computer sciences and mathematics forum

MDPI

Proceeding Paper

Discrete Multivariate Copula-Based Model Fitting to Longitudinal Count Data †

Yuvraj Sunecher [1,*], Naushad Mamode Khan [2] and Vandna Jowaheeer [3]

[1] Department of Accounting, Finance and Economics, University of Technology Mauritius, Port Louis 11134, Mauritius
[2] Department of Economics and Statistics, University of Mauritius, Réduit 80837, Mauritius; n.mamodekhan@uom.ac.mu
[3] Department of Mathematics, University of Mauritius, Réduit 80837, Mauritius; vandnaj@uom.ac.mu
* Correspondence: ysunecher@utm.ac.mu
† Presented at the 12th International Conference on Time Series and Forecasting, Canaria, Spain, 15–17 July 2026.

Abstract

In this paper, we develop the Poisson Integer-Valued Autoregressive (INAR) and negative binomial (NB) INAR models for longitudinal count data. As for the estimation of model parameters, we use the generalized estimating equation (GEE), generalized quasi-likelihood (GQL) and maximum likelihood (ML) estimation methods. The correlation parameters are estimated using the multivariate copula method. Through simulation studies, we compare the performance of GQL, GEE and ML. An application on number of seizures is also presented.

Keywords: longitudinal; copula; GQL; GEE; ML

1. Introduction

Longitudinal data comprise repeated outcomes measured over a specified number of time points for different independent subjects. This implies that the sequence of observations for a particular subject is inter-related and this relation can be borne through some forms of auto-correlation structures that might be known or unknown [1–6] or through some latent random effects [7,8]. However, most discussions occurred in the literature favour the usage of serial auto-correlation structures to model the longitudinal data, in particular, count data.

In the event the exact auto-correlation structure in the longitudinal count data is known, the stochastic model and likelihood equation can comfortably be constructed. Otherwise, Liang and Zeger [9] proposed a working auto-correlation structure to mimic the exact structure of the longitudinal series and implemented a generalized estimating equation (GEE) approach to estimate the model parameters. The working structures include the auto-regressive, moving average and equicorrelation structures. The GEE has the same structure as the quasi-likelihood function in Wedderburn [10] and the likelihood estimating function from the exponential dispersion family, comprising the gradient, covariance matrix and score vector. Since the introduction of the GEE approach, several authors, in particular, Prentice and Zhao [11], Fitzmaurice and Laird [12], Qu and Lindsay [13,14] and Qu and Song [15], proposed alternative representations of the GEE approach and the working structures in pursuit of obtaining more efficient parameter estimates. However, Crowder [16] identified deficiencies in the GEE approach in some context where the

Check for updates

Academic Editors: Olga Valenzuela, Fernando Rojas, Luis Javier Herrera, Hector Pomares and Ignacio Rojas

Published: 25 September 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

auto-correlation parameters cannot be estimated. On the other hand, Sutradhar and Das [1] noticed that the GEE based on the independence working structure may result in more efficient estimates than GEE based on other aforementioned working structures. Thus, Sutradhar and Das [1] proposed another general auto-correlation structure that can accommodate the common working structures and is more robust. This approach was termed the generalized quasi-likelihood approach (GQL). Sutradhar and Das [1] demonstrated that the GQL provides more efficient and less biased estimates than the GEE based on the different working structures.

However, in Jowaheer and Sutradhar [17], we noticed that the GQL approach may still involve some extra working structures such as the multivariate normality assumption in the presence of cross product scores. In particular, this happens where the distribution of the longitudinal outcome is not single parameterized. In addition, the GQL do not provide any information criteria to assess the fitting of the longitudinal model. Hence, be it the working or robust auto-correlation structure, the application of the quasi-likelihood method as an inferential procedure in longitudinal setting is quite restrictive. To overcome these shortcomings, this paper proposes a generalized multivariate discrete distribution for modelling the longitudinal counts using copula function. Hence, the formulation of a likelihood equation and establishing the fitting criteria are most feasible.

The organization of the paper is as follows: In the next section, the multivariate discrete distribution based from copula constructor is presented. Section 3 presents the simulation study with the generation of repeated time series data from the integer-valued auto-regressive process in Mckenzie [18]. In the same section, we apply both GQL and likelihood approaches to compare the consistency and efficiency of the estimators. In Section 4, we apply the multivariate model to the analysis of the epileptic seizure counts. The conclusion is presented in the last section.

