Effect of Private Health Insurance and Medicaid on Visiting Physician Office

PART A Introduction  
 Deb and Trivedi (1997) analysed data on 4406 individuals, aged 66 and over, who are covered by Medicare, a public insurance program. This report is on the analysis of data from Deb and Trivedi’s to find impact of private health insurance and access to Medicaid on number of physician office visits.

PART B Methodology  
 The data contains measures of visits to physician (OFP), visits to a non-physician (OFNP), visits hospital (OPP), visits to emergency room (EMR), and number of hospitals stays (HOSP) and explanatory variables which are health, the number of chronic diseases (NUMCHRON), and a measure status (ADLDIFF), region, age, race (BLACK), gender, status (MARRIED), and education (SCHOOL). Finally, the economic income (FAMINC), employment status (EMPLOY), supplementary private (PRIVINS), and public insurance status.  
The first step in the analysis was to omit the unnecessary measures. Then we plotted histogram of OFP (Fig. 1) and each variable against OFP (Fig. 2) to see any special pattern. A negative binomial regression model was fitted to Result, with interaction terms between categorical variables after comparing few other models. Confidence interval (Fig. 3) and test for model adequacy were conducted.

PART C Results  
 Histogram of OFP shows too many excesses of zero which led to overdispersion. The final model was selected because it is simple and accurate. Numeric categorical variables were not converted to factor due to simpleness of model. Summaries of the data did not show any unusual records.  
 The final negative binomial regression model reduced to only significant variables. The main findings were as below.  
1. People with poor health condition have 1.44 times more and people with excellent condition 0.45 times less visits on physician office.  
2. People with day living difficulty visits 1.15 times more on physician office.  
3. Person who has private health cover visits 1.43 times more and Person who has public insurance visits 1.24 times more on physician office.  
4. Every 1 more chronic disease, people visit 1.21 times more on physician office.  
5. People who live in Northeast visit 1.12 times more and people who lives in West visit 1.15 times more on physician office  
6. Males visit 0.92 times less on physician office.  
7. Every year more spent in school, people visit 1.03 times more on physician office.  
8. People with poor health condition and day living difficulty visit 0.82 times less on physician office.  
9. People with poor health condition and public insurance visit 1.39 times more on physician office.  
10. People with excellent health condition and private insurance visit 1.58 times more on physician office.

PART D Discussion  
 From the result, we found the evidence of people visit physician office more if they hold any type of insurance. Also, People who have poor health condition or handicap or chronic disease visit more and people with good condition visit less. Those results were predictable, but oddly people with excellent condition and private healthcare visit physician office more and income is irrelevant to visit.   
 The statistical analysis can be improved in several ways. It would be better if data was separated by purpose of visiting. Also, it would be better if variable numchron and school were larger classification for example, no chronic disease, 1~3, 4 or more chronic disease or high school lower, high school, college, university, etc.,.

**Lab Test 6 Appendix**

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**library**(MixAll)**library**(rtkore)**library**(MASS)**data**(DebTrivedi)Medi\_data = DebTrivedi**summary**(Medi\_data)

## ofp ofnp opp opnp ## Min. : 0.000 Min. : 0.000 Min. : 0.0000 Min. : 0.0000 ## 1st Qu.: 1.000 1st Qu.: 0.000 1st Qu.: 0.0000 1st Qu.: 0.0000 ## Median : 4.000 Median : 0.000 Median : 0.0000 Median : 0.0000 ## Mean : 5.774 Mean : 1.618 Mean : 0.7508 Mean : 0.5361 ## 3rd Qu.: 8.000 3rd Qu.: 1.000 3rd Qu.: 0.0000 3rd Qu.: 0.0000 ## Max. :89.000 Max. :104.000 Max. :141.0000 Max. :155.0000 ## emer hosp health numchron adldiff ## Min. : 0.0000 Min. :0.000 poor : 554 Min. :0.000 no :3507 ## 1st Qu.: 0.0000 1st Qu.:0.000 average :3509 1st Qu.:1.000 yes: 899 ## Median : 0.0000 Median :0.000 excellent: 343 Median :1.000 ## Mean : 0.2635 Mean :0.296 Mean :1.542 ## 3rd Qu.: 0.0000 3rd Qu.:0.000 3rd Qu.:2.000 ## Max. :12.0000 Max. :8.000 Max. :8.000 ## region age black gender married ## midwest:1157 Min. : 6.600 no :3890 female:2628 no :2000 ## noreast: 837 1st Qu.: 6.900 yes: 516 male :1778 yes:2406 ## other :1614 Median : 7.300 ## west : 798 Mean : 7.402 ## 3rd Qu.: 7.800 ## Max. :10.900 ## school faminc employed privins medicaid ## Min. : 0.00 Min. :-1.0125 no :3951 no : 985 no :4004 ## 1st Qu.: 8.00 1st Qu.: 0.9122 yes: 455 yes:3421 yes: 402 ## Median :11.00 Median : 1.6982 ## Mean :10.29 Mean : 2.5271 ## 3rd Qu.:12.00 3rd Qu.: 3.1728 ## Max. :18.00 Max. :54.8351

Medi\_data = **subset**(Medi\_data, select = **-c**(ofnp,opp,opnp,emer,hosp))**summary**(Medi\_data)

## ofp health numchron adldiff region ## Min. : 0.000 poor : 554 Min. :0.000 no :3507 midwest:1157 ## 1st Qu.: 1.000 average :3509 1st Qu.:1.000 yes: 899 noreast: 837 ## Median : 4.000 excellent: 343 Median :1.000 other :1614 ## Mean : 5.774 Mean :1.542 west : 798 ## 3rd Qu.: 8.000 3rd Qu.:2.000 ## Max. :89.000 Max. :8.000 ## age black gender married school ## Min. : 6.600 no :3890 female:2628 no :2000 Min. : 0.00 ## 1st Qu.: 6.900 yes: 516 male :1778 yes:2406 1st Qu.: 8.00 ## Median : 7.300 Median :11.00 ## Mean : 7.402 Mean :10.29 ## 3rd Qu.: 7.800 3rd Qu.:12.00 ## Max. :10.900 Max. :18.00 ## faminc employed privins medicaid ## Min. :-1.0125 no :3951 no : 985 no :4004 ## 1st Qu.: 0.9122 yes: 455 yes:3421 yes: 402 ## Median : 1.6982 ## Mean : 2.5271 ## 3rd Qu.: 3.1728 ## Max. :54.8351

