**Health Insurance and Medical Utilisation**  
Sean Park

Department of Engineering and Mathematical Sciences, University of Western Australia, Australia

[22209962@student.uwa.edu.au](mailto:22209962@student.uwa.edu.au)

**Keywords**: Medicare, public health insurance, private health insurance, usage of medical facility

**Abstract**

In the COVID-19 pandemic situation, health has become one of the biggest concerns. There is numerous research saying medical prescriptions such as vaccination and clinical screening are essential to keep people's well-being, but they are too costly. Many people are using health insurance to take out the burden and access easily to medical services. In this study, we investigate the relationship between visits to health care facilities and whether a person is insured by health cover. An approach to health care facilities is measured by counting visits to medical offices. There are other variables including health status and sociodemographic information used to see the link with visits. The data were transformed for clear comparison between different types of visits and analysed by using regression modelling to figure out the influence of health insurance on utilisation of medical services. The results showed that having health insurance encourages people to see a doctor more often. The outcome suggests that health cover can improve well-being in general.

**1. Introduction**

With the development of civilization and science, people live healthier and longer. Life expectancy has increased significantly over the course of the 20th and 21st centuries and it reflects the improvement of health care infrastructure and quality of public health (“Recent Trends “, 2018). It means people are now aware of the importance of well-being hence the expenditure on health has been increased. World Health Organisation (WHO) published a report saying that the global spending on health has reached US$ 8.3 trillion or 10% of global GDP in 2018 (Global Spending, 2020). Larger expenses imply better infrastructure and quality, but it also denotes that people have much more expenditure on their health care. Therefore, most countries in the world propose policies about public health insurance and many people take private health insurance as well.

However, there is a debate about the substantive effects of health insurance. The controversy is whether it improves people’s general health condition or not. Zhang, Congcong, et al. (2020) suggested people with private insurance tend not to use health care services, compared to those without insurance. On the other hand, they also indicate that the coverage may abate the financial burden on insured people.

Nevertheless, there are many opinions supporting that health cover does have positive impact on the (potential)patients. Erlangga, Darius, et al. (2019) analysed 8755 abstracts and 118 full-text articles about public health insurance and suggested that health cover generally appears to increase an access to health facilities, improve financial protection and improve health status.

Furthermore, the National Academies Press’ research indicates that uninsured people may receive less adequate medical service. It leads to poorer clinical outcomes and overall health than insured people (National Research Council, 2009).

The Australian Bureau of Statistics released a data report that shows 10.1 million (57.1% of 18 years and over) adult Australians are insured with private health insurance. (“PRIVATE HEALTH INSURANCE”, 2017)

Farrell, Caitlin M., and Aaron Gottlieb (2020) suggested that health insurance is closely related to increases in utilisation of outpatient, inpatient, and emergency department health care. They also denoted that expanding an approach to coverage in a broader population has the potential of a decrease in barriers to medical services.

As the research and analysis show, an access to medical services is undoubtedly related to people’s overall health condition and it denotes that health insurance can ease the barrier.

Our analysis is based on data gathered from 4406 individuals, aged 66 and over whom are covered by Medicare. An approach to medical services for individuals was measured as visits to health facilities. We expect people with private insurance or public health cover (Medicaid) will have more visits to medical services. Therefore, a Poisson, quasi-Poisson, and negative binomial model were fitted with the visits as response variables against health status, employment, sociodemographic information, and economic status. This followed with discussion and interpretation of the relationships between variables and responses from the model.

**2. Method**

Deb and Trivedi (1997) analysed data on 4406 individuals, aged 66 and over whom are covered by Medicare. The data were collected by the National Medical Expenditure Survey (NMES), 1987 and verified by cross-checking information provided by survey respondents with providers of health-care services. NMES provided information on health status, employment, sociodemographic information, and economic status. Six measures of medical facility utilisation and other variables stated above is described in Table 1. The response variables were collected separately but we added Type and Visits as new variables to see the relation between each Type easily. The data were analysed to determine the dependence of health service usage on private health insurance and access to Medicaid. The Poisson regression model was fitted to the data and tested for the overdispersion. Then, quasi-Poisson model and negative binomial model were performed due to overdispersion of the previous model. The interaction between variables were tested for more insights to the relationship.

**3. Results**

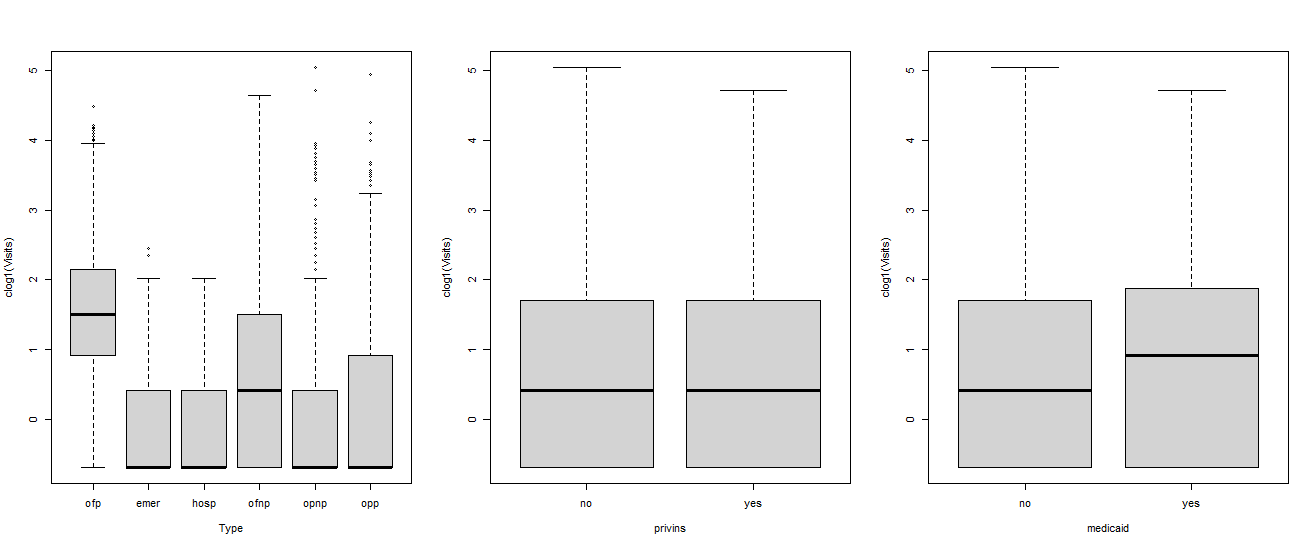
**3.1 Data description**

The variables in the data are described in Table 1 with summary information.

