

## DAFTAR PUSTAKA

- Anggreainy, M. S., Illyasu, A. M., Musyaffa, H., & Kansil, F. H. (2022). Analysis of Factors Influencing the COVID-19 Mortality Rate in Indonesia using Zero Inflated Negative Binomial Model. *IJACSA) International Journal of Advanced Computer Science and Applications*, 13(4), 728–734. [www.ijacsa.thesai.org](http://www.ijacsa.thesai.org)
- Aprilia, A. D. (2023). Regresi Zero Inflated Poisson Untuk Pemodelan Angka Positif Penyakit Malaria Di Jawa Timur. *Jurnal Ilmiah Matematika Volume 11 No 02 E-ISSN: 2716-506*, 11(2), 139–146.
- Azagi, I. A. (2022). Measles Disease Analysis in Bengkulu Province Using Zero Inflated Poisson Regression and Zero Inflated Negative Binomial Regression. *Journal of Statistics and Data Science*, 1(2), 1–9.
- Chan, J. S. K., Choy, S. T. B., Makov, U., Shamir, A., & Shapovalov, V. (2022). Variable Selection Algorithm for a Mixture of Poisson Regression for Handling Overdispersion in Claims Frequency Modeling Using Telematics Car Driving Data. *Risks*, 10(4). <https://doi.org/10.3390/risks10040083>
- C.R., M. D., & Yanti, T. S. (2021). Regresi Poisson Invers Gaussian (PIG) untuk Pemodelan Jumlah Kasus Pneumonia pada Balita di Provinsi Jawa Tengah Tahun 2019. *Jurnal Riset Statistika*, 1(1), 143–151.
- Darsyab, Muh. Y., & Ramadhan, M. N. (2022). Pemodelan Jumlah Kasus Penyakit Kusta di Provinsi Sulawesi Tenggara Menggunakan Metode Regresi Poisson Inverse Gaussian. *Jurnal Litbang Edusaintech*, 3(1), 11–24.
- Dinkes Kota Makassar. (2022). *Profil Dinas Kesehatan Kota Makassar Tahun 2021* (Dinas Kesehatan Kota Makassar, Ed.). Dinas Kesehatan Kota Makassar.
- Famoye, F., & Singh, K. P. (2006). Zero-Inflated Generalized Poisson Regression Model with an Application to Domestic Violence Data. *Journal of Data Science* 4, 117–130.
- Fávero, L. P., de Freitas Souza, R., Belfiore, P., Corrêa, H. L., & Haddad, M. F. C. (2021). Count Data Regression Analysis: Concepts, Overdispersion Detection, Zero-inflation Identification, and Applications with R. *Practical Assessment, Research and Evaluation*, 26, 1–22. <https://doi.org/10.7275/44nn-cj68>
- Feng, C., Li, L., & Sadeghpour, A. (2020). A comparison of residual diagnosis tools for diagnosing regression models for count data. *BMC Medical Research Methodology*, 20(1). <https://doi.org/10.1186/s12874-020-01055-2>
- Feng, C. X. (2021). A comparison of zero-inflated and hurdle models for modeling zero-inflated count data. In *Journal of Statistical Distributions and Applications* (Vol. 8, Issue 1). Springer Science and Business Media Deutschland GmbH. <https://doi.org/10.1186/s40488-021-00121-4>



