed form solution. Thus, an iterative algorithm must be used to find the set of regression coefficients that maximum the log-likelihood. Using the method of iteratively reweighted least squares, a solution may be found in five or six iterations. However, the algorithm requires a complete pass through the data at each iteration, so it is relatively slow for problems with a large number of rows. With today's computers, this is becoming less and less of an issue.

2.3. Distribution of the MLE's

Applying the usual maximum likelihood theory, the asymptotic distribution of the maximum likelihood estimates (MLE's) is multivariate normal. That is,

$$\hat{\beta} \sim N(\beta, \beta V_{\hat{\beta}}) \qquad (11)$$

Were

$$V_{\hat{\beta}} = \left(\sum_{i=1}^{n} \mu_i x_i x_i'\right)^{-1} \qquad (12)$$

Remember that in the Poisson model the mean and the variance are equal. In practice, the data almost always reject this restriction. Usually, the variance is greater than the mean a situation called overdispersion. The increase in variance is represented in the model by a constant multiple of the variance covariance matrix. That is, we use

$$V_{\hat{\beta}} = \phi\left(\sum_{i=1}^{n} \mu_i x_i x_i'\right)^{-1} \qquad (13)$$

where ϕ is estimated using

$$\hat{\phi} = \frac{1}{n-k}\sum_{i=1}^{n} \frac{(y_i - \hat{\mu}_i)^2}{\hat{\mu}_i}. \qquad (14)$$

2.4. Testing of Hypothesis

The test of hypothesis is constructed as model deviance which is based on a large sample test using the likelihood ratio test statistic. The model deviance is defined as

$$\mu^*(\beta) = 2\,log(saturated\ model) - 2\,log(\hat{\beta}) \qquad (15)$$

where the saturated model is based on all the p parameters of the model, and it fits the data perfectly.The statistic $\mu^*(\beta)$ has approximately $\chi^2(n-p)$ distribution when n is large. The large value of $\mu^*(\beta)$indicates that the model is not correctly fitted to the given data whereas small values of $\mu^*(\beta)$

indicating thatmodel is well fitted to the given set of data in the sense that it is as good as the saturated model.
For the hypothesis test
$H_0: \beta_i = 0$ versus $H_1: \beta_i \neq 0$ (or $H_1: \beta_i > 0$ or $H_1: \beta_i < 0$),

$$z = \frac{\hat{\beta}_i - \beta_0}{ASE} = \frac{\hat{\beta}_i}{ASE} \qquad (16)$$

where β_0 is the hypothesized value of β under the null hypothesis (i.e., $\beta_0 = 0$) and $ASE = \sqrt{V_{\hat{\beta}}[i,i]}$ is the asymptotic standard error of $\hat{\beta}$. If the null hypothesis is true, then the statistic z is approximately standard normal

$$z = \frac{\hat{\beta}_i}{ASE} \approx N(0,1). \qquad (17)$$

An estimated parameter divided by it's ASE and squared is a "Wald Statistic". It means that

$$z^2 = \left(\frac{\hat{\beta}_i}{ASE}\right)^2 \approx \chi^2(1) \qquad (18)$$

z^2 has (asymptotically) a chi-squared distribution with df = 1. Wald statistics are usually provided on computer output, along with p–values.

3. Negative Binomial Regression

Negative binomial regression is similar to regular multiple regression except that the dependent (Y) variables an observed count that follows the negative binomialdistribution. Thus, the possible values of Y are thenonnegative integers: 0, 1, 2, 3, and so on.Negative binomial regression is a generalization of Poisson regression which loosens the restrictiveassumption that the variance is equal to the mean made by the Poisson model. The traditional negativebinomial regression model, commonly known as NB2, is based on the Poisson-gamma mixture distribution.This formulation is popular because it allows the modelling of Poisson heterogeneity using a gammadistribution (for more details see Cameron and Trivedi (2013) and Hilbe (2014)).

