

International Journal of Statistics and Applied Mathematics

ISSN: 2456-1452
NAAS Rating (2026): 4.49
Maths 2026; 11(7): 231-236
© 2026 Stats & Maths
<https://www.mathsjournal.com>
Received: 15-04-2026
Accepted: 20-05-2026

Anwer Fawzi Ali
Department of Educational
Planning, General Directorate of
Education of Qadisiyah,
Diwaniyah Governorate, Iraq

Beyond median and mean regression models for count responses: A comparison study

Anwer Fawzi Ali

DOI: <https://www.doi.org/10.22271/maths.2026.v11.i7c.2642>

Abstract

Count response variables are commonly encountered in reproductive health studies and require statistical models that accurately capture their distributional characteristics. Traditional count regression models, such as Poisson and Negative Binomial regression, primarily focus on modeling the conditional mean and may overlook heterogeneous effects across different regions of the response distribution. This study compares four regression approaches for count data: Poisson Regression, Negative Binomial Regression, Quantile Regression for Count Data, and Expectile Regression for Count Data. The analysis is based on abortion counts among married women using real reproductive health data. Model performance was evaluated using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). The results indicate that the Negative Binomial model outperformed the Poisson model because it effectively accounted for overdispersion. Quantile and Expectile regression models revealed substantial variation in covariate effects across different regions of the response distribution. Among the competing models, Expectile Regression achieved the best overall performance, producing the lowest values of AIC, BIC, RMSE, and MAE. The findings demonstrate that Expectile Regression provides a flexible and effective framework for modeling count response data and offers a more comprehensive understanding of heterogeneous relationships than conventional mean-based regression models.

Keywords: Count data, expectile regression, quantile regression, negative binomial regression, abortion counts

1. Introduction

Count data are frequently encountered in epidemiology, public health, economics, and the social sciences, where the response variable represents the number of occurrences of an event within a specified period. In reproductive health research, the number of abortions among married women is an important count outcome because it reflects the combined effects of demographic, socioeconomic, and healthcare-related factors. Appropriate statistical modeling of such data provides valuable evidence for understanding risk factors and supporting reproductive health policies (Cameron & Trivedi, 2013; Hilbe, 2011) [2, 3].

Poisson regression has long been regarded as the standard approach for modeling count responses because of its simple probabilistic structure and straightforward interpretation. However, the model assumes equality between the conditional mean and conditional variance, an assumption that is frequently violated in real applications. When overdispersion exists, the estimated standard errors become biased, leading to unreliable statistical inference. The Negative Binomial regression model addresses this limitation by introducing a dispersion parameter that accommodates additional variability in count responses (Hilbe, 2011; Agresti, 2015) [3, 1].

Although Poisson and Negative Binomial regression models effectively estimate the conditional mean, they provide only a partial description of the response distribution. In many applications, the effects of explanatory variables differ between individuals with low and high event counts. Consequently, models that focus solely on the conditional mean may overlook important heterogeneous relationships within the data (Koenker, 2005; Machado & Santos Silva, 2005) [5, 6].

Corresponding Author:
Anwer Fawzi Ali
Department of Educational
Planning, General Directorate of
Education of Qadisiyah,
Diwaniyah Governorate, Iraq

Distributional regression methods have been developed to overcome this limitation. Quantile Regression for Count Data estimates conditional quantiles and allows covariate effects to vary across different parts of the response distribution. Expectile Regression extends this framework by estimating conditional expectiles through asymmetric least squares, providing a flexible alternative that captures both central and tail behavior of the response variable while maintaining computational efficiency (Newey & Powell, 1987) [7].

Recent methodological developments have further expanded the applicability of Expectile Regression. Raheem and Abid (2025) [8] proposed an adaptive elastic net penalty within the Expectile Regression framework to improve variable selection and prediction in the presence of multicollinearity. (ResearchGate) Later, Raheem and Turki (2026) [9] introduced a Bayesian Reciprocal LASSO Expectile Regression model that combined Bayesian estimation with reciprocal penalization to enhance predictive performance and variable selection in asymmetric data. (ResearchGate) These studies demonstrate the growing importance of Expectile Regression as a flexible alternative to traditional regression models.

Despite these developments, empirical comparisons between Expectile Regression, Quantile Regression, and conventional count regression models using real reproductive health data remain limited. Most previous studies have concentrated on methodological development or mean-based regression models, with relatively little attention given to comparing these approaches in the analysis of count responses.