- Firmansyah, D. C., Nadillah, F., Rizki, M. G., Septiani, N. H., Sinurat, S. R. Y., & Nooraeni, R. (2020). Penerapan Model Regresi Zero Inflated Poisson pada Kejadian Kelahiran di Luar Nikah WUS di Provinsi Nusa Tenggara Timur Tahun 2017 (Analisis Data SDKI 2017). *Eigen Mathematics Journal*, 3(1), 56–62.
- Fitrial, N. H., & Fatikhurriqi, A. (2020). Pemodelan Jumlah Kasus Covid-19 Di Indonesia Dengan Pendekatan Regresi Poisson Dan Regresi Binomial Negatif. *N Seminar Nasional Official Statistics*, 1(1), 6672.
- Green, J. A. (2021). Too many zeros and/or highly skewed? A tutorial on modelling health behaviour as count data with Poisson and negative binomial regression. *Health Psychology and Behavioral Medicine*, 9(1), 436–455. <https://doi.org/10.1080/21642850.2021.1920416>
- Handarzeni, S. A. (2022). Modeling of Tuberculosis Cases in Sumatra Region using Poisson Inverse Gaussian Regression. *Journal of Statistics and Data Science*, 1(2), 36–43.
- Ikhsani, N., Kalondeng, A., & Ilyas, N. (2023). Pemodelan Regresi Bivariate Poisson Inverse Gaussian pada Kasus Kematian Ibu dan Neonatal di Sulawesi Selatan. *Estimasi: Journal of Statistics and Its Application*, 4(1), 2721–379. <https://doi.org/10.20956/ejsa.vi.24113>
- Kemendes RI. (2021). *Profil Kesehatan Indonesia 2021*. Kementerian Kesehatan Republik Indonesia.
- Kyriazos, T., & Poga, M. (2023). Dealing with Multicollinearity in Factor Analysis: The Problem, Detections, and Solutions. *Open Journal of Statistics*, 13(03), 404–424. <https://doi.org/10.4236/ojs.2023.133020>
- Lukman, A. F., Adewuyi, E., & Månsson, K. (2021). A new estimator for the multicollinear Poisson regression model: simulation and application. *Kibria, B. G.*, 11(3732).
- Nariswari, R., Widhiyanthi, A. A., Arifin, S., & Yudistira, I. G. A. A. (2023). Zero Inflated Poisson Regression: A Solution of Overdispersion in Stunting Data. *AIP Conference Proceedings*, 2975(1), 1–8.
- Nur, M. S., Purhadi, & Choiruddin, A. (2021). Parameter Estimation and Hypothesis Testing of Geographically Weighted Bivariate Zero Inflated Poisson Inverse Gaussian Regression Models. *OP Conference Series: Materials Science and Engineering*, 1115(1), 1–14.
- Park, S., & Jun, S. (2023). Zero-Inflated Patent Data Analysis Using Compound Poisson Models. *Applied Sciences (Switzerland)*, 13(7). <https://doi.org/10.3390/app13074505>

Y. N., Ong, S. H., & Low, Y. C. (2021). Discrimination between Some Overdispersed Count Distributions. *ASM Science Journal*, 14, 1–8. <https://doi.org/10.32802/asmscj.2020.503>



- Rahayu, A. (2020). Model-Model Regresi Untuk Mengatasi Masalah Overdispersi Pada Regresi Poisson. *Journal Peqguruang: Conference Series*, 2(1), 1–5.
- Santi, V. M., Wiyono, A., & Sudarwanto. (2021). Pemodelan Jumlah Kasus Malaria di Indonesia Menggunakan Generalized Linear Model. *Jurnal Statistika Dan Aplikasinya*, 5(1), 112–120.
- Saraiva, E. F., Vigas, V. P., Flesch, M. V., Gannon, M., & Pereira, C. A. de B. (2022). Modeling Overdispersed Dengue Data via Poisson Inverse Gaussian Regression Model: A Case Study in the City of Campo Grande, MS, Brazil. *Entropy*, 24(9), 1–16.
- Sendow, J. M., & Chernovita, H. P. (2021). *Analisis Pengaruh Cuaca Terhadap Persebaran Penyakit Malaria di Kabupaten Mimika Menggunakan Sistem Informasi Geografis*.
- Vasconcelos, J. C. S., Speranza, E. A., Antunes, J. F. G., Barbosa, L. A. F., Christofolletti, D., Severino, F. J., & de Almeida Cançado, G. M. (2023). Development and Validation of a Model Based on Vegetation Indices for the Prediction of Sugarcane Yield. *AgriEngineering*, 5(2), 698–719. <https://doi.org/10.3390/agriengineering5020044>
- Wahyuni, S. T., Utami, T. W., & Darsyah, Moh. Y. (2021). Pemodelan Generalized Additive Model For Location, Scale, and Shape (Gamlss) Dengan Pemulusan Locally Estimated Scatterplot Smoothing (Loess) pada Kasus Hiv/Aids Di Jawa Timur. *Jurnal Litbang Edusaintech*, 2(1), 18–26.
- Wang, W., & Famoye, F. (1997). Modeling household fertility decisions with generalized Poisson regression. *Journal of Population Economics*, 10(3), 273–283. <https://doi.org/10.1007/s001480050043>