2. Methods

Firstly, we introduce some useful notations. Let Y_{it} be the random variable describing the longitudinal count observation for the i^{th} subject at the t^{th} time point, where $i = 1, 2, 3, \ldots, N$ and $t = 1, 2, 3, \ldots, T$. $X_{it,}$ is the vector of explanatory variables, such that, $X_{it} = \left[X_{it,1}, X_{it,2}, \ldots, X_{it,p}\right]^T$ and assuming the $E(Y_{it}) = \mu_{it} = \exp(X_{it}^T\beta)$, where $\beta = \left[\beta_1, \beta_2, \ldots, \beta_p\right]^T$. Similarly, $Y_{i,.}$ and $\mu_{i,.}$ denote the $T \times 1$ vectors $Y_i = \left[Y_{i1}, Y_{i2}, \ldots, Y_{iT}\right]^T$ and $\mu_i = \left[\mu_{i1}, \mu_{i2}, \ldots, \mu_{iT}\right]^T$.

We recall earlier that in the non-specification of the exact auto-correlation structure, researchers [9,19] considered the quasi-likelihood method to estimate the regression and other model parameters, based on the working or robust auto-correlation structure specification. This was forcibly due to the non-availability of the joint distribution of Y_i, and this also forms the main motivation of this paper. Alternatively, this paper proposes to specify the multivariate discrete distribution $f(Y_i)$ using the copula method described in Nikoloulopoulos, Aristidis and Karlis [20]. The copula has the additional advantage of separating the marginals and hence offers the flexibility of specifying a multivariate distribution with different marginal probability functions. The next question is how far the copula captures the serial dependence among the repeated observations. In the literature, in the context of the univariate time series, Nikoloulopoulos, Aristidis and Karlis [20] demonstrated that the usage of copulas offers much flexibility in modelling all forms of serial dependence.

By definition, a T-variate copula $C(u_1, \ldots, u_T)$ is a cumulative distribution function (cdf) with uniform marginals on the interval (0, 1) [20]. If $F_{ij}(y_{ij})$ is the cdf of a univariate random variable Y_{ij}, then $C(F_{i1}(y_{i1}), \ldots, F_{iT}(y_{iT}))$ is an m-variate distribution for $Y_i = (Y_{i1}, \ldots, Y_{iT})^T$ with marginal distributions F_{ij}, $j = 1, \ldots, T$. On the other hand, if H

is a T-variate cdf with univariate marginal cdfs $F_{i1}, \ldots, F_{iT}$, then there exists an T-variate copula C such for all $y_i = (y_{i1}, \ldots, y_{iT})^T$,

$$H(y_{i1}, \ldots, y_{iT}) = C(F_{i1}(y_{i1}), \ldots, F_{iT}(y_{iT})). \tag{1}$$

For the discrete integer-valued random vector $(Y_{i1}, \ldots, Y_{iT})^T$ with marginals $F_{i1}, \ldots, F_{iT}$ and joint cdf given by the copula representation $H(y_{i1}, \ldots, y_{iT}) = C(F_{i1}(y_{i1}), \ldots, F_{iT}(y_{iT}))$, let $c = (c_1, \ldots, c_T)$ be vertices where each c_k is equal to either y_{ik} or $y_{i,k-1}, k = 1, \ldots, T$. The joint pmf h(·) of the discrete random variables $Y_{i1}, \ldots, Y_{iT}$ is given by

$$h(y_{i1}, y_{i2}, \ldots, y_{iT}) = \sum sgn(c) C(F_{i1}(c_{i1}), \ldots, F_{iT}(c_{iT})), \tag{2}$$

where the sum is taken over all vertices c and sgn(c) is given by (see [20]),

$$sgn(c) = \begin{cases} 1, & \text{if } c_k = y_k - 1 \text{ for an even number of } k\text{'s}, \\ -1, & \text{if } c_k = y_k - 1 \text{ for an odd number of } k\text{'s} \end{cases} \tag{3}$$

In this paper, we consider a 4-variate Frank copula given by

$$\begin{aligned} C_\theta(u_1, u_2, u_3, u_4) = &-\frac{1}{\theta} - \frac{1}{\theta}\left(\frac{(\exp(-u_1\theta) - 1)(\exp(-u_2\theta) - 1)}{(\exp(-\theta) - 1)}\right) \\ &- \frac{1}{\theta}\left(\frac{(\exp(-u_3\theta) - 1)(\exp(-u_4\theta) - 1)}{(\exp(-\theta) - 1)}\right) \end{aligned} \tag{4}$$

where $0 \leq u_1, u_2, u_3, u_4 \leq 1, \theta \in (-\infty, \infty) - \{0\}$.