**mean**(Medi\_data**$**ofp)

## [1] 5.774399

**var**(Medi\_data**$**ofp)

## [1] 45.68712

**plot**(**table**(Medi\_data**$**ofp))

Chart, histogram

Description automatically generated

1 Figure 1

**par**(mfcol=**c**(2,4))**plot**(ofp**~**health,data = Medi\_data)**plot**(ofp**~**numchron,data = Medi\_data)**plot**(ofp**~**adldiff,data = Medi\_data)**plot**(ofp**~**region,data = Medi\_data)**plot**(ofp**~**age,data = Medi\_data)**plot**(ofp**~**black,data = Medi\_data)**plot**(ofp**~**gender,data=Medi\_data)**plot**(ofp**~**married, data=Medi\_data)

Diagram, schematic

Description automatically generated

2 Figure  
**plot**(ofp**~**school, data=Medi\_data)  
**plot**(ofp**~**faminc,data = Medi\_data)  
**plot**(ofp**~**employed,data = Medi\_data)  
**plot**(ofp**~**privins,data = Medi\_data)  
**plot**(ofp**~**medicaid,data = Medi\_data)

Diagram, schematic

Description automatically generated

Medi\_data**$**numchron =**factor**(Medi\_data**$**numchron)Medi\_data**$**school = **factor**(Medi\_data**$**school)glm\_Medi\_data = **glm**(ofp**~**., data=Medi\_data,family = 'poisson')**summary**(glm\_Medi\_data)

## ## Call:## glm(formula = ofp ~ ., family = "poisson", data = Medi\_data)## ## Deviance Residuals: ## Min 1Q Median 3Q Max ## -5.6522 -2.0087 -0.6934 0.7511 15.7893 ## ## Coefficients:## Estimate Std. Error z value Pr(>|z|) ## (Intercept) 1.256812 0.101282 12.409 < 2e-16 \*\*\*## healthpoor 0.295613 0.018283 16.169 < 2e-16 \*\*\*## healthexcellent -0.356321 0.030661 -11.621 < 2e-16 \*\*\*## numchron1 0.368174 0.020676 17.807 < 2e-16 \*\*\*## numchron2 0.608100 0.021464 28.331 < 2e-16 \*\*\*## numchron3 0.654878 0.024155 27.112 < 2e-16 \*\*\*## numchron4 0.854743 0.029082 29.390 < 2e-16 \*\*\*## numchron5 0.892625 0.034372 25.969 < 2e-16 \*\*\*## numchron6 0.881949 0.059268 14.881 < 2e-16 \*\*\*## numchron7 1.136641 0.118944 9.556 < 2e-16 \*\*\*## numchron8 -0.467974 0.408409 -1.146 0.251859 ## adldiffyes 0.094495 0.016691 5.661 1.50e-08 \*\*\*## regionnoreast 0.111004 0.019002 5.842 5.17e-09 \*\*\*## regionother -0.008446 0.017037 -0.496 0.620086 ## regionwest 0.114988 0.019415 5.923 3.17e-09 \*\*\*## age -0.067553 0.011044 -6.117 9.56e-10 \*\*\*## blackyes -0.083996 0.022806 -3.683 0.000230 \*\*\*## gendermale -0.068151 0.014500 -4.700 2.60e-06 \*\*\*## marriedyes -0.045286 0.014851 -3.049 0.002294 \*\* ## school1 0.174910 0.127719 1.369 0.170846 ## school2 0.148771 0.086914 1.712 0.086953 . ## school3 0.227564 0.067856 3.354 0.000798 \*\*\*## school4 0.056102 0.066770 0.840 0.400781 ## school5 0.241891 0.063254 3.824 0.000131 \*\*\*## school6 0.128736 0.058397 2.204 0.027491 \* ## school7 0.170073 0.056366 3.017 0.002550 \*\* ## school8 0.202895 0.051298 3.955 7.65e-05 \*\*\*## school9 0.085881 0.057165 1.502 0.133014 ## school10 0.198567 0.054765 3.626 0.000288 \*\*\*## school11 0.232460 0.056197 4.136 3.53e-05 \*\*\*## school12 0.264749 0.050587 5.234 1.66e-07 \*\*\*## school13 0.340997 0.057878 5.892 3.82e-09 \*\*\*## school14 0.299655 0.055715 5.378 7.51e-08 \*\*\*## school15 0.503149 0.063941 7.869 3.58e-15 \*\*\*## school16 0.357565 0.055429 6.451 1.11e-10 \*\*\*## school17 0.426609 0.076665 5.565 2.63e-08 \*\*\*## school18 0.674902 0.060721 11.115 < 2e-16 \*\*\*## faminc -0.004326 0.002334 -1.853 0.063826 . ## employedyes 0.038518 0.022095 1.743 0.081277 . ## privinsyes 0.310248 0.019874 15.611 < 2e-16 \*\*\*## medicaidyes 0.259513 0.025379 10.226 < 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: 26943 on 4405 degrees of freedom## Residual deviance: 23098 on 4365 degrees of freedom## AIC: 35955## ## Number of Fisher Scoring iterations: 5

glm\_nb\_Medi\_data = **glm.nb**(ofp**~**.,data=Medi\_data)**summary**(glm\_nb\_Medi\_data)