# LAMPIRAN



**Lampiran 1.** Data Jumlah Kasus Malaria dan Faktor-faktor yang Mempengaruhi di Puskesmas Kota Makassar Tahun 2021

Kecamatan	Puskesmas	Y	$X_1$	$X_2$	$X_3$	$X_4$
Ujung Tanah	Pattingalloang	1	3949	9	1	25
	Tabaringan	1	3153	10	2	25
Tallo	Ujung Pandang Baru	0	5500	27	1	36
	Rappokalling	0	9047	28	1	25
	Kaluku Bodoa	1	15273	49	1	26
Bontoala	Layang	1	7199	17	1	37
	Malimongan Baru	1	3586	10	2	20
Wajo	Tarakan	2	3197	5	1	25
	Andalas	0	3386	34	2	19
Ujung Pandang	Makkasau	0	6243	28	5	21
Makassar	Bara-baraya	0	7869	13	1	34
	Maccini Sawah	5	5294	10	1	50
	Maradekaya	0	5100	28	1	20
Mamajang	Mamajang	0	4595	19	4	26
	Cendrawasi	0	9673	14	1	27
Mariso	Dahlia	0	4369	16	1	22
	Pertiwi	0	3932	17	1	39
	Panambungan	0	4712	17	2	30
Tamalate	Tamalate	0	13078	45	3	21
	Jongaya	0	10700	26	2	30
	Barombong	0	2942	26	1	18
	Maccini Sombala	1	7010	19	1	29
Rappocini	Kassi-Kassi	0	19772	45	3	22
	Mangasa	0	22988	18	1	22
	Minasa Upa	0	4590	12	2	25
	Ballaparang	0	8864	32	4	35
Panakukang	Toddopuli	0	3581	11	1	44
	Pampang	1	10398	20	2	23
	Tamamaung	1	14450	33	3	22
	Karuwisi	0	6181	30	2	23
Manggala	Antang	1	6396	30	1	33
	Batua	1	8942	25	2	25
	Antang Perumnas	2	4738	16	1	45
	Tamangapa	0	2839	20	1	24
	Bangkala	1	5784	26	1	20



**Lampiran 1.** Data Jumlah Kasus Malaria dan Faktor-faktor yang Mempengaruhi di Puskesmas Kota Makassar Tahun 2021 (Lanjutan)

Biringkanaya	Sudiang	1	14463	61	2	20
	Bulurokeng	0	3293	13	2	19
	Sudiang Raya	1	11012	25	1	18
	Paccerakkang	0	12836	18	2	23
	Daya	2	4163	13	2	18
Tamalanrea	Tamalanrea	0	10023	25	1	27
	Tamalanrea Jaya	1	6935	21	1	19
	Bira	0	4517	24	1	23
	Tamalanrea Indah	1	7427	11	4	21
	Kapasa	1	4014	16	1	21
Pulau Sangkarrang	Barrang Lompo	0	2312	10	1	28
	Pulau Kodingareng	0	1003	6	1	25