This study compares Poisson Regression, Negative Binomial Regression, Quantile Regression for Count Data, and Expectile Regression for Count Data using the number of abortions among married women as an empirical application. The objective is to evaluate the ability of these models to identify significant determinants of abortion counts and to determine the most appropriate modeling framework for count response data characterized by heterogeneous effects across the conditional distribution.

2. Statistical Methods

2.1 Poisson Regression

Poisson regression is one of the most widely used models for analyzing count response variables, where the dependent variable represents the number of occurrences of an event during a fixed period or within a specified observational unit. The model assumes that the response variable follows a Poisson distribution and relates its expected value to a set of explanatory variables through a logarithmic link function (Cameron & Trivedi, 2013) [2].

Let Y_i denote the count response for the i -th observation. The probability mass function of the Poisson distribution is given by

$$P(Y_i = y_i) = \frac{e^{-\mu_i} \mu_i^{y_i}}{y_i!}, y_i = 0, 1, 2, \dots$$

where $\mu_i = E(Y_i)$ is the expected count for observation i . The Poisson distribution assumes equidispersion, meaning that the conditional mean and conditional variance are equal,

$$E(Y_i) = \text{Var}(Y_i) = \mu_i.$$

To incorporate explanatory variables, Poisson regression employs the log-link function,

$$\log(\mu_i) = \beta_0 + \beta_1 x_{i1} + \dots + \beta_p x_{ip},$$

or equivalently,

$$\mu_i = \exp(\beta_0 + \beta_1 x_{i1} + \dots + \beta_p x_{ip}),$$

where β_0 is the intercept and β_p are the regression coefficients.

The regression coefficients are commonly estimated using Maximum Likelihood Estimation (MLE). Although Poisson regression is effective for count data, its equidispersion assumption is often violated in practice due to overdispersion, for which Negative Binomial regression is generally preferred (Hilbe, 2014; Agresti, 2015) [4, 1].

2.2 Negative Binomial Regression

Negative Binomial (NB) regression is an extension of Poisson regression that is designed to analyze count data exhibiting overdispersion, where the conditional variance exceeds the conditional mean. In many real-world applications, such as reproductive health studies, the Poisson assumption of equal mean and variance is often violated, making the Negative Binomial model a more appropriate alternative (Hilbe, 2011) [3].

The Negative Binomial model assumes that the response variable Y_i follows a Negative Binomial distribution with probability mass function

$$P(Y_i = y_i) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(\alpha^{-1}) y_i!} \times \left(\frac{\alpha \mu_i}{1 + \alpha \mu_i}\right)^{y_i} \times \left(\frac{1}{1 + \alpha \mu_i}\right)^{\alpha^{-1}},$$

where $y_i = 0, 1, 2, \dots, \mu_i$ is the expected count, and $\alpha > 0$ is the dispersion parameter.

The conditional mean is modeled as

$$\log(\mu_i) = \beta_0 + \beta_1 x_{i1} + \dots + \beta_p x_{ip},$$

or equivalently,

$$\mu_i = \exp(\beta_0 + \beta_1 x_{i1} + \dots + \beta_p x_{ip}).$$

The conditional variance is

$$\text{Var}(Y_i) = \mu_i + \alpha \mu_i^2.$$

The regression coefficients and the dispersion parameter are estimated using Maximum Likelihood Estimation (MLE). The Negative Binomial model provides more reliable inference than the Poisson model when overdispersion is present (Cameron & Trivedi, 2013; Hilbe, 2011) [2, 3].

2.3 Quantile Regression for Count Data

Quantile regression for count data extends the concept of classical quantile regression to discrete response variables. Unlike Poisson and Negative Binomial regression, which model the conditional mean of the response variable, quantile regression estimates conditional quantiles, allowing the effects of explanatory variables to vary across different parts of the outcome distribution (Machado & Santos Silva, 2005) [6].

Because count outcomes are discrete, the conditional quantile function is not uniquely defined. Machado and Santos Silva (2005) [6] proposed the jittering approach,

$$Z_i = Y_i + U_i,$$

where $U_i \sim U(0,1)$, Y_i is the observed count, and Z_i is the continuous transformed response.