Table 1. Description of variables.

|  |  |
| --- | --- |
| Variable | Description |
| ofp | Number of physician office visits (mean = 5.77, sd = 6.76) |
| ofnp | Number of non-physician office visits (mean = 1.62, sd = 5.32) |
| opp | Number of physician hospital visits (mean = 0.75, sd =3.65) |
| opnp | Number of on-physician hospital visits (mean = 0.54, sd =3.88) |
| emer | Number of emergency room visits (mean = 0.26, sd = 0.70) |
| hosp | Number of days in hospital (mean =0.30, sd =0.75) |
| health | Self-perceived health is ‘excellent’ (343), ‘average’ (3509), ‘poor’ (554) |
| numchron | Number of chronic condition (0~8) (cancer, emphysema, etc.) |
| adldiff | If the person has a condition which limits daily living (yes = 899, no = 3507) |
| region | ‘noreast’ (837), ‘midwest’ (1157), ‘west’ (798), ‘other’ (1614) |
| age | Age in years (divided by 10) (mean = 7.4) |
| black | If the person is African American (yes = 516, no = 3890) |
| gender | ‘male’ (1778) or ‘female’ (2628) |
| married | Married (2406) or not married (2000) |
| school | Number of years of education |
| faminc | Family income in $10,000 (mean = 1.70) |
| employed | Employed (455) or not employed (3951) |
| privins | Covered by private insurance (3421) or not (985) |
| medicaid | Covered by Medicaid (402) or not (4004) |
| Type | Type of health facility (‘ofp’, ’ofnp’, ’opp’, ’opnp’, ’emer’, ’hosp’) |
| Visits | Number of visits of Type |

Number of visits has 26418 rows because we omitted negative faminc data. There is excess of 0 according to the histogram of Visits variable (017907 of 26418 were 0 visits to the medical office).

3.2 Performance

In Figure 1, graphs show relationship between Visits and Type, privins and Medicaid in order. ‘ofp’ shows relatively large count compared to other type of visits. It seems privins does not affect much on Visit but holding Medicaid has impact on visiting office more.

Figure 1. log(visits+0.5) vs type, privins, medicaid

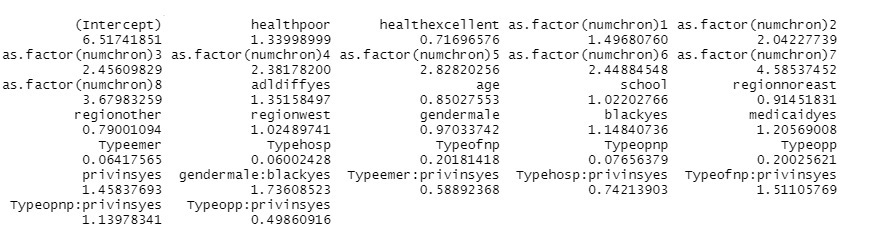
Firstly, Poisson regression model (McCullagh, 1983) was fitted to the visits against all the other variables. We conducted dispersion test from AER (Zeileis and Kleiber 2008) to see if there is any overdispersion symptom due to excess of zeros. The test distinguished the model is over-dispersed, so we fitted quasi-Poisson and negative binomial model for the data. (Hoef, 2007; Venables 2002)

We compared Pearson residuals against fitted values of quasi-Poisson and negative binomial model. The negative binomial model was selected since there are smaller errors.

The interactions between (Type:privins) and (gender:black) were added to the model to see relations between each type of health services and private insurance cover. The result of negative binomial regression model fitted to Visits is stated in Figure 2. The table contains variables which are statistically significant.

3.3 Effect of variables

Figure 2. Variables with coefficient.

* People with private health insurance visit 46% more and people with Medicaid visit 20% more.
* People with chronic diseases visit 50% to 350% more depends on number of chronic diseases. The result shows that if a person has more chronic diseases, they visit more.
* People who are male and black visit health service 74% more.
* People with private health insurance visit non-physician office 50% more but they visit physician hospital 50% less.
* People with Medicare visit physician office the most and non-physician office (80% less compared to physician office), physician hospital (80% less), non-physician hospital (92% less) and emergency room (94% less) in order.

**4. Discussion**

This analysis investigates visits to health care facilities based on health status, employment, sociodemographic information, and economic status for people aged 66+ and covered by Medicare. The Poisson regression model showed overdispersion hence quasi-Poisson and negative binomial models were fitted. Quasi-Poisson could solve the overdispersion problem, but it had much larger deviance compared to the negative binomial model. Finally, a negative binomial regression model was fitted, and it showed that health insurance coverage significantly influences the easier medical facility accesses. A key finding was that no matter what type, people with health insurance visit health care services more than those without.

However, private coverage does not always encourage people to go to medical facilities. According to the study, each type of insurance influence the different types of visits to medical services. For example, people with private cover tend to visit physician-hospital less and non-physician offices more. The Non-physician offices include midwives, optometrists, physical or occupational therapists, psychologists, and chiropractors. As stated in other research, people take private health cover not only to take off the burden of their medical expenses but also to reduce taxes (Medicare Levy Surcharge) or save money. (Graham, Daniel, 2021) It would be a compelling subject to investigate what makes people take private insurance.

As reported in many articles and journals, adequate utilisation of medical facilities and general health conditions are intimately related, if so, how can we make better insurances to make people see a doctor more often. Reducing taxes and functioning as saving accounts would make people take more insurance but it would not encourage them to visit doctors more often. Since there is a biased usage between different types of medical services, it may be a great idea to differentiate the weight of payback. For instance, when they visit a physician office, they get 50% of charges covered while a non-physician office only gets 30% back.

We must consider that the data were collected from elders who may see doctors more often than young people. Therefore, younger people probably do not visit medical services as much even though they are insured by public and private health care.

In this pandemic situation, people have more interests in health, and it makes diversification of the type of insurances and accelerates the health insurance market. Our study suggests that insured people utilise more medical facilities, but it does not encourage them to take every type of health insurance. It is crucial to inspect the item thoroughly and think if it is essential to yourselves. Anyhow, they are more advantages if you are insured for sure.

**References**

AER Zeileis A, Kleiber C (2008). AER: Applied Econometrics with R. R package version 0.9-0,  
URL http://CRAN.R-project.org/package=AER.

Broyles, Robert W., and Michael D. Rosko. “The Demand for Health Insurance and Health Care: A Review of the Empirical Literature.” *Medical Care Review*, vol. 45, no. 2, 1988, pp. 291–338. *Crossref*, doi:10.1177/107755878804500205.

Erlangga, Darius, et al. “The Impact of Public Health Insurance on Health Care Utilisation, Financial Protection and Health Status in Low- and Middle-Income Countries: A Systematic Review.” *PLOS ONE*, edited by Sandra C. Buttigieg, vol. 14, no. 8, 2019, p. e0219731. *Crossref*, doi:10.1371/journal.pone.0219731.

Farrell, Caitlin M., and Aaron Gottlieb. “The Effect of Health Insurance on Health Care Utilization in the Justice-Involved Population: United States, 2014–2016.” *American Journal of Public Health*, vol. 110, no. S1, 2020, pp. S78–84. *Crossref*, doi:10.2105/ajph.2019.305399.