This paper uses this mechanism to construct the joint distribution of Y_i, and thereon applies the maximum likelihood conditional (MLC) approach to estimate the model parameters. The ML approach looks statistically more robust as compared to the 'working' estimation approaches, as described in Liang and Zeger [9] and Qu and Lindsay [13,14]. Interestingly, we will compare the efficiency of estimators under these two classes of techniques in the next section on a simulation study.

3. Simulation

In the simulation part, we assume a discrete-valued auto-regressive process (INAR) from Mckenzie [18] to generate longitudinal count observations with Poisson (Poisson INAR) and negative binomial marginals (NB INAR).

3.1. Poisson-INAR Longitudinal Model

We start with the Poisson-INAR process is given as:

$$Y_{it} = \rho \circ Y_{i,t-1} + R_{it} \tag{5}$$

for $i = 1, 2, 3, \ldots, I$ and $t = 1, 2, 3, \ldots, T$. R_{it} is Poisson with mean $(1 - \rho)\mu_i$, where $\mu_i = \exp(\beta_0 + \beta_1 log(i))$ and $\rho \circ Y_{i,t-1} = \sum_{s=0}^{Y_{i,t-1}} b_s(\rho)$. The $\{b_s(.)\}$ is the sequence of identically and independently Bernoulli distributed random variables with probability ρ, for $0 < \rho < 1$. Equation (5) consists of three unknown parameters (β_0, β_1, ρ) to be estimated. We consider the three inferential procedures to estimate these parameters: GEE from Liang and Zeger [9] with the auto-regressive working structure, the GQL approach from Jowaheer and Sutradhar [17] and the multivariate copula-based likelihood approach discussed in Section 2. We assume the population parameters are $\beta_0 = 1, \beta_1 = 0.6, \rho = 0.8$ with $T = 4$ and generate longitudinal data for $I = 30, 60, 100$.

Table 1 displays the mean estimates of the regression and correlation parameters and the values in the brackets (.) represent their respective standard errors. It can be observed that the model estimates are consistent and as the time point increases, the standard errors listed in brackets decrease, confirming the asymptotic performance of the model estimates. However, the estimates of the MLC estimation method are better than GQL and GEE.

Table 1. Estimates of the model parameters for Poisson INAR.

I	T	Method	β_0	β_1	ρ_1	ρ_2	ρ_3
30	3	GEE	0.9812	0.5492	0.7652	0.5302	0.4114
			(0.1201)	(0.1332)			
		GQL	0.9855	0.5644	0.7773	0.6419	0.4504
			(0.1015)	(0.1201)			
		MLC	0.9860	0.5712	0.7798	0.6648	0.4210
			(0.0896)	(0.0858)	(0.0649)	(0.0650)	(0.0726)
	4	GEE	0.9830	0.5404	0.7647	0.6104	0.4587
			(0.1253)	(0.1391)			
		GQL	0.9814	0.5598	0.7764	0.6411	0.4538
			(0.1085)	(0.1292)			
		MLC	0.9870	0.5794	0.7804	0.5927	0.4480
			(0.0807)	(0.0855)	(0.0783)	(0.0649)	(0.0686)
60	3	GEE	0.9827	0.5559	0.7766	0.5530	0.4670
			(0.1166)	(0.1104)			
		GQL	0.9884	0.5738	0.7802	0.6753	0.4221
			(0.0969)	(0.1090)			
		MLC	0.9911	0.5875	0.7839	0.6346	0.4509
			(0.0780)	(0.0696)	(0.0602)	(0.0532)	(0.0641)
	4	GEE	0.9835	0.5532	0.7770	0.5915	0.4772
			(0.1157)	(0.1132)			
		GQL	0.9869	0.5677	0.7806	0.6814	0.4774
			(0.0905)	(0.1181)			
		MLC	0.9854	0.5862	0.7860	0.6226	0.5010
			(0.0780)	(0.0722)	(0.0711)	(0.0543)	(0.0520)
100	3	GEE	0.9808	0.5687	0.7766	0.5617	0.4851
			(0.1053)	(0.1062)			
		GQL	0.9982	0.5806	0.7916	0.6479	0.4960
			(0.0710)	(0.0721)			
		MLC	0.9985	0.5913	0.7901	0.6658	0.4729
			(0.0485)	(0.0476)	(0.0594)	(0.0340)	(0.0438)
	4	GEE	0.9885	0.5616	0.7836	0.5627	0.4600
			(0.1035)	(0.0946)			
		GQL	0.9961	0.5832	0.7951	0.6613	0.4577
			(0.0720)	(0.0888)			