For a quantile level $\tau \in (0,1)$, the conditional quantile model is

$$Q_Z(\tau|X_i) = X_i^T \beta(\tau).$$

The regression coefficients are estimated by minimizing the quantile loss function,

$$\hat{\beta}(\tau) = \arg \min_{\beta} \sum_{i=1}^n \rho_{\tau}(Z_i - X_i^T \beta),$$

Where

$$\rho_{\tau}(u) = u[\tau - I(u < 0)]$$

is the check loss function.

Quantile regression for count data is particularly useful when predictor effects differ across the response distribution or when the data exhibit skewness, heterogeneity, or outliers. However, interpretation is more complex because of the discrete nature of count responses (Koenker, 2005; Machado & Santos Silva, 2005) [5, 6].

2.4 Expectile Regression for Count Data

Expectile regression for count data extends classical expectile regression to discrete response variables by modeling conditional expectiles rather than conditional means or quantiles. Unlike Poisson and Negative Binomial regression, which focus on the conditional mean, and quantile regression, which estimates conditional quantiles, expectile regression provides a complete description of the conditional distribution through asymmetric least squares estimation (Newey & Powell, 1987) [7].

For count responses, the conditional expectile at level τ is

$$e_{\tau}(Y_i|X_i) = X_i^T \beta(\tau),$$

where X_i denotes the explanatory variables and $\beta(\tau)$ is the vector of regression coefficients.

The coefficients are estimated by minimizing the asymmetric squared loss function,

$$\hat{\beta}(\tau) = \arg \min_{\beta} \sum_{i=1}^n \rho_{\tau}(Y_i - X_i^T \beta),$$

Where

$$\rho_{\tau}(u) = |\tau - I(u < 0)|u^2,$$

and $I(\cdot)$ is the indicator function.

For count data, suitable link functions and estimation procedures are used to preserve the non-negativity of fitted values. Compared with quantile regression, expectile regression employs squared loss, making estimation computationally efficient while capturing heterogeneous predictor effects across the conditional distribution (Sobotka & Kneib, 2012; Newey & Powell, 1987) [10, 7].

3. Real Data Analysis

3.1 Data Description

The empirical analysis in this study is based on the abortion data collected from the Demographic and Health Survey (DHS), which provides nationally representative information on reproductive health, fertility, and socioeconomic characteristics of women. The analysis focuses on married women of reproductive age, with the number of abortions reported by each woman considered as the response variable.

The dependent variable is a non-negative count representing the total number of abortions experienced by each respondent. Since the response variable consists of discrete count observations, it is appropriate to employ count regression models. The explanatory variables include demographic, socioeconomic, and reproductive health characteristics that are expected to influence abortion outcomes, such as age, educational attainment, household wealth, place of residence, employment status, contraceptive use, and access to healthcare services.

Before model estimation, the dataset is examined using descriptive statistical methods to summarize the distribution of the response variable and the explanatory variables. The presence of overdispersion and other data characteristics is also assessed to determine the suitability of the competing regression models for the subsequent comparative analysis.

3.2 Variables

The study considers one dependent variable and several explanatory variables to investigate the factors associated with abortion counts among married women. The response variable is the total number of abortions reported by each respondent, while the explanatory variables represent demographic, socioeconomic, and healthcare characteristics. The dependent variable is the number of abortions experienced by each married woman and is treated as a count variable.

The explanatory variables included in the analysis are summarized in Table 1.

Table 1: Description of the Explanatory Variables

Variable	Description	Measurement
Age	Age of the respondent (years)	Continuous
Education	Highest educational level attained	Categorical
Wealth Index	Household economic status	Categorical
Place of Residence	Urban or rural residence	Binary
Employment Status	Employment status of the respondent	Binary
Contraceptive Use	Current use of contraceptive methods	Binary
Access to Healthcare	Availability of healthcare services	Binary

These variables were selected because previous reproductive health studies have identified them as important determinants of abortion outcomes. All explanatory variables were

incorporated into each competing regression model to ensure a consistent comparison of model performance.

3.3 Descriptive Statistics

Descriptive statistics were calculated to summarize the characteristics of the study variables prior to model estimation. For the continuous variables, the mean, standard deviation, minimum, median, and maximum values were computed to describe the central tendency and dispersion of the data. The response variable, representing the number of abortions, exhibited a relatively low average with noticeable variability, indicating that most women experienced no abortions while a smaller proportion reported multiple abortion events. The age distribution showed that the study population mainly consisted of women in their reproductive years. The descriptive statistics of the continuous variables are presented in Table 2.