Graham, Daniel. “Will Private Health Insurance Save You Money?” CHOICE, 25 June 2021, www.choice.com.au/money/insurance/health/articles/do-you-need-private-health-insurance.

Global spending on health 2020: weathering the storm. Geneva: World Health Organization;  
2020. Licence: CC BY-NC-SA 3.0 IGO.

Hoef, Jay M. ver, and Peter L. Boveng. “QUASI-POISSON VS. NEGATIVE BINOMIAL REGRESSION: HOW SHOULD WE MODEL OVERDISPERSED COUNT DATA?” *Ecology*, vol. 88, no. 11, 2007, pp. 2766–72. *Crossref*, doi:10.1890/07-0043.1.

McCullagh, P., and J. Nelder. *Generalized Linear Models (Monographs on Statistics and Applied Probability)*. 1st ed., Springer, 1983.

“Models for Count Data With Overdispersion.” *German Rodriguez*, 2013, data.princeton.edu/wws509/notes/c4a.pdf.

National Research Council. *Care Without Coverage: Too Little, Too Late*. National Academies Press, 2009.

“PRIVATE HEALTH INSURANCE.” *Australian Bureau of Statistic*, 2017, www.abs.gov.au/ausstats/abs@.nsf/Lookup/by%20Subject/4364.0.55.002~2014-15~Main%20Features~Private%20health%20insurance~5.

“Recent Trends in Life Expectancy across High Income Countries: Retrospective Observational Study.” *BMJ*, 2018, p. k3622. *Crossref*, doi:10.1136/bmj.k3622.

Venables, W., and B. Ripley. *Modern Applied Statistics with S (Statistics and Computing)*. 4th ed., Springer, 2002.

Zhang, Congcong, et al. “Utilization of Public Health Care by People with Private Health Insurance: A Systematic Review and Meta-Analysis.” *BMC Public Health*, vol. 20, no. 1, 2020. *Crossref*, doi:10.1186/s12889-020-08861-9.

**Appendix**

**Exam**

Sean Park

2021 10 20

**library**(MixAll)**library**(rtkore)**library**(AER)**library**(MASS)

**data**("DebTrivedi")db = DebTrivedi

dbl = **reshape**(db, varying = **c**("ofp","ofnp","opp","opnp","emer","hosp"), v.names="Visits", timevar = "Type", times = **c**("ofp","ofnp","opp","opnp","emer","hosp"), new.row.names = 1**:**30000, direction = "long")

**head**(dbl)

## health numchron adldiff region age black gender married school faminc## 1 average 2 no other 6.9 yes male yes 6 2.8810## 2 average 2 no other 7.4 no female yes 10 2.7478## 3 poor 4 yes other 6.6 yes female no 10 0.6532## 4 poor 2 yes other 7.6 no male yes 3 0.6588## 5 average 2 yes other 7.9 no female yes 6 0.6588## 6 poor 5 yes other 6.6 no female no 7 0.3301## employed privins medicaid Type Visits id## 1 yes yes no ofp 5 1## 2 no yes no ofp 1 2## 3 no no yes ofp 13 3## 4 no yes no ofp 16 4## 5 no yes no ofp 3 5## 6 no no yes ofp 17 6

**summary**(dbl)

## health numchron adldiff region age ## poor : 3324 Min. :0.000 no :21042 midwest:6942 Min. : 6.600 ## average :21054 1st Qu.:1.000 yes: 5394 noreast:5022 1st Qu.: 6.900 ## excellent: 2058 Median :1.000 other :9684 Median : 7.300 ## Mean :1.542 west :4788 Mean : 7.402 ## 3rd Qu.:2.000 3rd Qu.: 7.800 ## Max. :8.000 Max. :10.900 ## black gender married school faminc ## no :23340 female:15768 no :12000 Min. : 0.00 Min. :-1.012 ## yes: 3096 male :10668 yes:14436 1st Qu.: 8.00 1st Qu.: 0.912 ## Median :11.00 Median : 1.698 ## Mean :10.29 Mean : 2.527 ## 3rd Qu.:12.00 3rd Qu.: 3.173 ## Max. :18.00 Max. :54.835 ## employed privins medicaid Type Visits ## no :23706 no : 5910 no :24024 Length:26436 Min. : 0.00 ## yes: 2730 yes:20526 yes: 2412 Class :character 1st Qu.: 0.00 ## Mode :character Median : 0.00 ## Mean : 1.54 ## 3rd Qu.: 1.00 ## Max. :155.00 ## id ## Min. : 1 ## 1st Qu.:1102 ## Median :2204 ## Mean :2204 ## 3rd Qu.:3305 ## Max. :4406

**hist**(dbl**$**faminc)

Chart, histogram

Description automatically generated

dbl = dbl[dbl**$**faminc **>=** 0,]dbl = **subset**(dbl, select = **-c**(id))dbl**$**Type = **factor**(dbl**$**Type)dbl**$**Type = **relevel**(dbl**$**Type, ref = "ofp")dbl**$**health = **relevel**(dbl**$**health, ref = "average")

**par**(mfrow=**c**(2,2))**hist**(dbl**$**age)**plot**(dbl**$**health)**plot**(dbl**$**medicaid)**plot**(dbl**$**privins)

Chart, waterfall chart

Description automatically generated

clog = **function**(x) **log**(x+0.5)**par**(mfrow=**c**(2,2))**plot**(**clog**(Visits) **~** health, data = dbl)**plot**(**clog**(Visits) **~** privins, data = dbl)**plot**(**clog**(Visits) **~** medicaid, data = dbl)**plot**(**clog**(Visits) **~** Type, data = dbl)

Diagram, schematic, box and whisker chart

Description automatically generated

visit.glm = **glm**(Visits **~** ., family = poisson, data = dbl)**summary**(visit.glm)