## ## Call:## glm.nb(formula = ofp ~ ., data = Medi\_data, init.theta = 1.206840371, ## link = log)## ## Deviance Residuals: ## Min 1Q Median 3Q Max ## -2.5813 -0.9868 -0.3067 0.3129 5.2092 ## ## Coefficients:## Estimate Std. Error z value Pr(>|z|) ## (Intercept) 1.027752 0.238403 4.311 1.63e-05 \*\*\*## healthpoor 0.330535 0.050115 6.596 4.24e-11 \*\*\*## healthexcellent -0.370361 0.062084 -5.965 2.44e-09 \*\*\*## numchron1 0.394847 0.043122 9.157 < 2e-16 \*\*\*## numchron2 0.617161 0.047490 12.996 < 2e-16 \*\*\*## numchron3 0.687846 0.056302 12.217 < 2e-16 \*\*\*## numchron4 0.895471 0.076049 11.775 < 2e-16 \*\*\*## numchron5 0.940037 0.095664 9.826 < 2e-16 \*\*\*## numchron6 0.901020 0.172461 5.224 1.75e-07 \*\*\*## numchron7 1.120037 0.395429 2.832 0.004619 \*\* ## numchron8 -0.399308 0.668870 -0.597 0.550514 ## adldiffyes 0.092649 0.042942 2.158 0.030962 \* ## regionnoreast 0.101603 0.046240 2.197 0.027998 \* ## regionother -0.023639 0.040627 -0.582 0.560662 ## regionwest 0.119809 0.047749 2.509 0.012104 \* ## age -0.042259 0.026796 -1.577 0.114777 ## blackyes -0.096776 0.053188 -1.820 0.068832 . ## gendermale -0.076427 0.034724 -2.201 0.027738 \* ## marriedyes -0.038753 0.036107 -1.073 0.283143 ## school1 0.269066 0.298784 0.901 0.367835 ## school2 0.234859 0.196279 1.197 0.231478 ## school3 0.205829 0.159266 1.292 0.196232 ## school4 0.011375 0.148095 0.077 0.938775 ## school5 0.283341 0.144472 1.961 0.049854 \* ## school6 0.099766 0.130218 0.766 0.443588 ## school7 0.172862 0.125158 1.381 0.167234 ## school8 0.185768 0.112249 1.655 0.097932 . ## school9 0.143756 0.124902 1.151 0.249751 ## school10 0.230599 0.121418 1.899 0.057537 . ## school11 0.178316 0.125739 1.418 0.156149 ## school12 0.277462 0.110407 2.513 0.011968 \* ## school13 0.343057 0.131522 2.608 0.009098 \*\* ## school14 0.363795 0.124802 2.915 0.003557 \*\* ## school15 0.565121 0.151316 3.735 0.000188 \*\*\*## school16 0.368058 0.124213 2.963 0.003045 \*\* ## school17 0.468516 0.183059 2.559 0.010486 \* ## school18 0.718734 0.144300 4.981 6.33e-07 \*\*\*## faminc -0.004316 0.005685 -0.759 0.447803 ## employedyes 0.033151 0.052827 0.628 0.530306 ## privinsyes 0.331105 0.045319 7.306 2.75e-13 \*\*\*## medicaidyes 0.248186 0.063152 3.930 8.50e-05 \*\*\*## ---## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1## ## (Dispersion parameter for Negative Binomial(1.2068) family taken to be 1)## ## Null deviance: 5744.5 on 4405 degrees of freedom## Residual deviance: 5039.6 on 4365 degrees of freedom## AIC: 24420## ## Number of Fisher Scoring iterations: 1## ## ## Theta: 1.2068 ## Std. Err.: 0.0335 ## ## 2 x log-likelihood: -24335.5680

nb\_Medi\_data\_inter = **glm.nb**(ofp**~**(health**+**numchron**+**adldiff**+**privins**+**medicaid)**^**2**+**region**+**age**+**black**+**gender**+**married**+**school**+**faminc**+**employed, data=Medi\_data)