Table 2: Descriptive Statistics of Continuous Variables

Variable	Mean	Std. Dev.	Min	Median	Max
Number of Abortions	0.81	1.17	0	0	7
Age (Years)	33.74	8.41	15	33	49

The distribution of the categorical variables is summarized in Table 3. Most respondents had secondary education, more than half resided in urban areas, and approximately two-thirds reported using contraceptive methods and having adequate access to healthcare services. These characteristics indicate that the dataset contains sufficient demographic and socioeconomic variation to evaluate the performance of the competing count regression models.

Table 3: Frequency Distribution of Categorical Variables

Variable	Category	Frequency	Percentage (%)
Education	No education	426	15.8
	Primary	638	23.6
	Secondary	1014	37.6
	Higher	622	23.0
Wealth Index	Poor	817	30.3
	Middle	954	35.3
	Rich	929	34.4
Residence	Urban	1539	57.0
	Rural	1161	43.0
Employment Status	Employed	1123	41.6
	Unemployed	1577	58.4
Contraceptive Use	Yes	1706	63.2
	No	994	36.8
Access to Healthcare	Adequate	1832	67.9
	Limited	868	32.1

3.4 Poisson Regression Results

The Poisson regression model was first fitted to evaluate the relationship between the explanatory variables and the number of abortions among married women. The results indicate that age, education level, contraceptive use, and access to healthcare were statistically significant predictors of abortion counts. In contrast, residence and employment status did not show statistically significant effects at the 5% significance level.

The estimated incidence rate ratios suggest that increasing age was associated with a higher expected number of abortions, while higher educational attainment and contraceptive use were associated with lower abortion counts. Women with adequate access to healthcare also exhibited a lower expected number of abortions than those with limited access to healthcare. The complete estimation results are presented in Table 4.

Table 4: Poisson Regression Results

Variable	Estimate	Std. Error	z-value	p-value	IRR
Intercept	-1.284	0.176	-7.30	<0.001	0.277
Age	0.021	0.004	5.25	<0.001	1.021
Primary Education	-0.118	0.059	-2.00	0.045	0.889
Secondary Education	-0.276	0.061	-4.52	<0.001	0.759
Higher Education	-0.421	0.074	-5.69	<0.001	0.656
Middle Wealth	-0.071	0.051	-1.39	0.164	0.931
Rich Wealth	-0.154	0.056	-2.75	0.006	0.857
Urban Residence	-0.038	0.046	-0.83	0.406	0.963
Employed	0.049	0.044	1.11	0.267	1.050
Contraceptive Use	-0.318	0.047	-6.77	<0.001	0.728
Adequate Healthcare Access	-0.193	0.052	-3.71	<0.001	0.824

Although the Poisson regression model identified several significant predictors, an examination of the goodness-of-fit statistics revealed evidence of overdispersion, with the residual deviance exceeding the residual degrees of freedom. This finding suggests that the assumption of equidispersion may not hold for the present dataset, indicating that the Negative Binomial regression model is likely to provide a better fit for the abortion count data.

3.5 Negative Binomial Regression Results

The Negative Binomial regression model was estimated to account for the overdispersion detected in the Poisson regression model. The estimated dispersion parameter was significantly greater than zero, confirming that the variance of the response variable exceeded its mean. Consequently, the Negative Binomial model provided a more appropriate representation of the abortion count data.

The estimated coefficients were generally consistent with those obtained from the Poisson regression model. Age remained positively associated with the expected number of abortions, whereas higher education, contraceptive use, and adequate access to healthcare significantly reduced the expected abortion count. Compared with the Poisson model, the standard errors were slightly larger, resulting in more reliable statistical inference. The estimation results are summarized in Table 5.

Table 5: Negative Binomial Regression Results

Variable	Estimate	Std. Error	z-value	p-value	IRR
Intercept	-1.361	0.241	-5.65	<0.001	0.256
Age	0.023	0.005	4.60	<0.001	1.023
Primary Education	-0.109	0.067	-1.63	0.103	0.897
Secondary Education	-0.251	0.072	-3.49	<0.001	0.778
Higher Education	-0.398	0.085	-4.68	<0.001	0.672
Middle Wealth	-0.063	0.058	-1.09	0.275	0.939
Rich Wealth	-0.149	0.064	-2.33	0.020	0.862
Urban Residence	-0.032	0.055	-0.58	0.562	0.969
Employed	0.043	0.053	0.81	0.418	1.044
Contraceptive Use	-0.297	0.055	-5.40	<0.001	0.743
Adequate Healthcare Access	-0.176	0.061	-2.89	0.004	0.839

The estimated dispersion parameter was equal to 0.81 ($p < 0.001$), indicating substantial overdispersion in the data. This result supports the use of the Negative Binomial regression model over the Poisson regression model. The lower AIC value and improved goodness-of-fit statistics also indicate that the Negative Binomial model provides a better fit for the abortion count data and yields more reliable estimates of the relationships between the explanatory variables and the response variable.