## ## Call:## glm(formula = Visits ~ ., family = poisson, data = dbl)## ## Deviance Residuals: ## Min 1Q Median 3Q Max ## -6.106 -1.205 -0.813 -0.487 39.227 ## ## Coefficients:## Estimate Std. Error z value Pr(>|z|) ## (Intercept) 1.954950 0.070033 27.915 < 2e-16 \*\*\*## healthpoor 0.220787 0.014605 15.117 < 2e-16 \*\*\*## healthexcellent -0.331173 0.023620 -14.021 < 2e-16 \*\*\*## numchron 0.168985 0.003592 47.047 < 2e-16 \*\*\*## adldiffyes 0.173560 0.013110 13.239 < 2e-16 \*\*\*## regionnoreast 0.024688 0.014826 1.665 0.095865 . ## regionother -0.119486 0.013152 -9.085 < 2e-16 \*\*\*## regionwest 0.089433 0.014891 6.006 1.91e-09 \*\*\*## age -0.140647 0.008699 -16.167 < 2e-16 \*\*\*## blackyes 0.117694 0.016949 6.944 3.81e-12 \*\*\*## gendermale -0.043027 0.011233 -3.831 0.000128 \*\*\*## marriedyes -0.007560 0.011672 -0.648 0.517184 ## school 0.026944 0.001557 17.308 < 2e-16 \*\*\*## faminc -0.003348 0.001835 -1.824 0.068091 . ## employedyes -0.056584 0.017861 -3.168 0.001534 \*\* ## privinsyes 0.289745 0.015445 18.760 < 2e-16 \*\*\*## medicaidyes 0.211235 0.020025 10.548 < 2e-16 \*\*\*## Typeemer -3.086137 0.030011 -102.833 < 2e-16 \*\*\*## Typehosp -2.969982 0.028394 -104.599 < 2e-16 \*\*\*## Typeofnp -1.271528 0.013404 -94.865 < 2e-16 \*\*\*## Typeopnp -2.375910 0.021511 -110.452 < 2e-16 \*\*\*## Typeopp -2.039074 0.018484 -110.318 < 2e-16 \*\*\*## ---## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1## ## (Dispersion parameter for poisson family taken to be 1)## ## Null deviance: 140553 on 26417 degrees of freedom## Residual deviance: 85317 on 26396 degrees of freedom## AIC: 110293## ## Number of Fisher Scoring iterations: 7

visit.glm1 = **glm**(Visits **~** health **+** **as.factor**(numchron) **+** adldiff **+** region **+** age **+** faminc **+** black **+** gender **+** married **+** school **+** age **+** privins **+** medicaid **+** Type, data = dbl, family = poisson)**summary**(visit.glm1)

## ## Call:## glm(formula = Visits ~ health + as.factor(numchron) + adldiff + ## region + age + faminc + black + gender + married + school + ## age + privins + medicaid + Type, family = poisson, data = dbl)## ## Deviance Residuals: ## Min 1Q Median 3Q Max ## -5.426 -1.216 -0.818 -0.465 39.043 ## ## Coefficients:## Estimate Std. Error z value Pr(>|z|) ## (Intercept) 1.796462 0.070112 25.623 < 2e-16 \*\*\*## healthpoor 0.235049 0.014562 16.142 < 2e-16 \*\*\*## healthexcellent -0.283092 0.023675 -11.957 < 2e-16 \*\*\*## as.factor(numchron)1 0.409878 0.016441 24.930 < 2e-16 \*\*\*## as.factor(numchron)2 0.659525 0.017087 38.597 < 2e-16 \*\*\*## as.factor(numchron)3 0.752078 0.018984 39.617 < 2e-16 \*\*\*## as.factor(numchron)4 0.846551 0.023528 35.980 < 2e-16 \*\*\*## as.factor(numchron)5 0.922741 0.027449 33.617 < 2e-16 \*\*\*## as.factor(numchron)6 0.873303 0.048557 17.985 < 2e-16 \*\*\*## as.factor(numchron)7 1.147443 0.090780 12.640 < 2e-16 \*\*\*## as.factor(numchron)8 0.780240 0.175066 4.457 8.32e-06 \*\*\*## adldiffyes 0.172786 0.013090 13.200 < 2e-16 \*\*\*## regionnoreast 0.021477 0.014833 1.448 0.14765 ## regionother -0.127419 0.013160 -9.683 < 2e-16 \*\*\*## regionwest 0.080132 0.014901 5.378 7.54e-08 \*\*\*## age -0.143662 0.008629 -16.648 < 2e-16 \*\*\*## faminc -0.004177 0.001820 -2.295 0.02173 \* ## blackyes 0.103319 0.016998 6.078 1.21e-09 \*\*\*## gendermale -0.035114 0.011230 -3.127 0.00177 \*\* ## marriedyes -0.010655 0.011676 -0.913 0.36148 ## school 0.025810 0.001557 16.577 < 2e-16 \*\*\*## privinsyes 0.273205 0.015548 17.572 < 2e-16 \*\*\*## medicaidyes 0.199486 0.020164 9.893 < 2e-16 \*\*\*## Typeemer -3.086137 0.030011 -102.833 < 2e-16 \*\*\*## Typehosp -2.969982 0.028394 -104.599 < 2e-16 \*\*\*## Typeofnp -1.271528 0.013404 -94.865 < 2e-16 \*\*\*## Typeopnp -2.375910 0.021511 -110.452 < 2e-16 \*\*\*## Typeopp -2.039074 0.018484 -110.318 < 2e-16 \*\*\*## ---## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1## ## (Dispersion parameter for poisson family taken to be 1)## ## Null deviance: 140553 on 26417 degrees of freedom## Residual deviance: 84792 on 26390 degrees of freedom## AIC: 109780## ## Number of Fisher Scoring iterations: 7

**anova**(visit.glm,visit.glm1)

## Analysis of Deviance Table## ## Model 1: Visits ~ health + numchron + adldiff + region + age + black + ## gender + married + school + faminc + employed + privins + ## medicaid + Type## Model 2: Visits ~ health + as.factor(numchron) + adldiff + region + age + ## faminc + black + gender + married + school + age + privins + ## medicaid + Type## Resid. Df Resid. Dev Df Deviance## 1 26396 85317 ## 2 26390 84792 6 525.19

**dispersiontest**(visit.glm1, alternative = "two.sided")

## ## Dispersion test## ## data: visit.glm1## z = 4.1668, p-value = 3.09e-05## alternative hypothesis: true dispersion is not equal to 1## sample estimates:## dispersion ## 12.12855

**plot**(**residuals**(visit.glm1, "pearson") **~** **fitted**(visit.glm1))

Chart, histogram

Description automatically generated

visit.qp = **glm**(Visits **~** health **+** **as.factor**(numchron) **+** adldiff **+** region **+** age **+** faminc **+** black **+** gender **+** married **+** school **+** age **+** privins **+** medicaid **+** Type, data = dbl, family = quasipoisson)**summary**(visit.qp)