https://doi.org/10.3390/cmsf2026016010

Table 1. *Cont.*

I	T	Method	β_0	β_1	ρ_1	ρ_2	ρ_3
		MLC	0.9945	0.5968	0.7980	0.6485	0.5239
			(0.0531)	(0.0555)	(0.0610)	(0.0434)	(0.0479)

3.2. Negative Binomial INAR Model

Marginally, y_{it} has the negative binomial distribution with probability mass function

$$f(y_{it}) = \frac{\Gamma(c^{-1} + y_{it})}{\Gamma(c^{-1})y_{it}!}(\frac{1}{1 + c\theta_{it}})^{c^{-1}}(\frac{c\theta_{it}}{1 + c\theta_{it}})^{y_{it}} \quad (6)$$

i.e.,

$$y_{it} \sim \text{NeBin}(1/c, c\theta_{it}) \quad (7)$$

where c is the over-dispersion parameter and the expectation and variance are given by

$$E(Y_{it}) = \theta_{it} = \exp(x_{it}^T\beta), Var(Y_{it}) = \theta_{it} + c\theta_{it}^2 \quad (8)$$

where $c > 0$.

Let $y_{i,t-1} \sim \text{NeBin}(1/c, c\theta_{i1})$ and $d_{it} \sim \text{NeBin}\{(1-\rho)/c, c\theta_{i1}\}$ where $0 < \rho < 1$. $y_{i,t-1}$ and d_{it} are independent. The relation between y_{it} and $y_{i,t-1}$ is given by

$$y_{it} = \alpha_{it} * y_{i,t-1} + d_{it} \quad (9)$$

where $0 < \alpha_{it} < 1$ and $\alpha_{it} \sim \text{Beta}(\frac{\rho}{c}, \frac{1-\rho}{c})$.

From Table 2, it can be observed that again the model estimates are consistent and as the time point increases, the standard errors listed in brackets decrease. The estimates of the MLC are better than GQL and GEE.

Table 2. Estimates of the model parameters.

I	T	Method	β_0	β_1	c	ρ_1	ρ_2	ρ_3
30	3	GEE	0.9808	0.5511	0.9621	0.7575	0.5495	0.4302
			(0.1185)	(0.1283)				
		GQL	0.9853	0.5670	0.9743	0.7850	0.6311	0.4457
			(0.1072)	(0.1103)				
		MLC	0.9888	0.5790	0.9736	0.7873	0.6705	0.4406
			(0.0893)	(0.0844)	(0.0953)	(0.0640)	(0.0729)	(0.0790)
	4	GEE	0.9879	0.5433	0.9620	0.7690	0.6304	0.4728
			(0.1391)	(0.1260)				
		GQL	0.9810	0.5501	0.9794	0.7786	0.6661	0.4602
			(0.1017)	(0.1220)				
		MLC	0.9879	0.5709	0.9846	0.7872	0.5827	0.4640
			(0.0866)	(0.0888)	(0.1011)	(0.0711)	(0.0642)	(0.0674)
60	3	GEE	0.9892	0.5502	0.9784	0.7601	0.5414	0.4622
			(0.1139)	(0.1119)				
		GQL	0.9863	0.5785	0.9818	0.7803	0.6871	0.4340
			(0.0906)	(0.1019)				