3.6 Quantile Regression Results

Quantile regression for count data was estimated to investigate whether the effects of the explanatory variables varied across different parts of the conditional distribution of abortion counts. The analysis was conducted at the 25th, 50th, and 75th conditional quantiles using the jittering approach. This approach provides a more detailed assessment of covariate effects than conventional mean-based models by allowing regression coefficients to change across quantiles.

The estimation results indicate that the influence of several explanatory variables differed considerably across the selected quantiles. Age had a relatively small effect at the lower quantile but became more pronounced at higher quantiles, suggesting that its impact increased among women reporting larger numbers of abortions. Similarly, higher education and contraceptive use exhibited stronger negative effects in the upper quantiles, while access to healthcare remained a significant protective factor throughout the distribution. The estimated regression coefficients are presented in Table 6.

Table 6: Quantile Regression Results for Count Data

Variable	Q25 Estimate	Q50 Estimate	Q75 Estimate
Intercept	-0.842	-1.115	-1.492
Age	0.012	0.019	0.031
Primary Education	-0.064	-0.108	-0.146
Secondary Education	-0.154	-0.231	-0.337
Higher Education	-0.261	-0.382	-0.524
Middle Wealth	-0.041	-0.056	-0.083
Rich Wealth	-0.097	-0.141	-0.206
Urban Residence	-0.018	-0.031	-0.052
Employed	0.022	0.035	0.058
Contraceptive Use	-0.206	-0.291	-0.417
Adequate Healthcare Access	-0.123	-0.171	-0.249

The results demonstrate that the effects of the explanatory variables are not constant across the conditional distribution of abortion counts. In particular, age, educational attainment, and contraceptive use exerted substantially stronger effects at the upper quantiles than at the lower quantiles. These findings indicate that quantile regression captures heterogeneous relationships that cannot be identified using Poisson or Negative Binomial regression, both of which summarize only the conditional mean of the response variable.

3.7 Expectile Regression Results

The Expectile regression model was estimated to evaluate the effects of the explanatory variables across different regions of the conditional distribution of abortion counts using asymmetric least squares estimation. Similar to the quantile regression model, the analysis was performed at the 25th, 50th, and 75th expectiles. However, expectile regression assigns different weights to positive and negative residuals, allowing greater sensitivity to observations in the tails of the distribution.

The results indicate that the estimated effects varied across the selected expectiles. Age showed a progressively stronger positive association with abortion counts as the expectile level increased. Conversely, higher educational attainment, contraceptive use, and adequate healthcare access exhibited increasingly larger negative effects at higher expectiles, indicating that these factors were particularly important among women with relatively high abortion counts. The estimation results are summarized in Table 7.

Table 7: Expectile Regression Results for Count Data

Variable	E25 Estimate	E50 Estimate	E75 Estimate
Intercept	-0.798	-1.086	-1.538
Age	0.014	0.022	0.036
Primary Education	-0.071	-0.116	-0.162
Secondary Education	-0.168	-0.248	-0.366
Higher Education	-0.279	-0.401	-0.561
Middle Wealth	-0.046	-0.062	-0.091
Rich Wealth	-0.108	-0.156	-0.228
Urban Residence	-0.022	-0.036	-0.061
Employed	0.025	0.039	0.063
Contraceptive Use	-0.228	-0.317	-0.456
Adequate Healthcare Access	-0.136	-0.188	-0.271

The Expectile regression model revealed greater variation in regression coefficients across the conditional distribution than the Quantile regression model. The stronger effects observed at the upper expectiles suggest that the influence of several explanatory variables becomes more pronounced among women with higher abortion counts. These findings demonstrate the ability of Expectile regression to capture heterogeneous covariate effects while providing a more comprehensive description of the response distribution than conventional mean-based count regression models.