## ## Call:## glm(formula = Visits ~ health + as.factor(numchron) + adldiff + ## region + age + faminc + black + gender + married + school + ## age + privins + medicaid + Type, family = quasipoisson, data = dbl)## ## Deviance Residuals: ## Min 1Q Median 3Q Max ## -5.426 -1.216 -0.818 -0.465 39.043 ## ## Coefficients:## Estimate Std. Error t value Pr(>|t|) ## (Intercept) 1.796462 0.244096 7.360 1.90e-13 \*\*\*## healthpoor 0.235049 0.050697 4.636 3.56e-06 \*\*\*## healthexcellent -0.283092 0.082425 -3.435 0.000594 \*\*\*## as.factor(numchron)1 0.409878 0.057240 7.161 8.24e-13 \*\*\*## as.factor(numchron)2 0.659525 0.059490 11.086 < 2e-16 \*\*\*## as.factor(numchron)3 0.752078 0.066092 11.379 < 2e-16 \*\*\*## as.factor(numchron)4 0.846551 0.081914 10.335 < 2e-16 \*\*\*## as.factor(numchron)5 0.922741 0.095562 9.656 < 2e-16 \*\*\*## as.factor(numchron)6 0.873303 0.169052 5.166 2.41e-07 \*\*\*## as.factor(numchron)7 1.147443 0.316052 3.631 0.000283 \*\*\*## as.factor(numchron)8 0.780240 0.609496 1.280 0.200507 ## adldiffyes 0.172786 0.045573 3.791 0.000150 \*\*\*## regionnoreast 0.021477 0.051641 0.416 0.677503 ## regionother -0.127419 0.045815 -2.781 0.005420 \*\* ## regionwest 0.080132 0.051876 1.545 0.122437 ## age -0.143662 0.030043 -4.782 1.75e-06 \*\*\*## faminc -0.004177 0.006336 -0.659 0.509761 ## blackyes 0.103319 0.059179 1.746 0.080843 . ## gendermale -0.035114 0.039096 -0.898 0.369119 ## marriedyes -0.010655 0.040649 -0.262 0.793235 ## school 0.025810 0.005421 4.761 1.93e-06 \*\*\*## privinsyes 0.273205 0.054130 5.047 4.51e-07 \*\*\*## medicaidyes 0.199486 0.070202 2.842 0.004492 \*\* ## Typeemer -3.086137 0.104484 -29.537 < 2e-16 \*\*\*## Typehosp -2.969982 0.098854 -30.044 < 2e-16 \*\*\*## Typeofnp -1.271528 0.046665 -27.248 < 2e-16 \*\*\*## Typeopnp -2.375910 0.074890 -31.725 < 2e-16 \*\*\*## Typeopp -2.039074 0.064351 -31.687 < 2e-16 \*\*\*## ---## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1## ## (Dispersion parameter for quasipoisson family taken to be 12.12092)## ## Null deviance: 140553 on 26417 degrees of freedom## Residual deviance: 84792 on 26390 degrees of freedom## AIC: NA## ## Number of Fisher Scoring iterations: 7

**par**(mfrow=**c**(1,2))**plot**(**residuals**(visit.qp, "pearson") **~** **fitted**(visit.qp))**plot**(**residuals**(visit.glm1, "pearson") **~** **fitted**(visit.glm1))

Chart, histogram

Description automatically generated

**anova**(visit.glm1,visit.qp)

## Analysis of Deviance Table## ## Model 1: Visits ~ health + as.factor(numchron) + adldiff + region + age + ## faminc + black + gender + married + school + age + privins + ## medicaid + Type## Model 2: Visits ~ health + as.factor(numchron) + adldiff + region + age + ## faminc + black + gender + married + school + age + privins + ## medicaid + Type## Resid. Df Resid. Dev Df Deviance## 1 26390 84792 ## 2 26390 84792 0 0

visit.nbm = **glm.nb**(Visits **~** health **+** **as.factor**(numchron) **+** adldiff **+** region **+** age **+** faminc **+** black **+** gender **+** married **+** school **+** age **+** privins **+** medicaid **+** Type, data = dbl)**summary**(visit.nbm)

## ## Call:## glm.nb(formula = Visits ~ health + as.factor(numchron) + adldiff + ## region + age + faminc + black + gender + married + school + ## age + privins + medicaid + Type, data = dbl, init.theta = 0.344331654, ## link = log)## ## Deviance Residuals: ## Min 1Q Median 3Q Max ## -1.7309 -0.8383 -0.6341 -0.1826 11.3503 ## ## Coefficients:## Estimate Std. Error z value Pr(>|z|) ## (Intercept) 2.065851 0.184299 11.209 < 2e-16 \*\*\*## healthpoor 0.276474 0.042034 6.577 4.79e-11 \*\*\*## healthexcellent -0.312541 0.054778 -5.706 1.16e-08 \*\*\*## as.factor(numchron)1 0.411720 0.038180 10.784 < 2e-16 \*\*\*## as.factor(numchron)2 0.715102 0.041535 17.217 < 2e-16 \*\*\*## as.factor(numchron)3 0.920877 0.048155 19.123 < 2e-16 \*\*\*## as.factor(numchron)4 0.894624 0.065107 13.741 < 2e-16 \*\*\*## as.factor(numchron)5 1.041511 0.080066 13.008 < 2e-16 \*\*\*## as.factor(numchron)6 0.897784 0.144933 6.194 5.85e-10 \*\*\*## as.factor(numchron)7 1.604299 0.310117 5.173 2.30e-07 \*\*\*## as.factor(numchron)8 1.543343 0.448788 3.439 0.000584 \*\*\*## adldiffyes 0.295255 0.036271 8.140 3.94e-16 \*\*\*## regionnoreast -0.083742 0.039672 -2.111 0.034785 \* ## regionother -0.230230 0.034438 -6.685 2.30e-11 \*\*\*## regionwest 0.020925 0.040457 0.517 0.605008 ## age -0.172807 0.022667 -7.624 2.46e-14 \*\*\*## faminc -0.004644 0.004829 -0.962 0.336279 ## blackyes 0.382801 0.043695 8.761 < 2e-16 \*\*\*## gendermale 0.026274 0.029511 0.890 0.373301 ## marriedyes 0.016908 0.031000 0.545 0.585463 ## school 0.019592 0.004030 4.861 1.17e-06 \*\*\*## privinsyes 0.227418 0.038876 5.850 4.92e-09 \*\*\*## medicaidyes 0.122497 0.053664 2.283 0.022451 \* ## Typeemer -3.145288 0.048224 -65.222 < 2e-16 \*\*\*## Typehosp -3.044564 0.047305 -64.360 < 2e-16 \*\*\*## Typeofnp -1.252001 0.039000 -32.103 < 2e-16 \*\*\*## Typeopnp -2.454202 0.043153 -56.872 < 2e-16 \*\*\*## Typeopp -2.122206 0.041555 -51.070 < 2e-16 \*\*\*## ---## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1## ## (Dispersion parameter for Negative Binomial(0.3443) family taken to be 1)## ## Null deviance: 28848 on 26417 degrees of freedom## Residual deviance: 18750 on 26390 degrees of freedom## AIC: 65749## ## Number of Fisher Scoring iterations: 1## ## ## Theta: 0.34433 ## Std. Err.: 0.00602 ## ## 2 x log-likelihood: -65691.18100

**plot**(**residuals**(visit.nbm, "pearson") **~** **fitted**(visit.nbm))

Chart, histogram

Description automatically generated

visit.nbm1 = **glm.nb**(Visits **~** health **+** **as.factor**(numchron) **+** adldiff **+** region **+** age **+** faminc **+** black **+** gender **\*** married **+** school **+** privins **+** medicaid **+** Type, data = dbl)**summary**(visit.nbm1)