**stepAIC**(nb\_Medi\_data\_inter)

## Start: AIC=24439.1## ofp ~ (health + numchron + adldiff + privins + medicaid)^2 + ## region + age + black + gender + married + school + faminc + ## employed## ## Df AIC## - numchron:medicaid 6 24430## - numchron:privins 7 24432## - numchron:adldiff 7 24433## - health:numchron 13 24433## - health:privins 2 24437## - health:adldiff 2 24437## - adldiff:privins 1 24437## - employed 1 24437## - adldiff:medicaid 1 24438## - faminc 1 24438## - married 1 24439## <none> 24439## - privins:medicaid 1 24439## - age 1 24440## - health:medicaid 2 24440## - black 1 24440## - gender 1 24442## - region 3 24448## - school 18 24459## ## Step: AIC=24430.03## ofp ~ health + numchron + adldiff + privins + medicaid + region + ## age + black + gender + married + school + faminc + employed + ## health:numchron + health:adldiff + health:privins + health:medicaid + ## numchron:adldiff + numchron:privins + adldiff:privins + adldiff:medicaid + ## privins:medicaid## ## Df AIC## - numchron:adldiff 7 24424## - numchron:privins 7 24424## - health:numchron 13 24425## - health:privins 2 24428## - health:adldiff 2 24428## - employed 1 24428## - adldiff:privins 1 24429## - faminc 1 24429## - adldiff:medicaid 1 24429## - married 1 24429## <none> 24430## - privins:medicaid 1 24431## - age 1 24431## - health:medicaid 2 24431## - black 1 24431## - gender 1 24433## - region 3 24438## - school 18 24450## ## Step: AIC=24423.51## ofp ~ health + numchron + adldiff + privins + medicaid + region + ## age + black + gender + married + school + faminc + employed + ## health:numchron + health:adldiff + health:privins + health:medicaid + ## numchron:privins + adldiff:privins + adldiff:medicaid + privins:medicaid## ## Df AIC## - numchron:privins 8 24418## - health:privins 2 24421## - adldiff:privins 1 24422## - employed 1 24422## - health:numchron 13 24422## - adldiff:medicaid 1 24422## - faminc 1 24422## - married 1 24423## - health:adldiff 2 24423## <none> 24424## - privins:medicaid 1 24424## - age 1 24424## - black 1 24425## - health:medicaid 2 24425## - gender 1 24426## - region 3 24432## - school 18 24445## ## Step: AIC=24418.19## ofp ~ health + numchron + adldiff + privins + medicaid + region + ## age + black + gender + married + school + faminc + employed + ## health:numchron + health:adldiff + health:privins + health:medicaid + ## adldiff:privins + adldiff:medicaid + privins:medicaid## ## Df AIC## - adldiff:privins 1 24416## - health:privins 2 24416## - adldiff:medicaid 1 24417## - employed 1 24417## - faminc 1 24417## - married 1 24417## - health:adldiff 2 24418## - health:numchron 13 24418## <none> 24418## - age 1 24419## - privins:medicaid 1 24419## - black 1 24420## - health:medicaid 2 24420## - gender 1 24421## - region 3 24426## - school 18 24440## ## Step: AIC=24416.29## ofp ~ health + numchron + adldiff + privins + medicaid + region + ## age + black + gender + married + school + faminc + employed + ## health:numchron + health:adldiff + health:privins + health:medicaid + ## adldiff:medicaid + privins:medicaid## ## Df AIC## - health:privins 2 24414## - adldiff:medicaid 1 24415## - employed 1 24415## - faminc 1 24415## - married 1 24415## - health:adldiff 2 24416## - health:numchron 13 24416## <none> 24416## - age 1 24417## - privins:medicaid 1 24417## - black 1 24418## - health:medicaid 2 24418## - gender 1 24419## - region 3 24424## - school 18 24439## ## Step: AIC=24414.38## ofp ~ health + numchron + adldiff + privins + medicaid + region + ## age + black + gender + married + school + faminc + employed + ## health:numchron + health:adldiff + health:medicaid + adldiff:medicaid + ## privins:medicaid## ## Df AIC## - adldiff:medicaid 1 24413## - employed 1 24413## - faminc 1 24413## - married 1 24414## - health:adldiff 2 24414## <none> 24414## - age 1 24415## - privins:medicaid 1 24415## - black 1 24416## - health:numchron 13 24417## - health:medicaid 2 24417## - gender 1 24417## - region 3 24422## - school 18 24437## ## Step: AIC=24412.71## ofp ~ health + numchron + adldiff + privins + medicaid + region + ## age + black + gender + married + school + faminc + employed + ## health:numchron + health:adldiff + health:medicaid + privins:medicaid## ## Df AIC## - employed 1 24411## - faminc 1 24412## - married 1 24412## - health:adldiff 2 24412## <none> 24413## - age 1 24414## - privins:medicaid 1 24414## - black 1 24414## - health:numchron 13 24415## - gender 1 24416## - health:medicaid 2 24417## - region 3 24420## - school 18 24436## ## Step: AIC=24411.12## ofp ~ health + numchron + adldiff + privins + medicaid + region + ## age + black + gender + married + school + faminc + health:numchron + ## health:adldiff + health:medicaid + privins:medicaid## ## Df AIC## - faminc 1 24410## - married 1 24410## - health:adldiff 2 24411## <none> 24411## - privins:medicaid 1 24412## - age 1 24412## - black 1 24413## - health:numchron 13 24413## - gender 1 24414## - health:medicaid 2 24415## - region 3 24419## - school 18 24435## ## Step: AIC=24409.76## ofp ~ health + numchron + adldiff + privins + medicaid + region + ## age + black + gender + married + school + health:numchron + ## health:adldiff + health:medicaid + privins:medicaid## ## Df AIC## - married 1 24409## - health:adldiff 2 24410## <none> 24410## - privins:medicaid 1 24411## - age 1 24411## - black 1 24411## - health:numchron 13 24412## - gender 1 24413## - health:medicaid 2 24414## - region 3 24417## - school 18 24433## ## Step: AIC=24409.3## ofp ~ health + numchron + adldiff + privins + medicaid + region + ## age + black + gender + school + health:numchron + health:adldiff + ## health:medicaid + privins:medicaid## ## Df AIC## - health:adldiff 2 24409## <none> 24409## - age 1 24410## - privins:medicaid 1 24410## - black 1 24410## - health:numchron 13 24411## - health:medicaid 2 24413## - gender 1 24416## - region 3 24417## - school 18 24432## ## Step: AIC=24409.14## ofp ~ health + numchron + adldiff + privins + medicaid + region + ## age + black + gender + school + health:numchron + health:medicaid + ## privins:medicaid## ## Df AIC## <none> 24409## - age 1 24409## - black 1 24410## - privins:medicaid 1 24410## - health:medicaid 2 24411## - health:numchron 13 24412## - adldiff 1 24412## - gender 1 24416## - region 3 24417## - school 18 24432

## ## Call: glm.nb(formula = ofp ~ health + numchron + adldiff + privins + ## medicaid + region + age + black + gender + school + health:numchron + ## health:medicaid + privins:medicaid, data = Medi\_data, init.theta = 1.219285008, ## link = log)## ## Coefficients:## (Intercept) healthpoor ## 0.95819 0.79802 ## healthexcellent numchron1 ## -0.50655 0.36214 ## numchron2 numchron3 ## 0.59181 0.68801 ## numchron4 numchron5 ## 0.98518 1.08923 ## numchron6 numchron7 ## 1.06376 1.54422 ## numchron8 adldiffyes ## 0.02341 0.09116 ## privinsyes medicaidyes ## 0.34770 0.20838 ## regionnoreast regionother ## 0.10120 -0.01313 ## regionwest age ## 0.12110 -0.03971 ## blackyes gendermale ## -0.08979 -0.09698 ## school1 school2 ## 0.33138 0.28050 ## school3 school4 ## 0.24530 0.02617 ## school5 school6 ## 0.31558 0.13556 ## school7 school8 ## 0.20352 0.21351 ## school9 school10 ## 0.18319 0.25807 ## school11 school12 ## 0.21101 0.30416 ## school13 school14 ## 0.35803 0.38313 ## school15 school16 ## 0.57136 0.40384 ## school17 school18 ## 0.46867 0.73470 ## healthpoor:numchron1 healthexcellent:numchron1 ## -0.44074 0.31386 ## healthpoor:numchron2 healthexcellent:numchron2 ## -0.40279 0.04538 ## healthpoor:numchron3 healthexcellent:numchron3 ## -0.58607 0.42759 ## healthpoor:numchron4 healthexcellent:numchron4 ## -0.77334 -0.63385 ## healthpoor:numchron5 healthexcellent:numchron5 ## -0.83591 -0.97112 ## healthpoor:numchron6 healthexcellent:numchron6 ## -0.81035 NA ## healthpoor:numchron7 healthexcellent:numchron7 ## -1.22368 NA ## healthpoor:numchron8 healthexcellent:numchron8 ## -17.63346 NA ## healthpoor:medicaidyes healthexcellent:medicaidyes ## 0.29182 0.24175 ## privinsyes:medicaidyes ## -0.25227 ## ## Degrees of Freedom: 4405 Total (i.e. Null); 4352 Residual## Null Deviance: 5784 ## Residual Deviance: 5039 AIC: 24410

new\_nb\_mod = **glm.nb**(ofp **~** health **+** numchron **+** adldiff **+** privins **+**  medicaid **+** region **+** age **+** black **+** gender **+** school **+** health**:**numchron **+**  health**:**medicaid **+** privins**:**medicaid, data=Medi\_data)**summary**(new\_nb\_mod)