**Lampiran 2.** Uji Kecocokan Distribusi

Mean 0,574468

Y	Frekuensi	$F_k$	$F_n(Y)$	$F_0(Y)$	$ F_n(Y) - F_0(Y) $
0	27	27	0,56300	0,57447	0,01146
1	16	43	0,88643	0,91489	0,02846
2	3	46	0,97933	0,97872	0,00061
3	0	46	0,99712	0,97872	0,01840
4	0	46	0,99968	0,97872	0,02095
5	1	47	0,99997	1,00000	0,00003

$$D_{hitu} = 0,2846$$

$$D_{47;0,05} = 0,1942$$



Lampiran 3. Tabel Kolmogorov-Smirnov

Test de Kolmogorov-Smirnov								
Nivel de significación $\alpha$								
n	0.20	0.10	0.05	0.02	0.01	0.005	0.002	0.001
1	0.90000	0.95000	0.97500	0.99000	0.99500	0.99750	0.99900	0.99950
2	0.68337	0.77639	0.84189	0.90000	0.92929	0.95000	0.96838	0.97764
3	0.56481	0.63604	0.70760	0.78456	0.82900	0.86428	0.90000	0.92065
4	0.49265	0.56522	0.62394	0.68887	0.73424	0.77639	0.82217	0.85047
5	0.44698	0.50945	0.56328	0.62718	0.66853	0.70543	0.75000	0.78137
6	0.41037	0.46799	0.51926	0.57741	0.61661	0.65287	0.69571	0.72479
7	0.38148	0.43607	0.48342	0.53844	0.57581	0.60975	0.65071	0.67930
8	0.35831	0.40962	0.45427	0.50654	0.54179	0.57429	0.61368	0.64098
9	0.33910	0.38746	0.43001	0.47960	0.51332	0.54443	0.58210	0.60846
10	0.32260	0.36866	0.40925	0.45562	0.48893	0.51872	0.55500	0.58042
11	0.30829	0.35242	0.39122	0.43670	0.46770	0.49539	0.53135	0.55588
12	0.29577	0.33815	0.37543	0.41918	0.44905	0.47672	0.51047	0.53422
13	0.28470	0.32549	0.36143	0.40362	0.43247	0.45921	0.49189	0.51490
14	0.27481	0.31417	0.34890	0.38970	0.41762	0.44352	0.47520	0.49753
15	0.26589	0.30397	0.33750	0.37713	0.40420	0.42934	0.45611	0.48182
16	0.25778	0.29472	0.32733	0.36571	0.39201	0.41644	0.44637	0.46750
17	0.25039	0.28627	0.31796	0.35528	0.38086	0.40464	0.43380	0.45540
18	0.24360	0.27851	0.30936	0.34569	0.37062	0.39380	0.42224	0.44234
19	0.23735	0.27136	0.30143	0.33685	0.36117	0.38379	0.41156	0.43119
20	0.23156	0.26473	0.29408	0.32866	0.35241	0.37451	0.40165	0.42085
21	0.22517	0.25858	0.28724	0.32104	0.34426	0.36588	0.39243	0.41122
22	0.22115	0.25283	0.28087	0.31394	0.33666	0.35782	0.38382	0.40223
23	0.21646	0.24746	0.27491	0.30728	0.32954	0.35027	0.37575	0.39380
24	0.21205	0.24242	0.26931	0.30104	0.32286	0.34318	0.36787	0.38588
25	0.20790	0.23768	0.26404	0.29518	0.31657	0.33651	0.36104	0.37743
26	0.20399	0.23320	0.25908	0.28962	0.30963	0.33022	0.35431	0.37139
27	0.20030	0.22898	0.25438	0.28438	0.30502	0.32425	0.34794	0.36473
28	0.19680	0.22497	0.24993	0.27942	0.29971	0.31862	0.34190	0.35842
29	0.19348	0.22117	0.24571	0.27471	0.29466	0.31327	0.33617	0.35242
30	0.19032	0.21756	0.24170	0.27023	0.28986	0.30818	0.33072	0.34672
31	0.18732	0.21412	0.23788	0.26596	0.28529	0.30333	0.32553	0.34129
32	0.18445	0.21085	0.23424	0.26189	0.28094	0.29870	0.32058	0.33611
33	0.18171	0.20771	0.23076	0.25801	0.27577	0.29428	0.31584	0.33115
34	0.17909	0.21472	0.22743	0.25429	0.27271	0.29005	0.31131	0.32641
35	0.17659	0.20185	0.22425	0.25073	0.26897	0.28600	0.30597	0.32187
36	0.17418	0.19910	0.22119	0.24732	0.26532	0.28211	0.30281	0.31751
37	0.17188	0.19646	0.21826	0.24404	0.26180	0.27838	0.29882	0.31333
38	0.16966	0.19392	0.21544	0.24089	0.25843	0.27483	0.29498	0.30931
39	0.16753	0.19148	0.21273	0.23785	0.25518	0.27135	0.29125	0.30544
40	0.16547	0.18913	0.21012	0.23494	0.25205	0.26803	0.28772	0.30171
41	0.16349	0.18687	0.20760	0.23213	0.24904	0.26482	0.28429	0.29811
42	0.16158	0.18468	0.20517	0.22941	0.24613	0.26173	0.28097	0.29465
43	0.15974	0.18257	0.20283	0.22679	0.24332	0.25875	0.27778	0.29130
44	0.15795	0.18051	0.20056	0.22426	0.24060	0.25587	0.27468	0.28806
45	0.15623	0.17856	0.19837	0.22181	0.23798	0.25308	0.27169	0.28493
46	0.15457	0.17665	0.19625	0.21944	0.23544	0.25038	0.26880	0.28190
47	0.15295	0.17481	0.19420	0.21715	0.23298	0.24776	0.26600	0.27896
48	0.15139	0.17301	0.19221	0.21493	0.23059	0.24523	0.26328	0.27611
49	0.14987	0.17128	0.19028	0.21281	0.22832	0.24281	0.26069	0.27339
50	0.14840	0.16959	0.18841	0.21068	0.22604	0.24039	0.25809	0.27067
n>50	1.07	1.22	1.36	1.52	1.63	1.73	1.85	1.95
	$\sqrt{n}$	$\sqrt{n}$	$\sqrt{n}$	$\sqrt{n}$	$\sqrt{n}$	$\sqrt{n}$	$\sqrt{n}$	$\sqrt{n}$