## ## Call:## glm.nb(formula = Visits ~ health + as.factor(numchron) + adldiff + ## region + age + faminc + black + gender \* married + school + ## privins + medicaid + Type, data = dbl, init.theta = 0.3449669392, ## link = log)## ## Deviance Residuals: ## Min 1Q Median 3Q Max ## -1.7241 -0.8370 -0.6338 -0.1821 11.1923 ## ## Coefficients:## Estimate Std. Error z value Pr(>|z|) ## (Intercept) 2.148249 0.185627 11.573 < 2e-16 \*\*\*## healthpoor 0.284836 0.042040 6.775 1.24e-11 \*\*\*## healthexcellent -0.306758 0.054737 -5.604 2.09e-08 \*\*\*## as.factor(numchron)1 0.410098 0.038172 10.744 < 2e-16 \*\*\*## as.factor(numchron)2 0.711303 0.041534 17.126 < 2e-16 \*\*\*## as.factor(numchron)3 0.908243 0.048176 18.853 < 2e-16 \*\*\*## as.factor(numchron)4 0.893166 0.065081 13.724 < 2e-16 \*\*\*## as.factor(numchron)5 1.043287 0.079984 13.044 < 2e-16 \*\*\*## as.factor(numchron)6 0.891667 0.144909 6.153 7.59e-10 \*\*\*## as.factor(numchron)7 1.609117 0.309799 5.194 2.06e-07 \*\*\*## as.factor(numchron)8 1.513650 0.450821 3.358 0.000786 \*\*\*## adldiffyes 0.293981 0.036266 8.106 5.22e-16 \*\*\*## regionnoreast -0.078703 0.039646 -1.985 0.047130 \* ## regionother -0.230179 0.034426 -6.686 2.29e-11 \*\*\*## regionwest 0.023693 0.040453 0.586 0.558077 ## age -0.178110 0.022710 -7.843 4.40e-15 \*\*\*## faminc -0.004135 0.004824 -0.857 0.391265 ## blackyes 0.380338 0.043705 8.702 < 2e-16 \*\*\*## gendermale -0.152834 0.051132 -2.989 0.002799 \*\* ## marriedyes -0.068524 0.037417 -1.831 0.067046 . ## school 0.018629 0.004038 4.613 3.96e-06 \*\*\*## privinsyes 0.227994 0.038875 5.865 4.50e-09 \*\*\*## medicaidyes 0.108725 0.053806 2.021 0.043313 \* ## Typeemer -3.144468 0.048209 -65.226 < 2e-16 \*\*\*## Typehosp -3.044654 0.047297 -64.373 < 2e-16 \*\*\*## Typeofnp -1.249889 0.038971 -32.072 < 2e-16 \*\*\*## Typeopnp -2.453992 0.043137 -56.888 < 2e-16 \*\*\*## Typeopp -2.123131 0.041541 -51.109 < 2e-16 \*\*\*## gendermale:marriedyes 0.266340 0.062581 4.256 2.08e-05 \*\*\*## ---## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1## ## (Dispersion parameter for Negative Binomial(0.345) family taken to be 1)## ## Null deviance: 28881 on 26417 degrees of freedom## Residual deviance: 18751 on 26389 degrees of freedom## AIC: 65733## ## Number of Fisher Scoring iterations: 1## ## ## Theta: 0.34497 ## Std. Err.: 0.00603 ## ## 2 x log-likelihood: -65673.38000

visit.nbm3 = **glm.nb**(Visits **~** health **+** **as.factor**(numchron) **+** adldiff **+** age **+** faminc**\***medicaid**+** school **+** region **+** gender **+** black **+** married **+** Type**\***privins, data = dbl)**summary**(visit.nbm3)

## ## Call:## glm.nb(formula = Visits ~ health + as.factor(numchron) + adldiff + ## age + faminc \* medicaid + school + region + gender + black + ## married + Type \* privins, data = dbl, init.theta = 0.3500731251, ## link = log)## ## Deviance Residuals: ## Min 1Q Median 3Q Max ## -1.7320 -0.8320 -0.6320 -0.1887 12.4978 ## ## Coefficients:## Estimate Std. Error z value Pr(>|z|) ## (Intercept) 1.852915 0.188604 9.824 < 2e-16 \*\*\*## healthpoor 0.290221 0.041789 6.945 3.79e-12 \*\*\*## healthexcellent -0.328205 0.054794 -5.990 2.10e-09 \*\*\*## as.factor(numchron)1 0.407266 0.038095 10.691 < 2e-16 \*\*\*## as.factor(numchron)2 0.716700 0.041410 17.307 < 2e-16 \*\*\*## as.factor(numchron)3 0.916369 0.047997 19.092 < 2e-16 \*\*\*## as.factor(numchron)4 0.877447 0.064916 13.517 < 2e-16 \*\*\*## as.factor(numchron)5 1.030167 0.079668 12.931 < 2e-16 \*\*\*## as.factor(numchron)6 0.909076 0.143981 6.314 2.72e-10 \*\*\*## as.factor(numchron)7 1.498952 0.309423 4.844 1.27e-06 \*\*\*## as.factor(numchron)8 1.315201 0.453287 2.901 0.003714 \*\* ## adldiffyes 0.289070 0.036106 8.006 1.18e-15 \*\*\*## age -0.160368 0.022582 -7.102 1.23e-12 \*\*\*## faminc -0.003494 0.004860 -0.719 0.472232 ## medicaidyes 0.252067 0.064660 3.898 9.69e-05 \*\*\*## school 0.020385 0.004018 5.074 3.89e-07 \*\*\*## regionnoreast -0.092591 0.039577 -2.340 0.019307 \* ## regionother -0.233692 0.034328 -6.808 9.92e-12 \*\*\*## regionwest 0.025562 0.040294 0.634 0.525823 ## gendermale 0.024256 0.029424 0.824 0.409735 ## blackyes 0.352690 0.043522 8.104 5.33e-16 \*\*\*## marriedyes 0.021718 0.030909 0.703 0.482271 ## Typeemer -2.737902 0.097894 -27.968 < 2e-16 \*\*\*## Typehosp -2.795417 0.098886 -28.269 < 2e-16 \*\*\*## Typeofnp -1.603026 0.085291 -18.795 < 2e-16 \*\*\*## Typeopnp -2.511906 0.094399 -26.609 < 2e-16 \*\*\*## Typeopp -1.592708 0.085222 -18.689 < 2e-16 \*\*\*## privinsyes 0.374146 0.067123 5.574 2.49e-08 \*\*\*## faminc:medicaidyes -0.113577 0.034441 -3.298 0.000975 \*\*\*## Typeemer:privinsyes -0.532671 0.112298 -4.743 2.10e-06 \*\*\*## Typehosp:privinsyes -0.316213 0.112342 -2.815 0.004882 \*\* ## Typeofnp:privinsyes 0.415569 0.095793 4.338 1.44e-05 \*\*\*## Typeopnp:privinsyes 0.073798 0.105935 0.697 0.486032 ## Typeopp:privinsyes -0.707118 0.097496 -7.253 4.08e-13 \*\*\*## ---## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1## ## (Dispersion parameter for Negative Binomial(0.3501) family taken to be 1)## ## Null deviance: 29144 on 26417 degrees of freedom## Residual deviance: 18759 on 26384 degrees of freedom## AIC: 65603## ## Number of Fisher Scoring iterations: 1## ## ## Theta: 0.35007 ## Std. Err.: 0.00614 ## ## 2 x log-likelihood: -65532.97500

visit.nbm2 = **glm.nb**(Visits **~** health **+** **as.factor**(numchron) **+** adldiff **+** age **+** faminc **+** school **+** region **+** gender**\***black **+** married **+** medicaid**+** Type**\***privins, data = dbl)**summary**(visit.nbm2)