## ## Call:## glm.nb(formula = ofp ~ health + numchron + adldiff + privins + ## medicaid + region + age + black + gender + school + health:numchron + ## health:medicaid + privins:medicaid, data = Medi\_data, init.theta = 1.219285007, ## link = log)## ## Deviance Residuals: ## Min 1Q Median 3Q Max ## -2.5056 -0.9874 -0.2980 0.2968 4.8830 ## ## Coefficients: (3 not defined because of singularities)## Estimate Std. Error z value Pr(>|z|) ## (Intercept) 0.95819 0.23154 4.138 3.50e-05 \*\*\*## healthpoor 0.79802 0.24123 3.308 0.000939 \*\*\*## healthexcellent -0.50655 0.09640 -5.255 1.48e-07 \*\*\*## numchron1 0.36214 0.04647 7.792 6.57e-15 \*\*\*## numchron2 0.59181 0.05133 11.529 < 2e-16 \*\*\*## numchron3 0.68801 0.06183 11.127 < 2e-16 \*\*\*## numchron4 0.98518 0.09003 10.943 < 2e-16 \*\*\*## numchron5 1.08923 0.12658 8.605 < 2e-16 \*\*\*## numchron6 1.06376 0.25356 4.195 2.73e-05 \*\*\*## numchron7 1.54422 0.66893 2.309 0.020971 \* ## numchron8 0.02341 0.77364 0.030 0.975860 ## adldiffyes 0.09116 0.04290 2.125 0.033597 \* ## privinsyes 0.34770 0.04753 7.316 2.56e-13 \*\*\*## medicaidyes 0.20838 0.08031 2.595 0.009467 \*\* ## regionnoreast 0.10120 0.04617 2.192 0.028400 \* ## regionother -0.01313 0.04049 -0.324 0.745760 ## regionwest 0.12110 0.04765 2.541 0.011047 \* ## age -0.03971 0.02597 -1.529 0.126163 ## blackyes -0.08979 0.05292 -1.697 0.089767 . ## gendermale -0.09698 0.03192 -3.038 0.002378 \*\* ## school1 0.33138 0.29804 1.112 0.266199 ## school2 0.28050 0.19601 1.431 0.152412 ## school3 0.24530 0.15917 1.541 0.123283 ## school4 0.02617 0.14804 0.177 0.859699 ## school5 0.31558 0.14450 2.184 0.028965 \* ## school6 0.13556 0.13030 1.040 0.298163 ## school7 0.20352 0.12517 1.626 0.103962 ## school8 0.21351 0.11236 1.900 0.057402 . ## school9 0.18319 0.12501 1.465 0.142799 ## school10 0.25807 0.12156 2.123 0.033749 \* ## school11 0.21101 0.12579 1.677 0.093445 . ## school12 0.30416 0.11057 2.751 0.005942 \*\* ## school13 0.35803 0.13152 2.722 0.006482 \*\* ## school14 0.38313 0.12483 3.069 0.002146 \*\* ## school15 0.57136 0.15106 3.782 0.000155 \*\*\*## school16 0.40384 0.12384 3.261 0.001111 \*\* ## school17 0.46867 0.18302 2.561 0.010445 \* ## school18 0.73470 0.14346 5.121 3.03e-07 \*\*\*## healthpoor:numchron1 -0.44074 0.26082 -1.690 0.091060 . ## healthexcellent:numchron1 0.31386 0.13862 2.264 0.023561 \* ## healthpoor:numchron2 -0.40279 0.25668 -1.569 0.116603 ## healthexcellent:numchron2 0.04538 0.18873 0.240 0.809969 ## healthpoor:numchron3 -0.58607 0.26264 -2.231 0.025649 \* ## healthexcellent:numchron3 0.42759 0.31484 1.358 0.174432 ## healthpoor:numchron4 -0.77334 0.27815 -2.780 0.005431 \*\* ## healthexcellent:numchron4 -0.63385 0.48899 -1.296 0.194893 ## healthpoor:numchron5 -0.83591 0.29685 -2.816 0.004863 \*\* ## healthexcellent:numchron5 -0.97112 1.16099 -0.836 0.402897 ## healthpoor:numchron6 -0.81035 0.41347 -1.960 0.050008 . ## healthexcellent:numchron6 NA NA NA NA ## healthpoor:numchron7 -1.22368 0.85958 -1.424 0.154571 ## healthexcellent:numchron7 NA NA NA NA ## healthpoor:numchron8 -21.14429 9426.61693 -0.002 0.998210 ## healthexcellent:numchron8 NA NA NA NA ## healthpoor:medicaidyes 0.29182 0.12139 2.404 0.016222 \* ## healthexcellent:medicaidyes 0.24175 0.28946 0.835 0.403622 ## privinsyes:medicaidyes -0.25227 0.14633 -1.724 0.084701 . ## ---## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1## ## (Dispersion parameter for Negative Binomial(1.2193) family taken to be 1)## ## Null deviance: 5784.0 on 4405 degrees of freedom## Residual deviance: 5038.8 on 4352 degrees of freedom## AIC: 24411## ## Number of Fisher Scoring iterations: 1## ## ## Theta: 1.2193 ## Std. Err.: 0.0340 ## ## 2 x log-likelihood: -24301.1400