Table 2. *Cont.*

I	T	Method	β_0	β_1	c	ρ_1	ρ_2	ρ_3
		MLC	0.9910	0.5836	0.9877	0.7850	0.6639	0.4541
			(0.0703)	(0.0681)	(0.0830)	(0.0647)	(0.0554)	(0.0603)
	4	GEE	0.9839	0.5529	0.9729	0.7761	0.5810	0.4886
			(0.1140)	(0.1132)				
		GQL	0.9850	0.5631	0.9820	0.7898	0.6628	0.4491
			(0.0981)	(0.1135)				
		MLC	0.9855	0.5887	0.9871	0.7890	0.6311	0.4981
			(0.0795)	(0.0749)	(0.0717)	(0.0761)	(0.0589)	(0.0535)
100	3	GEE	0.9833	0.5694	0.9811	0.7717	0.5671	0.4891
			(0.1028)	(0.1097)				
		GQL	0.9925	0.5827	0.9916	0.7920	0.6711	0.4695
			(0.0760)	(0.0710)				
		MLC	0.9992	0.5946	0.9961	0.7999	0.6651	0.4696
			(0.0418)	(0.0482)	(0.0660)	(0.0476)	(0.0350)	(0.0460)
	4	GEE	0.9815	0.5630	0.9887	0.7822	0.5771	0.4813
			(0.1096)	(0.0918)				
		GQL	0.9935	0.5832	0.9932	0.7958	0.6831	0.4719
			(0.0718)	(0.0815)				
		MLC	0.9919	0.5970	0.9975	0.7931	0.6556	0.5345
			(0.0520)	(0.0518)	(0.0627)	(0.0641)	(0.0471)	(0.0417)

4. Application

We revisit the epileptic dataset that was analysed by Jowaheer and Sutradhar [17]. The data consists of 59 epileptic patients for whom the number of seizures occurring at each of four successive two weekly clinic visits were reported. The summary statistics for these responses are given in Table 3.

Table 3. Summary statistics of the epileptic seizure counts.

	Visit 1	Visit 2	Visit 3	Visit 4
Sample mean	8.949	8.356	8.441	7.305
Sample variance	220.084	103.785	200.182	93.112

We note that the variances are greater than their corresponding means for each time point indicating that the data are clearly over-dispersed. There are five covariates namely the intercept term denoted by x_{it1}, the treatment parameter x_{it2}, coded as 0 for placebo and 1 for progabide, the baseline-seizure rates denoted by x_{it3}, the age of the person denoted by x_{it4} and the interaction effect between treatment and baseline seizure rates x_{it5}. Note that the covariates are time-independent. The mean parameter of the negative binomial distribution for the ith person is given by $\theta_i = \exp(x_i^T\beta)$ with $x_i = (x_{it1}, x_{it2}, \ldots, x_{it5})^T$ for $t = 1, \ldots, 4$. Here β is the 5×1 vector of regression parameters. Jowaheer and Sutradhar [17] used the negative binomial model and estimate the model parameters using the true general auto-correlation structure based GQL approach. We analyse the epileptic data assuming

that the counts follow the unstructured covariance matrix and estimate the parameters using the MLC approach, as shown in Tables 4 and 5.

Table 4. Epileptic data: estimates of the regression using GQL and MLC approaches.

Method	INTC	TR	BR	Age	INTA
MLC	0.4582	−0.2471	0.0027	0.0210	0.0011
	(0.4321)	(0.1521)	(0.0040)	(0.0109)	(0.0048)
GQL	0.3721	−0.2671	0.0356	0.0212	0.0012
	(0.4372)	(0.1643)	(0.0055)	(0.0111)	(0.0056)

Table 5. Epileptic data: estimates of the over-dispersion and correlation parameters using GQL and MLC approaches.

Method	$\hat{c}$	$\hat{\rho_1}$	$\hat{\rho_2}$	$\hat{\rho_3}$
MLC	0.5142	0.5222	0.3371	0.2030
	(0.3121)			
GQL	0.5431			
	(0.4214)			

We choose small starting values for the longitudinal correlations and small positive values for the regression and over-dispersion parameters. To obtain GQL estimates, we apply the iterative equation and calculate $\hat{\rho}$. Some starting values also lead to computational difficulties in calculating the inverse of the covariance matrix in the GQL approach.

The auto-correlation values under MLC are large, indicating high longitudinal correlations. The values of c under both methods justify that the data are over-dispersed. The treatment parameter in both methods is negative which indicate that the predicted seizure counts will be less in the treatment group than in the placebo group. The age factor is positive indicating that as age increases, the patients are more likely to obtain more epileptic attacks. The interaction between the treatment and the baseline seizure rate does not appear to be significant in both methods.

Based on the standard errors, we note that the estimates of the parameters under the MLC approach are more efficient than GQL especially for the over-dispersion parameter.

5. Conclusions

In this paper, we have presented the Poisson INAR and NB INAR models. We then develop the GQL, GEE and MLC estimation approaches, by using the multivariate copula to estimate the correlation parameters of the proposed model. Through simulation studies, we have seen that MLC provides more efficient estimates particularly for the over-dispersion parameter. GEE yields less efficient estimates of the regression parameters with minor discrepancies in the standard errors as in the Poisson case but the method fails to provide efficient estimates of the over-dispersion parameter. This may be because the method does not take into consideration the correlations among the responses. The model is also applied on an epileptic data series with efficient estimates of the MLC.