**Lampiran 4.** Uji Multikolinearitas

```
> library(car)
> model_lm<-lm(Y~X1+X2+X3+X4, data=malaria2)
> vif(model_lm)
      x1      x2      x3      x4
1.522 1.603 1.102 1.095
```



**Lampiran 5.** Uji Overdispersi

```
> library(AER)
> model<-glm(Y~X1+X2+X3+X4, family="poisson", data=malaria2)
> model_glm
Call: glm(formula = Y ~ X1 + X2 + X3 + X4, family = "poisson", data =
malaria2)

Coefficients:
(Intercept)          X1          X2          X3          X4
-1.279067      0.000023     -0.023640     -0.121968      0.044072

Degrees of Freedom: 46 Total (i.e. Null); 42 Residual
Null Deviance:      54.3
Residual Deviance: 46.9  AIC: 100
> D<-model_glm$deviance
> db<-model_glm$df.residual
> Psi<-D/db
> Psi
[1] 1.118
```



**Lampiran 6.** Estimasi Parameter Model ZIPIG

```
> summary(m1<-gamlss(Y~X1+X2+X3+X4,data = malaria2, family = ZIPIG, method = RS(100)))
```

Family: c("ZIPIG", "Zero inflated Poisson inverse Gaussian")

Call: `gamlss(formula = Y ~ X1 + X2 + X3 + X4, family = ZIPIG, data = malaria2, method = RS(100))`

Fitting method: RS(100)

```
-----
Mu link function: log
Mu Coefficients:
      Estimate Std. Error t value      Pr(>|t|)
(Intercept)  2.3117801  0.9375150    2.47      0.018 *
X1            0.0012501  0.0000169   73.81 <0.0000000000000002 ***
X2           -0.4424008  0.0154597  -28.62 <0.0000000000000002 ***
X3           -3.3508840  0.2191655  -15.29 <0.0000000000000002 ***
X4            0.0082559  0.0241824    0.34      0.735
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
-----
Sigma link function: log
Sigma Coefficients:
      Estimate Std. Error t value      Pr(>|t|)
(Intercept) -0.21130733  0.00000486  -43452 <0.0000000000000002 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
-----
Nu link function: logit
Nu Coefficients:
      Estimate Std. Error t value Pr(>|t|)
(Intercept)  -1.491      0.542   -2.75  0.0084 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
-----
No. of observations in the fit: 47
Degrees of Freedom for the fit: 7
      Residual Deg. of Freedom: 40
      at cycle: 83
```

```
Global Deviance: 188.6
AIC: 202.6
SBC: 215.5
```