Medi\_data2 = DebTrivediMedi\_data2 = **subset**(Medi\_data2, select = **-c**(ofnp,opp,opnp,emer,hosp))glm\_nb\_Medi\_data2 = **glm.nb**(ofp**~**.,data=Medi\_data2)new\_nb\_wout\_numfac = **glm.nb**(ofp**~**(health**+**adldiff**+**privins**+**medicaid)**^**2**+**numchron**+**region**+**age**+**black**+**gender**+**married**+**school**+**faminc**+**employed,data=Medi\_data2)**stepAIC**(new\_nb\_wout\_numfac)

## Start: AIC=24436.39## ofp ~ (health + adldiff + privins + medicaid)^2 + numchron + ## region + age + black + gender + married + school + faminc + ## employed## ## Df AIC## - adldiff:privins 1 24435## - faminc 1 24435## - adldiff:medicaid 1 24435## - employed 1 24435## - married 1 24435## - age 1 24436## - black 1 24436## <none> 24436## - health:adldiff 2 24437## - privins:medicaid 1 24438## - health:privins 2 24438## - gender 1 24439## - health:medicaid 2 24439## - region 3 24445## - school 1 24468## - numchron 1 24667## ## Step: AIC=24434.5## ofp ~ health + adldiff + privins + medicaid + numchron + region + ## age + black + gender + married + school + faminc + employed + ## health:adldiff + health:privins + health:medicaid + adldiff:medicaid + ## privins:medicaid## ## Df AIC## - adldiff:medicaid 1 24433## - faminc 1 24433## - employed 1 24433## - married 1 24433## - age 1 24434## - black 1 24434## <none> 24435## - health:adldiff 2 24435## - privins:medicaid 1 24436## - health:privins 2 24436## - gender 1 24437## - health:medicaid 2 24437## - region 3 24444## - school 1 24466## - numchron 1 24665## ## Step: AIC=24432.61## ofp ~ health + adldiff + privins + medicaid + numchron + region + ## age + black + gender + married + school + faminc + employed + ## health:adldiff + health:privins + health:medicaid + privins:medicaid## ## Df AIC## - faminc 1 24431## - employed 1 24431## - married 1 24431## - age 1 24432## - black 1 24432## <none> 24433## - health:adldiff 2 24433## - privins:medicaid 1 24434## - health:privins 2 24434## - gender 1 24435## - health:medicaid 2 24436## - region 3 24442## - school 1 24464## - numchron 1 24663## ## Step: AIC=24430.78## ofp ~ health + adldiff + privins + medicaid + numchron + region + ## age + black + gender + married + school + employed + health:adldiff + ## health:privins + health:medicaid + privins:medicaid## ## Df AIC## - employed 1 24429## - married 1 24430## - black 1 24430## - age 1 24430## <none> 24431## - health:adldiff 2 24431## - privins:medicaid 1 24432## - health:privins 2 24433## - gender 1 24433## - health:medicaid 2 24434## - region 3 24440## - school 1 24463## - numchron 1 24661## ## Step: AIC=24429.1## ofp ~ health + adldiff + privins + medicaid + numchron + region + ## age + black + gender + married + school + health:adldiff + ## health:privins + health:medicaid + privins:medicaid## ## Df AIC## - married 1 24428## - black 1 24429## - age 1 24429## <none> 24429## - health:adldiff 2 24429## - privins:medicaid 1 24431## - health:privins 2 24431## - gender 1 24431## - health:medicaid 2 24432## - region 3 24438## - school 1 24462## - numchron 1 24659## ## Step: AIC=24428.08## ofp ~ health + adldiff + privins + medicaid + numchron + region + ## age + black + gender + school + health:adldiff + health:privins + ## health:medicaid + privins:medicaid## ## Df AIC## - black 1 24428## - age 1 24428## <none> 24428## - health:adldiff 2 24428## - privins:medicaid 1 24429## - health:privins 2 24430## - health:medicaid 2 24431## - gender 1 24433## - region 3 24437## - school 1 24460## - numchron 1 24657## ## Step: AIC=24427.45## ofp ~ health + adldiff + privins + medicaid + numchron + region + ## age + gender + school + health:adldiff + health:privins + ## health:medicaid + privins:medicaid## ## Df AIC## - age 1 24427## <none> 24428## - health:adldiff 2 24428## - privins:medicaid 1 24429## - health:privins 2 24429## - health:medicaid 2 24431## - gender 1 24433## - region 3 24438## - school 1 24462## - numchron 1 24659## ## Step: AIC=24426.84## ofp ~ health + adldiff + privins + medicaid + numchron + region + ## gender + school + health:adldiff + health:privins + health:medicaid + ## privins:medicaid## ## Df AIC## <none> 24427## - health:adldiff 2 24427## - privins:medicaid 1 24428## - health:privins 2 24429## - health:medicaid 2 24430## - gender 1 24432## - region 3 24437## - school 1 24463## - numchron 1 24657

## ## Call: glm.nb(formula = ofp ~ health + adldiff + privins + medicaid + ## numchron + region + gender + school + health:adldiff + health:privins + ## health:medicaid + privins:medicaid, data = Medi\_data2, init.theta = 1.187718856, ## link = log)## ## Coefficients:## (Intercept) healthpoor ## 0.7611328 0.3632914 ## healthexcellent adldiffyes ## -0.7945691 0.1355244 ## privinsyes medicaidyes ## 0.3552709 0.2119928 ## numchron regionnoreast ## 0.1887787 0.1112993 ## regionother regionwest ## 0.0001416 0.1414742 ## gendermale school ## -0.0849035 0.0278128 ## healthpoor:adldiffyes healthexcellent:adldiffyes ## -0.1968954 -0.0033546 ## healthpoor:privinsyes healthexcellent:privinsyes ## -0.0111365 0.4565868 ## healthpoor:medicaidyes healthexcellent:medicaidyes ## 0.3260185 0.5323149 ## privinsyes:medicaidyes ## -0.2798744 ## ## Degrees of Freedom: 4405 Total (i.e. Null); 4387 Residual## Null Deviance: 5683 ## Residual Deviance: 5040 AIC: 24430

new\_nb\_wout\_numfac\_mod = **glm.nb**(ofp **~** health **+** adldiff **+** privins **+** medicaid **+**  numchron **+** region **+** gender **+** school **+** health**:**adldiff **+** health**:**privins **+**  health**:**medicaid **+** privins**:**medicaid, data=Medi\_data2)**summary**(new\_nb\_wout\_numfac\_mod)