Author Contributions: Conceptualization, N.M.K.; methodology, Y.S.; software, N.M.K.; validation, V.J. and Dr Y.S.; formal analysis, N.M.K.; investigation, Y.S.; resources, N.M.K.; data curation, N.M.K.; writing—original draft preparation, V.J.; writing—review and editing, N.M.K. and Y.S.; visualization, Y.S.; supervision, V.J.; project administration, Y.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Available in Software R (Robustbase package, Data epilepsy).

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Sutradhar, B.; Das, K. On the efficiency of regression estimators in generalised linear models for longitudinal data. *Biometrika* **1999**, *86*, 459–465. [CrossRef]
2. Sutradhar, B.; Das, K. A higher order approximation to likelihood inference in the Poisson mixed model. *Stat. Probab. Lett.* **2001**, *52*, 59–67. [CrossRef]
3. Sutradhar, B.; Farrell, P. Analyzing muiltivariate longitudinal binary data: A generalized estimating equations approach. *Can. J. Stat.* **2004**, *32*, 39–55. [CrossRef]
4. Sutradhar, B.; Jowaheer, V. On familial longitudinal poisson mixed models with gamma random effects. *J. Multivar. Anal.* **2003**, *87*, 398–412. [CrossRef]
5. Sutradhar, B.; Kovacevic, M. Analysing ordinal longitudinal survey data: Generalised estimating equations approach. *Biometrika* **2000**, *87*, 837–848. [CrossRef]
6. Sutradhar, B.; Qu, Z. On approximate likelihood inference in a Poisson mixed model. *Can. J. Stat.* **1988**, *26*, 169–186.
7. Thall, P.; Vail, S. Some covariance models for longitudinal count data with overdispersion. *Biometrics* **1990**, *46*, 657–671. [CrossRef]
8. Laird, N.; Ware, J. Random-effects models for longitudinal data. *Biometrics* **1982**, *38*, 963–974. [CrossRef]
9. Liang, K.; Zeger, S. Longitudinal data analysis using generalized linear models. *Biometrika* **1986**, *73*, 13–22. [CrossRef]
10. Wedderburn, R.W. Quasi-likelihood functions, generalizedlinear models and the Gauss-Newton method. *Biometrika* **1974**, *61*, 439–447. [CrossRef] [PubMed]
11. Prentice, R.; Zhao, L. Estimating equations for parameters in means and covariances of multivariate discrete and continuous responses. *Biometrics* **1991**, *47*, 825–839. [CrossRef]
12. FitzMaurice, G.; Laird, N.; Rotnizky, A. Regression models for discrete longitudinal responses. *Stat. Sci.* **1993**, *8*, 284–309. [CrossRef]
13. Qu, A.; Lindsay, B. Building adaptive estimating equations when inverse of covariance estimation is difficult. *J. R. Stat. Soc.* **2003**, *65*, 127–142. [CrossRef]
14. Qu, A.; Lindsay, B.; Li, B. Improving generalised estimating equations using quadratic inference functions. *Biometrika* **2000**, *87*, 823–836. [CrossRef]
15. Qu, A.; Song, P. Assessing robustness of generalized estimating equations and quadratic inference functions. *Biometrika* **2004**, *91*, 447–459. [CrossRef]
16. Crowder, M. On the use of a working correlation matrix in using generalized linear models for repeated measures. *Biometrika* **1995**, *82*, 407–410. [CrossRef]
17. Jowaheer, V.; Sutradhar, B. Analysing longitudinal count data with overdipsersion. *Biometrika* **2002**, *89*, 389–399. [CrossRef]
18. McKenzie, E. Autoregressive moving-average processes with negative binomial and geometric marginal distrbutions. *Adv. Appl. Probab.* **1986**, *18*, 679–705. [CrossRef]
19. Zeger, S.; Qaqish, B. Markov regression models for time series: A quasi-likelihood approach. *Biometrics* **1988**, *44*, 1019–1031. [CrossRef]
20. Nikoloulopoulos, A.K.; Karlis, D. Modeling multivariate count data using copulas. *Commun.-Stat.-Simul. Comput.* **2009**, *39*, 172–187. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.