\*\*\*\*\*



**Lampiran 6. Estimasi Parameter Model ZIPIG (Lanjutan)**

```
> summary(m3<-gamlss(Y~X1+X2+X4,data = malaria2, family = ZIPIG, method = RS(100)))
```

Family: c("ZIPIG", "Zero inflated Poisson inverse Gaussian")

Call:

```
gamlss(formula = Y ~ X1 + X2 + X4, family = ZIPIG, data = malaria2, method = RS(100))
```

Fitting method: RS(100)

-----  
Mu link function: log

Mu Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-1.081215	2.432240	-0.44	0.6589
X1	0.000727	0.000288	2.53	0.0153 *
X2	-0.213862	0.075799	-2.82	0.0072 **
X4	0.075668	0.078843	0.96	0.3426

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

-----  
Sigma link function: log

Sigma Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	3.72	0.56	6.65	0.000000031 ***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

-----  
Nu link function: logit

Nu Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-1.22	0.55	-2.22	0.031 *

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

-----  
No. of observations in the fit: 47  
Degrees of Freedom for the fit: 6  
Residual Deg. of Freedom: 41  
at cycle: 76

Global Deviance: 123.5  
AIC: 135.5  
SBC: 146.6

\*\*\*\*\*



**Lampiran 6. Estimasi Parameter Model ZIPIG (Lanjutan)**

```
> summary(m6<-gamlss(Y~X1+X2,data = malaria2, family = ZIPIG, method =
RS(100)))
```

Family: c("ZIPIG", "Zero inflated Poisson inverse Gaussian")

Call:

```
gamlss(formula = Y ~ X1 + X2, family = ZIPIG, data = malaria2,
method = RS(100))
```

Fitting method: RS(100)

-----  
Mu link function: log

Mu Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	0.723785	1.101497	0.66	0.5145
X1	0.000703	0.000267	2.63	0.0117 *
X2	-0.216513	0.068409	-3.16	0.0028 **

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

-----  
Sigma link function: log

Sigma Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	3.479	0.524	6.64	0.000000032 ***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

-----  
Nu link function: logit

Nu Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-1.394	0.597	-2.34	0.024 *

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

-----  
No. of observations in the fit: 47

Degrees of Freedom for the fit: 5

Residual Deg. of Freedom: 42

at cycle: 72

Global Deviance: 123.2

AIC: 133.2

SBC: 142.4

\*\*\*\*\*



```
> summary(m13<-gamlss(Y~X2,data = malaria2, family = ZIPIG, method =
RS(100)))
```

```
Family: c("ZIPIG", "Zero inflated Poisson inverse Gaussian")
```

```
Call:
```

```
gamlss(formula = Y ~ X2, family = ZIPIG, data = malaria2, method = RS(100))
```

```
Fitting method: RS(100)
```

```
-----
Mu link function: log
```

```
Mu Coefficients:
```

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	0.1591	0.6729	0.24	0.81
X2	-0.0341	0.0257	-1.33	0.19

```
-----
Sigma link function: log
```

```
Sigma Coefficients:
```

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	1.262	0.559	2.26	0.029 *

```
---
```

```
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
-----
Nu link function: logit
```

```
Nu Coefficients:
```

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	-36	14586	0	1

```
-----
No. of observations in the fit: 47
```

```
Degrees of Freedom for the fit: 4
```

```
Residual Deg. of Freedom: 43
```

```
at cycle: 7
```

```
Global Deviance: 100.5
```

```
AIC: 108.5
```

```
SBC: 115.9
```

```
*****
```