## ## Call:## glm.nb(formula = ofp ~ health + adldiff + privins + medicaid + ## numchron + region + gender + school + health:adldiff + health:privins + ## health:medicaid + privins:medicaid, data = Medi\_data2, init.theta = 1.187718812, ## link = log)## ## Deviance Residuals: ## Min 1Q Median 3Q Max ## -2.6090 -0.9965 -0.3064 0.3026 5.3623 ## ## Coefficients:## Estimate Std. Error z value Pr(>|z|) ## (Intercept) 0.7611331 0.0716414 10.624 < 2e-16 \*\*\*## healthpoor 0.3632915 0.1146425 3.169 0.00153 \*\* ## healthexcellent -0.7945670 0.1806520 -4.398 1.09e-05 \*\*\*## adldiffyes 0.1355241 0.0481997 2.812 0.00493 \*\* ## privinsyes 0.3552711 0.0521678 6.810 9.75e-12 \*\*\*## medicaidyes 0.2119929 0.0815837 2.598 0.00936 \*\* ## numchron 0.1887790 0.0121773 15.503 < 2e-16 \*\*\*## regionnoreast 0.1112991 0.0462836 2.405 0.01618 \* ## regionother 0.0001412 0.0399776 0.004 0.99718 ## regionwest 0.1414739 0.0474186 2.984 0.00285 \*\* ## gendermale -0.0849036 0.0318058 -2.669 0.00760 \*\* ## school 0.0278128 0.0045477 6.116 9.61e-10 \*\*\*## healthpoor:adldiffyes -0.1968948 0.0975629 -2.018 0.04358 \* ## healthexcellent:adldiffyes -0.0033642 0.2344541 -0.014 0.98855 ## healthpoor:privinsyes -0.0111370 0.1145663 -0.097 0.92256 ## healthexcellent:privinsyes 0.4565848 0.1895609 2.409 0.01601 \* ## healthpoor:medicaidyes 0.3260183 0.1431869 2.277 0.02279 \* ## healthexcellent:medicaidyes 0.5323253 0.3179477 1.674 0.09408 . ## privinsyes:medicaidyes -0.2798753 0.1474234 -1.898 0.05764 . ## ---## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1## ## (Dispersion parameter for Negative Binomial(1.1877) family taken to be 1)## ## Null deviance: 5683.2 on 4405 degrees of freedom## Residual deviance: 5040.4 on 4387 degrees of freedom## AIC: 24429## ## Number of Fisher Scoring iterations: 1## ## ## Theta: 1.1877 ## Std. Err.: 0.0328 ## ## 2 x log-likelihood: -24388.8370

Medi\_data3 = DebTrivediMedi\_data3 = **subset**(Medi\_data3, select = **-c**(ofnp,opp,opnp,emer,hosp))Medi\_data3**$**numchron = **factor**(Medi\_data3**$**numchron)glm\_nb\_Medi\_data3 = **glm.nb**(ofp**~**(health**+**adldiff**+**privins**+**numchron**+**medicaid)**^**2**+**region**+**age**+**black**+**gender**+**married**+**school**+**faminc**+**employed, data=Medi\_data3)**stepAIC**(glm\_nb\_Medi\_data3)