## ## Call:## glm.nb(formula = Visits ~ health + as.factor(numchron) + adldiff + ## age + faminc + school + region + gender \* black + married + ## medicaid + Type \* privins, data = dbl, init.theta = 0.3508960137, ## link = log)## ## Deviance Residuals: ## Min 1Q Median 3Q Max ## -1.7454 -0.8309 -0.6311 -0.1933 11.5393 ## ## Coefficients:## Estimate Std. Error z value Pr(>|z|) ## (Intercept) 1.857598 0.188335 9.863 < 2e-16 \*\*\*## healthpoor 0.289977 0.041759 6.944 3.81e-12 \*\*\*## healthexcellent -0.327521 0.054771 -5.980 2.23e-09 \*\*\*## as.factor(numchron)1 0.403211 0.038092 10.585 < 2e-16 \*\*\*## as.factor(numchron)2 0.714887 0.041394 17.270 < 2e-16 \*\*\*## as.factor(numchron)3 0.897868 0.048048 18.687 < 2e-16 \*\*\*## as.factor(numchron)4 0.870047 0.064891 13.408 < 2e-16 \*\*\*## as.factor(numchron)5 1.037666 0.079648 13.028 < 2e-16 \*\*\*## as.factor(numchron)6 0.895702 0.143683 6.234 4.55e-10 \*\*\*## as.factor(numchron)7 1.521563 0.308962 4.925 8.45e-07 \*\*\*## as.factor(numchron)8 1.306681 0.454769 2.873 0.004062 \*\* ## adldiffyes 0.303094 0.036095 8.397 < 2e-16 \*\*\*## age -0.160130 0.022555 -7.099 1.25e-12 \*\*\*## faminc -0.006135 0.004835 -1.269 0.204487 ## school 0.022544 0.004021 5.607 2.06e-08 \*\*\*## regionnoreast -0.088921 0.039566 -2.247 0.024614 \* ## regionother -0.238306 0.034344 -6.939 3.96e-12 \*\*\*## regionwest 0.025806 0.040278 0.641 0.521718 ## gendermale -0.034068 0.031031 -1.098 0.272265 ## blackyes 0.139123 0.054185 2.568 0.010242 \* ## marriedyes 0.020354 0.030862 0.660 0.509560 ## medicaidyes 0.185401 0.053277 3.480 0.000502 \*\*\*## Typeemer -2.744786 0.097797 -28.066 < 2e-16 \*\*\*## Typehosp -2.812391 0.098965 -28.418 < 2e-16 \*\*\*## Typeofnp -1.602284 0.085146 -18.818 < 2e-16 \*\*\*## Typeopnp -2.568547 0.095021 -27.031 < 2e-16 \*\*\*## Typeopp -1.607258 0.085179 -18.869 < 2e-16 \*\*\*## privinsyes 0.377686 0.067039 5.634 1.76e-08 \*\*\*## gendermale:blackyes 0.551985 0.082167 6.718 1.84e-11 \*\*\*## Typeemer:privinsyes -0.531165 0.112218 -4.733 2.21e-06 \*\*\*## Typehosp:privinsyes -0.299135 0.112388 -2.662 0.007776 \*\* ## Typeofnp:privinsyes 0.413714 0.095645 4.325 1.52e-05 \*\*\*## Typeopnp:privinsyes 0.128850 0.106473 1.210 0.226214 ## Typeopp:privinsyes -0.698087 0.097452 -7.163 7.87e-13 \*\*\*## ---## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1## ## (Dispersion parameter for Negative Binomial(0.3509) family taken to be 1)## ## Null deviance: 29186 on 26417 degrees of freedom## Residual deviance: 18751 on 26384 degrees of freedom## AIC: 65571## ## Number of Fisher Scoring iterations: 1## ## ## Theta: 0.35090 ## Std. Err.: 0.00615 ## ## 2 x log-likelihood: -65501.26400

**anova**(visit.nbm,visit.nbm2)

## Likelihood ratio tests of Negative Binomial Models## ## Response: Visits## Model## 1 health + as.factor(numchron) + adldiff + region + age + faminc + black + gender + married + school + age + privins + medicaid + Type## 2 health + as.factor(numchron) + adldiff + age + faminc + school + region + gender \* black + married + medicaid + Type \* privins## theta Resid. df 2 x log-lik. Test df LR stat. Pr(Chi)## 1 0.3443317 26390 -65691.18 ## 2 0.3508960 26384 -65501.26 1 vs 2 6 189.9171 0

**stepAIC**(visit.nbm2)

## Start: AIC=65569.26## Visits ~ health + as.factor(numchron) + adldiff + age + faminc + ## school + region + gender \* black + married + medicaid + Type \* ## privins## ## Df AIC## - married 1 65568## - faminc 1 65569## <none> 65569## - medicaid 1 65579## - school 1 65600## - gender:black 1 65610## - age 1 65616## - region 3 65629## - adldiff 1 65638## - health 2 65652## - Type:privins 5 65709## - as.factor(numchron) 8 66079## ## Step: AIC=65567.68## Visits ~ health + as.factor(numchron) + adldiff + age + faminc + ## school + region + gender + black + medicaid + Type + privins + ## gender:black + Type:privins## ## Df AIC## - faminc 1 65567## <none> 65568## - medicaid 1 65577## - school 1 65598## - gender:black 1 65609## - age 1 65618## - region 3 65628## - adldiff 1 65636## - health 2 65651## - Type:privins 5 65707## - as.factor(numchron) 8 66078## ## Step: AIC=65566.93## Visits ~ health + as.factor(numchron) + adldiff + age + school + ## region + gender + black + medicaid + Type + privins + gender:black + ## Type:privins## ## Df AIC## <none> 65567## - medicaid 1 65577## - school 1 65596## - gender:black 1 65608## - age 1 65617## - region 3 65626## - adldiff 1 65635## - health 2 65652## - Type:privins 5 65706## - as.factor(numchron) 8 66077