3.1. The Negative Binomial Distribution

The Poisson distribution may be generalized by including a gamma noise variable which has a mean of 1 and a scale parameter of ν. The Poisson-gamma mixture (negative binomial) distribution that results is

$$\Pr(Y = y_i | \mu_i, \alpha^{-1}) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(y_i + 1)\Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_i}\right)^{\alpha^{-1}} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_i}\right)^{y_i} \qquad (19)$$

Where $\mu_i = t_i \mu$, $\alpha = \frac{1}{\nu}$. The parameter μ is the mean incidence rate of y per unit of exposure. Exposure may be time, space, distance, area, volume, or population size. Because exposure is often a period of time, we use the symbol $t_i$to represent the exposure for a particular observation. When no exposure given, it is assumed to be one.The parameter μ may be interpreted as the risk of a new occurrence of the event during a specified exposure period, t.The results below make use of the following relationship derived from the definition of the gamma function

$$\log\left(\frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(\alpha^{-1})}\right) = \sum_{j=0}^{y_i - 1} \log(j + \alpha^{-1}) \qquad (20)$$

In negative binomial regression, the mean of y is determined by the exposure time t and a set of k regressor variables (the x's). The expression relating these quantities is

$$\mu_i = \exp(\log(t_i) + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki}) \qquad (21)$$

Often, $x_1 = 1$, in which case β_1 is called the intercept. The regression coefficients $\beta_1, \beta_2, \ldots, \beta_k$ are unknownparameters that are estimated from a set of data. Their estimates are symbolized as $b_1, b_2, \ldots, b_k$.

3.2. Maximum Likelihood Estimation

Suppose that $Y_1, \ldots, Y_n$ is a random sample of negative binomial distribution. The regression coefficients are estimated using the method of maximum likelihood. Cameron (2013, page81) gives the logarithm of the likelihood function as

$$l(\beta) = \sum_{i=1}^{n} [\log(\Gamma(y_i + \alpha^{-1})) - \log\Gamma(\alpha^{-1}) - \log(\Gamma(y_i + 1)) - \alpha^{-1}\log(1 + \alpha\mu_i) - y_i \log(1 + \alpha\mu_i) + y_i \log(\alpha) + y_i \log(\mu_i)] \quad (22)$$

The first derivatives of $l(\beta)$ were given by Cameron (2013) and Lawless (1987) as

$$\frac{\partial l(\beta)}{\partial \beta_j} = \sum_{i=1}^{n} \frac{x_{ij}(y_i - \mu_i)}{1 + \alpha\mu_i}, \qquad j = 1,2,\ldots,k \quad (23)$$

And

$$\frac{\partial l(\beta)}{\partial \alpha} = \sum_{i=1}^{n} \left\{ \alpha^{-2} \left(\log(1 + \alpha\mu_i) - \sum_{j=0}^{y_i - 1} \frac{1}{j + \alpha^{-1}} \right) + \frac{y_i - \mu_i}{\alpha(1 + \alpha\mu_i)} \right\} \quad (24)$$

Equating the gradients to zero gives the following set of likelihood equations

$$\sum_{i=1}^{n} \frac{x_{ij}(y_i - \mu_i)}{1 + \alpha\mu_i} = 0, \qquad j = 1,2,\ldots,k \quad (25)$$

and

$$\sum_{i=1}^{n} \left\{ \alpha^{-2} \left(\log(1 + \alpha\mu_i) - \sum_{j=0}^{y_i - 1} \frac{1}{j + \alpha^{-1}} \right) + \frac{y_i - \mu_i}{\alpha(1 + \alpha\mu_i)} \right\} = 0 \quad (26)$$

3.3. Distribution of the MLE's

Cameron (2013) gives the asymptotic distribution of the maximum likelihood estimates as multivariatenormal as follows

$$\begin{bmatrix} \hat{\beta} \\ \hat{\alpha} \end{bmatrix} \sim N \begin{bmatrix} V(\hat{\beta}) & Cov(\hat{\beta}, \hat{\alpha}) \\ Cov(\hat{\beta}, \hat{\alpha}) & V(\hat{\alpha}) \end{bmatrix} \quad (27)$$