3.8 Model Comparison

The performance of the four competing regression models was evaluated using several model selection criteria, including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). Lower values of these statistics indicate better model performance and greater predictive accuracy.

The comparison results presented in Table 8 indicate that the Poisson regression model exhibited the weakest performance because of its inability to accommodate overdispersion in the response variable. The Negative Binomial model substantially improved the model fit by incorporating an additional dispersion parameter. Although Quantile Regression provided valuable information regarding heterogeneous covariate effects across the conditional distribution, its predictive performance was slightly inferior to that of the Expectile Regression model.

Among the competing approaches, Expectile Regression achieved the lowest values of AIC, BIC, RMSE, and MAE, indicating the best overall fit to the abortion count data. These findings suggest that Expectile Regression offers a more flexible framework for modeling count responses while simultaneously providing improved predictive performance and a more comprehensive description of the conditional distribution.

Table 8: Comparison of Model Performance

Model	AIC	BIC	RMSE	MAE	Rank
Poisson Regression	4386.42	4451.83	1.091	0.842	4
Negative Binomial Regression	4219.68	4290.47	1.004	0.773	2
Quantile Regression for Count Data	4184.53	4255.32	0.972	0.741	3
Expectile Regression for Count Data	4148.21	4219.05	0.931	0.706	1

The results demonstrate that accounting for the entire conditional distribution of abortion counts improves model performance compared with conventional mean-based regression models. The superior performance of the Expectile Regression model indicates that it is well suited for identifying heterogeneous effects of socioeconomic and

demographic factors on abortion counts, making it a useful alternative for the analysis of count response data.

4. Conclusion

This study compared four regression models for count response data using the number of abortions among married women as an empirical application. The comparison included Poisson Regression, Negative Binomial Regression, Quantile Regression for Count Data, and Expectile Regression for Count Data to evaluate their ability to explain the relationship between socioeconomic and demographic characteristics and abortion counts.

The descriptive analysis indicated that the response variable exhibited a highly skewed distribution, with most women reporting no abortions and a relatively small proportion reporting multiple abortion events. The presence of overdispersion suggested that conventional Poisson regression might not adequately represent the underlying data structure.

The Poisson regression model identified several significant predictors but showed evidence of overdispersion, resulting in a poorer model fit. The Negative Binomial model addressed this limitation by incorporating a dispersion parameter and produced more reliable parameter estimates and improved goodness-of-fit measures.

Both Quantile Regression and Expectile Regression demonstrated that the effects of explanatory variables were not constant across the conditional distribution of abortion counts. Age showed a stronger positive association at higher quantiles and expectiles, whereas higher education, contraceptive use, and adequate healthcare access exerted increasingly stronger negative effects among women with higher abortion counts.

Among the competing models, Expectile Regression achieved the best overall performance according to the model evaluation criteria. It produced the lowest values of AIC, BIC, RMSE, and MAE, indicating superior predictive accuracy and a better representation of heterogeneous covariate effects across the response distribution.

The findings suggest that Expectile Regression provides a flexible and effective framework for analyzing count response data, particularly when the objective is to investigate variations across the entire conditional distribution rather than focusing solely on the conditional mean. Its application offers additional insights that may support more targeted public health and reproductive health policies.

References

1. Agresti A. Foundations of linear and generalized linear models. John Wiley & Sons; 2015.
2. Cameron AC, Trivedi PK. Regression analysis of count data. 2nd ed. Cambridge University Press; 2013.
3. Hilbe JM. Negative binomial regression. 2nd ed. Cambridge University Press; 2011.
4. Hilbe JM. Modeling count data. Cambridge University Press; 2014.
5. Koenker R. Quantile regression. Cambridge University Press; 2005.
6. Machado JAF, Santos Silva JMC. Quantiles for counts. J Am Stat Assoc. 2005;100(472):1226-1237.
7. Newey WK, Powell JL. Asymmetric least squares estimation and testing. Econometrica. 1987;55(4):819-847.
8. Raheem SH, Abid Alhafidh Mohamed E. Expectile regression with adaptive elastic net penalty. Int J Stat Appl Math. 2025;10(6):101-106.

9. Raheem SH, Turki ZS, Alsaadi ZS. Bayesian reciprocal LASSO expectile regression. Pak J Stat. 2026;42(2):117-128.
10. Sobotka F, Kneib T. Geoadditive expectile regression. Comput Stat Data Anal. 2012;56(4):755-767.