## ## Call: glm.nb(formula = Visits ~ health + as.factor(numchron) + adldiff + ## age + school + region + gender + black + medicaid + Type + ## privins + gender:black + Type:privins, data = dbl, init.theta = 0.3508466138, ## link = log)## ## Coefficients:## (Intercept) healthpoor healthexcellent ## 1.87448 0.29266 -0.33273 ## as.factor(numchron)1 as.factor(numchron)2 as.factor(numchron)3 ## 0.40333 0.71407 0.89858 ## as.factor(numchron)4 as.factor(numchron)5 as.factor(numchron)6 ## 0.86785 1.03965 0.89562 ## as.factor(numchron)7 as.factor(numchron)8 adldiffyes ## 1.52288 1.30287 0.30128 ## age school regionnoreast ## -0.16219 0.02179 -0.08936 ## regionother regionwest gendermale ## -0.23571 0.02459 -0.03011 ## blackyes medicaidyes Typeemer ## 0.13838 0.18705 -2.74613 ## Typehosp Typeofnp Typeopnp ## -2.81301 -1.60041 -2.56962 ## Typeopp privinsyes gendermale:blackyes ## -1.60815 0.37733 0.55166 ## Typeemer:privinsyes Typehosp:privinsyes Typeofnp:privinsyes ## -0.52946 -0.29822 0.41281 ## Typeopnp:privinsyes Typeopp:privinsyes ## 0.13083 -0.69594 ## ## Degrees of Freedom: 26417 Total (i.e. Null); 26386 Residual## Null Deviance: 29180 ## Residual Deviance: 18750 AIC: 65570

final.nbm = **glm.nb**(Visits **~** health **+** **as.factor**(numchron) **+** adldiff **+** age **+** school **+** region **+** gender**\***black **+** medicaid**+** Type**\***privins, data = dbl)**summary**(final.nbm)

## ## Call:## glm.nb(formula = Visits ~ health + as.factor(numchron) + adldiff + ## age + school + region + gender \* black + medicaid + Type \* ## privins, data = dbl, init.theta = 0.3508469867, link = log)## ## Deviance Residuals: ## Min 1Q Median 3Q Max ## -1.7426 -0.8312 -0.6317 -0.1931 11.5177 ## ## Coefficients:## Estimate Std. Error z value Pr(>|z|) ## (Intercept) 1.874478 0.183514 10.214 < 2e-16 \*\*\*## healthpoor 0.292662 0.041741 7.011 2.36e-12 \*\*\*## healthexcellent -0.332727 0.054702 -6.083 1.18e-09 \*\*\*## as.factor(numchron)1 0.403335 0.038072 10.594 < 2e-16 \*\*\*## as.factor(numchron)2 0.714066 0.041389 17.252 < 2e-16 \*\*\*## as.factor(numchron)3 0.898574 0.048034 18.707 < 2e-16 \*\*\*## as.factor(numchron)4 0.867849 0.064899 13.372 < 2e-16 \*\*\*## as.factor(numchron)5 1.039641 0.079627 13.056 < 2e-16 \*\*\*## as.factor(numchron)6 0.895617 0.143683 6.233 4.57e-10 \*\*\*## as.factor(numchron)7 1.522872 0.308862 4.931 8.20e-07 \*\*\*## as.factor(numchron)8 1.302867 0.453939 2.870 0.004103 \*\* ## adldiffyes 0.301278 0.036057 8.356 < 2e-16 \*\*\*## age -0.162195 0.022062 -7.352 1.95e-13 \*\*\*## school 0.021789 0.003951 5.515 3.48e-08 \*\*\*## regionnoreast -0.089358 0.039541 -2.260 0.023830 \* ## regionother -0.235708 0.034326 -6.867 6.57e-12 \*\*\*## regionwest 0.024593 0.040219 0.611 0.540888 ## gendermale -0.030111 0.028896 -1.042 0.297377 ## blackyes 0.138376 0.054089 2.558 0.010518 \* ## medicaidyes 0.187052 0.053162 3.519 0.000434 \*\*\*## Typeemer -2.746131 0.097818 -28.074 < 2e-16 \*\*\*## Typehosp -2.813006 0.098974 -28.422 < 2e-16 \*\*\*## Typeofnp -1.600408 0.085136 -18.798 < 2e-16 \*\*\*## Typeopnp -2.569631 0.095037 -27.038 < 2e-16 \*\*\*## Typeopp -1.608158 0.085187 -18.878 < 2e-16 \*\*\*## privinsyes 0.377324 0.066954 5.636 1.74e-08 \*\*\*## gendermale:blackyes 0.551633 0.082154 6.715 1.89e-11 \*\*\*## Typeemer:privinsyes -0.529459 0.112238 -4.717 2.39e-06 \*\*\*## Typehosp:privinsyes -0.298219 0.112398 -2.653 0.007972 \*\* ## Typeofnp:privinsyes 0.412810 0.095637 4.316 1.59e-05 \*\*\*## Typeopnp:privinsyes 0.130838 0.106486 1.229 0.219190 ## Typeopp:privinsyes -0.695933 0.097458 -7.141 9.28e-13 \*\*\*## ---## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1## ## (Dispersion parameter for Negative Binomial(0.3508) family taken to be 1)## ## Null deviance: 29184 on 26417 degrees of freedom## Residual deviance: 18751 on 26386 degrees of freedom## AIC: 65569## ## Number of Fisher Scoring iterations: 1## ## ## Theta: 0.35085 ## Std. Err.: 0.00615 ## ## 2 x log-likelihood: -65502.92700

**plot**(**residuals**(final.nbm, "pearson") **~** **fitted**(final.nbm))

Chart, histogram

Description automatically generated

**exp**(**coef**(final.nbm))

## (Intercept) healthpoor healthexcellent ## 6.51741851 1.33998999 0.71696576 ## as.factor(numchron)1 as.factor(numchron)2 as.factor(numchron)3 ## 1.49680760 2.04227739 2.45609829 ## as.factor(numchron)4 as.factor(numchron)5 as.factor(numchron)6 ## 2.38178200 2.82820256 2.44884548 ## as.factor(numchron)7 as.factor(numchron)8 adldiffyes ## 4.58537452 3.67983259 1.35158497 ## age school regionnoreast ## 0.85027553 1.02202766 0.91451831 ## regionother regionwest gendermale ## 0.79001094 1.02489741 0.97033742 ## blackyes medicaidyes Typeemer ## 1.14840736 1.20569008 0.06417565 ## Typehosp Typeofnp Typeopnp ## 0.06002428 0.20181418 0.07656379 ## Typeopp privinsyes gendermale:blackyes ## 0.20025621 1.45837693 1.73608523 ## Typeemer:privinsyes Typehosp:privinsyes Typeofnp:privinsyes ## 0.58892368 0.74213903 1.51105769 ## Typeopnp:privinsyes Typeopp:privinsyes ## 1.13978341 0.49860916