Were

$$V(\hat{\beta}) = \left[\sum_{i=1}^{n} \frac{\mu_i}{1 + \alpha\mu_i} x_i x_i' \right]^{-1}, \quad Cov(\hat{\beta}, \hat{\alpha}) = 0 \quad (28)$$

$$V(\hat{\alpha}) = \sum_{i=1}^{n} \left\{ \alpha^{-4} \left(\log(1 + \alpha\mu_i) - \sum_{j=0}^{y_i - 1} \frac{1}{j + \alpha^{-1}} \right)^2 + \frac{\mu_i}{\alpha^2(1 + \alpha\mu_i)} \right\}^{-1} \quad (29)$$

4. Akaike's Information Criterion

The Akaike's information criterion is used to determine the superiority between thedistributions or models to the data, denoted by the symbol AIC, and can be calculated as follows:

$$AIC = -2\log\left(L(\hat{\theta})\right) + 2p \quad (30)$$

Where $L(\hat{\theta})$ is the maximum value of the likelihood function for the estimation of the parameters and p is the number of model parameters. Among the fitted models, the distribution where AIC is lower than the others is preferred.

4.1. Really Data

Factors affecting the occurrence of divorce have been one of the main axes investigated in sociological researches in recent years, and from the point of view of social and psychological experts, many economic, social and cultural, psychological, behavioral and even physical reasons are involved in leading a relationship to divorce. Above all, there are economic problems. By looking at the statistics and comparing it with the phenomenon of divorce, we find out that the statistics of cohabitation collapse has grown significantly along with inflation and unemployment.

The disproportion of salaries and wages with the growth of prices and annual inflation and the aggravation of the gap between expenses and income have faced many harms to the joint life, and 70% inflation, the increase in food prices, and the high cost of housing and rent are among the factors influencing the end of the joint life.Scientific findings also show that economic problems affect practically all aspects of life and individual, family and social needs of people. Therefore, psychologists believe that in a society where the economy is in trouble, it is very ridiculous to talk about why the divorce rate is increasing; Because there are still more basic needs to be met.

The research results and findings indicate that the probability of divorce is higher in women than in men and in urban areas than in rural areas. Education has a negative relationship with the probability of divorce. Also, unemployment and job instability have a positive and strong relationship with the possibility of divorce.

Therefore, research entitled "Sociological investigation of economic factors affecting the growth of divorce rate" shows that the most important factor in the growth of divorce rate is due to mismanagement at the macroeconomic level. Therefore, there is a relatively strong and inverse relationship between the increase in the divorce rate and the economic stability of families, and as economic problems increase, divorce grows.

Job instability of the head of the family and increasing and sudden inflations and income inequality are part of the economic factors affecting the growth of divorce. Another article entitled "Analysis of economic-social characteristics related to divorce in Iraq" emphasizes the positive relationship between unemployment and increasing the probability of divorce, and on the other hand, employment contributes to the stability and continuity of life together. "According to this research, having a job reduces the probability of experiencing divorce by 23%, but being unemployed or looking for a job increases the probability of being divorced by 51%, which is reduced to 39% by controlling other variables. Also, having income without work reduces the probability of divorce by 32%. Being in a poor socio-economic status increases the probability of divorce by 44% and by controlling other variables, this issue increases to 46%. Also, average socio-economic status increases the probability of divorce by 23%. According to the above researches, the economic events of 2018 and later led to the increasing growth of inflation, unfavorable job situation, wave of layoffs and economic recession and heavy inflation in the housing sector and gradually weakened the foundation of the family and increased the number of divorces in the last one or two years. In the end, the rise of the dollar and the heavy inflation that followed caused the final blow to the shaky body of the family economy, so that divorce reached its peak in the early months of this year.

Therefore, in this research, we try to measure the effect of three factors: unemployment, inflation and income inequality on the divorce rate in Iraq.Table 1 show the values of unemployment rate, inflation, Gini coefficient and the number of registered divorces people in Iraq for the years 2002 to 2023.

Table 1.
The values of unemployment rate, inflation, Gini coefficient divorces people in Iraq for the years 2001 to 2023.

Year	Unemployment (%)	Inflation (%)	Gini coefficient (%)	Divorces per 100 thousand
2002	13.1	15.8	41.91	67256
2003	11.6	15.6	41.56	72359
2004	10.4	15.2	40.01	63125
2005	11.2	10.4	40.02	84241
2006	11.1	11.9	40.0	94040
2007	10.3	18.4	40.45	99852
2008	10.2	25.4	38.56	110510
2009	12.0	10.8	39.41	125747
2010	13.8	12.4	38.11	137200
2011	12.1	21.5	37.41	142841
2012	12.0	30.5	38.33	150324
2013	10.3	34.7	39.40	155369
2014	10.6	15.6	39.91	163569
2015	10.8	11.9	39.54	163765
2016	12.2	9.0	40.46	181049
2017	11.9	9.6	39.84	182623
2018	11.8	31.2	40.93	179374
2019	10.1	41.2	39.92	178812
2020	9.6	47.1	40.06	187553
2021	9.2	46.2	39.38	203904
2022	9.1	45.8	38.77	204301
2023	8.2	40.7	36.14	202183

Now we intend to measure the impact of each of these three economic factors on the divorce rate by fitting the Poisson and negative binomial regression models.This task was done using R software and its results are listed in Table 2 and Table 3.

Table 2.
Results of fitting poisson regression model to data.

Coefficients	Estimate	Std. error	z value	Pr(>|z|)	AIC
Intercept	1.380e+01	1.841e-02	749.77	<2e-16 ***	21291
Unemployment	2.189e-02	5.909e-04	37.04	<2e-16 ***	
Inflation	1.368e-02	5.951e-05	229.89	<2e-16 ***	
GF	-6.354e-02	4.497e-04	-141.31	<2e-16 ***	

Table 3.
Results of fitting negative binomial regression model to data.

Coefficients	Estimate	Std. error	z value	Pr(>|z|)	AIC
Intercept	14.411	2.086	6.908	4.91e-12 ***	537.33
Unemployment	0.023	0.063	0.370	0.711	
Inflation	0.012	0.006	1.993	0.0463 *	
GF	-0.078	0.050	-1.567	0.117	

The following results can be expressed according to Table 2.

1) According to the p-value, all three variables are significant at the 0.01 error level, which means that each variable of unemployment rate, inflation and income inequality has an effect on divorces.
2) We consider the results of the above table in the row of unemployment rate. The regression coefficient is equal to 2.189e-02. Its positivity indicates a direct relationship between

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unemployment rate and divorces. In other words, the higher the unemployment rate, the higher the average of divorces.

3) The regression coefficient number for the inflation variable is equal to 1.368e-02. Its positivity indicates a direct relationship between inflation rate and divorces. In other words, the higher the inflation, the higher the higher the average of divorces.
4) The noteworthy point is that the regression coefficient number for the Gini coefficient variable is equal to -6.354e-02, which is a negative number. Its negativity indicates the inverse relationship between the Gini coefficient as an indicator of income inequality and divorce. In other words, the higher this index is, the lower the average number of divorces.

According to Table 3, it can be said that only the coefficient of the intercept and the coefficient of the inflation factor are significant, which means that among the three factors of unemployment, inflation and income inequality, only inflation has an effect on the number of divorces. It is worth noting that according to the AIC values, the negative binomial regression model has a better fit than the Poisson regression model because its AIC value is lower. Therefore, the results of Table 3 are preferable.

5. Summary and Conclusion

In this research, we seek to find the relationship between unemployment, inflation and income inequality and the average number of divorces in Iraq by using Poisson and negative binomial regression models. The results were deferent. The results ofPoissonregression model show that there is a significant relationship between the unemployment rate and the divorce rate, and with the increase in the unemployment rate, the average number of divorces increases. The results of this research on unemployment due to the existence of a significant positive relationship between the unemployment rate and divorce are similar to the results of most of the studies conducted abroad, and in fact, the experimental findings are a confirmation of the theoretical foundations used in this research. We also saw that the relationship between inflation rate and divorce is direct and significant.

The results of negative binomial regression modelshow thatonly inflation has an effect on the number of divorces.Both models show that the inflation factor is an influencing factor on the number of divorces.Stability of inflation can be a factor that, although it will reduce economic growth in the short term, but in the long term, it will have significant effects on economic growth, and as a result, we will have a reduction in divorce and social damage.

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