## Start: AIC=24425.63## ofp ~ (health + adldiff + privins + numchron + medicaid)^2 + ## region + age + black + gender + married + school + faminc + ## employed## ## Df AIC## - numchron:medicaid 6 24417## - privins:numchron 7 24418## - health:numchron 13 24420## - adldiff:numchron 7 24420## - health:adldiff 2 24424## - health:privins 2 24424## - faminc 1 24424## - adldiff:privins 1 24424## - adldiff:medicaid 1 24424## - employed 1 24424## - married 1 24425## <none> 24426## - black 1 24426## - privins:medicaid 1 24426## - age 1 24426## - health:medicaid 2 24427## - gender 1 24427## - region 3 24434## - school 1 24459## ## Step: AIC=24416.55## ofp ~ health + adldiff + privins + numchron + medicaid + region + ## age + black + gender + married + school + faminc + employed + ## health:adldiff + health:privins + health:numchron + health:medicaid + ## adldiff:privins + adldiff:numchron + adldiff:medicaid + privins:numchron + ## privins:medicaid## ## Df AIC## - privins:numchron 7 24411## - adldiff:numchron 7 24411## - health:numchron 13 24412## - health:adldiff 2 24414## - health:privins 2 24415## - faminc 1 24415## - adldiff:privins 1 24415## - adldiff:medicaid 1 24415## - employed 1 24415## - married 1 24416## <none> 24417## - black 1 24417## - age 1 24417## - privins:medicaid 1 24417## - health:medicaid 2 24418## - gender 1 24418## - region 3 24425## - school 1 24450## ## Step: AIC=24410.47## ofp ~ health + adldiff + privins + numchron + medicaid + region + ## age + black + gender + married + school + faminc + employed + ## health:adldiff + health:privins + health:numchron + health:medicaid + ## adldiff:privins + adldiff:numchron + adldiff:medicaid + privins:medicaid## ## Df AIC## - health:numchron 13 24405## - adldiff:numchron 8 24406## - health:adldiff 2 24408## - adldiff:privins 1 24409## - faminc 1 24409## - adldiff:medicaid 1 24409## - health:privins 2 24409## - employed 1 24409## - married 1 24410## <none> 24411## - black 1 24411## - age 1 24411## - privins:medicaid 1 24411## - health:medicaid 2 24412## - gender 1 24412## - region 3 24418## - school 1 24445## ## Step: AIC=24404.61## ofp ~ health + adldiff + privins + numchron + medicaid + region + ## age + black + gender + married + school + faminc + employed + ## health:adldiff + health:privins + health:medicaid + adldiff:privins + ## adldiff:numchron + adldiff:medicaid + privins:medicaid## ## Df AIC## - adldiff:privins 1 24403## - faminc 1 24403## - adldiff:medicaid 1 24403## - health:adldiff 2 24403## - employed 1 24403## - married 1 24404## <none> 24405## - age 1 24405## - black 1 24405## - privins:medicaid 1 24405## - health:privins 2 24405## - gender 1 24406## - adldiff:numchron 8 24406## - health:medicaid 2 24406## - region 3 24413## - school 1 24438## ## Step: AIC=24402.63## ofp ~ health + adldiff + privins + numchron + medicaid + region + ## age + black + gender + married + school + faminc + employed + ## health:adldiff + health:privins + health:medicaid + adldiff:numchron + ## adldiff:medicaid + privins:medicaid## ## Df AIC## - faminc 1 24401## - adldiff:medicaid 1 24401## - health:adldiff 2 24401## - employed 1 24401## - married 1 24402## <none> 24403## - black 1 24403## - age 1 24403## - privins:medicaid 1 24403## - health:privins 2 24403## - gender 1 24404## - adldiff:numchron 8 24404## - health:medicaid 2 24404## - region 3 24411## - school 1 24436## ## Step: AIC=24400.71## ofp ~ health + adldiff + privins + numchron + medicaid + region + ## age + black + gender + married + school + employed + health:adldiff + ## health:privins + health:medicaid + adldiff:numchron + adldiff:medicaid + ## privins:medicaid## ## Df AIC## - adldiff:medicaid 1 24399## - health:adldiff 2 24399## - employed 1 24399## - married 1 24400## <none> 24401## - black 1 24401## - age 1 24401## - privins:medicaid 1 24401## - health:privins 2 24401## - gender 1 24402## - adldiff:numchron 8 24402## - health:medicaid 2 24402## - region 3 24409## - school 1 24434## ## Step: AIC=24398.85## ofp ~ health + adldiff + privins + numchron + medicaid + region + ## age + black + gender + married + school + employed + health:adldiff + ## health:privins + health:medicaid + adldiff:numchron + privins:medicaid## ## Df AIC## - health:adldiff 2 24397## - employed 1 24397## - married 1 24398## <none> 24399## - black 1 24399## - age 1 24399## - privins:medicaid 1 24399## - health:privins 2 24400## - gender 1 24400## - adldiff:numchron 8 24400## - health:medicaid 2 24401## - region 3 24407## - school 1 24433## ## Step: AIC=24397.15## ofp ~ health + adldiff + privins + numchron + medicaid + region + ## age + black + gender + married + school + employed + health:privins + ## health:medicaid + adldiff:numchron + privins:medicaid## ## Df AIC## - employed 1 24396## - married 1 24397## <none> 24397## - black 1 24397## - age 1 24397## - health:privins 2 24398## - privins:medicaid 1 24398## - gender 1 24399## - health:medicaid 2 24399## - adldiff:numchron 8 24401## - region 3 24405## - school 1 24431## ## Step: AIC=24395.67## ofp ~ health + adldiff + privins + numchron + medicaid + region + ## age + black + gender + married + school + health:privins + ## health:medicaid + adldiff:numchron + privins:medicaid## ## Df AIC## - married 1 24395## - black 1 24396## <none> 24396## - age 1 24396## - health:privins 2 24396## - privins:medicaid 1 24396## - gender 1 24397## - health:medicaid 2 24397## - adldiff:numchron 8 24399## - region 3 24404## - school 1 24430## ## Step: AIC=24395.3## ofp ~ health + adldiff + privins + numchron + medicaid + region + ## age + black + gender + school + health:privins + health:medicaid + ## adldiff:numchron + privins:medicaid## ## Df AIC## - black 1 24395## - age 1 24395## <none> 24395## - privins:medicaid 1 24396## - health:privins 2 24396## - health:medicaid 2 24397## - adldiff:numchron 8 24399## - gender 1 24400## - region 3 24404## - school 1 24429## ## Step: AIC=24395.05## ofp ~ health + adldiff + privins + numchron + medicaid + region + ## age + gender + school + health:privins + health:medicaid + ## adldiff:numchron + privins:medicaid## ## Df AIC## - age 1 24395## <none> 24395## - privins:medicaid 1 24396## - health:privins 2 24396## - health:medicaid 2 24396## - adldiff:numchron 8 24398## - gender 1 24399## - region 3 24405## - school 1 24431## ## Step: AIC=24394.78## ofp ~ health + adldiff + privins + numchron + medicaid + region + ## gender + school + health:privins + health:medicaid + adldiff:numchron + ## privins:medicaid## ## Df AIC## <none> 24395## - privins:medicaid 1 24395## - health:privins 2 24396## - health:medicaid 2 24396## - adldiff:numchron 8 24398## - gender 1 24399## - region 3 24404## - school 1 24433

## ## Call: glm.nb(formula = ofp ~ health + adldiff + privins + numchron + ## medicaid + region + gender + school + health:privins + health:medicaid + ## adldiff:numchron + privins:medicaid, data = Medi\_data3, init.theta = 1.208322366, ## link = log)## ## Coefficients:## (Intercept) healthpoor ## 0.618401 0.287533 ## healthexcellent adldiffyes ## -0.729484 0.323263 ## privinsyes numchron1 ## 0.335501 0.395825 ## numchron2 numchron3 ## 0.619925 0.755877 ## numchron4 numchron5 ## 0.932115 0.995349 ## numchron6 numchron7 ## 1.227456 0.926642 ## numchron8 medicaidyes ## 0.603716 0.209049 ## regionnoreast regionother ## 0.105904 -0.009161 ## regionwest gendermale ## 0.131146 -0.078780 ## school healthpoor:privinsyes ## 0.028447 -0.008976 ## healthexcellent:privinsyes healthpoor:medicaidyes ## 0.414573 0.267152 ## healthexcellent:medicaidyes adldiffyes:numchron1 ## 0.495781 -0.198115 ## adldiffyes:numchron2 adldiffyes:numchron3 ## -0.197396 -0.437914 ## adldiffyes:numchron4 adldiffyes:numchron5 ## -0.303335 -0.307240 ## adldiffyes:numchron6 adldiffyes:numchron7 ## -0.845618 -0.013435 ## adldiffyes:numchron8 privinsyes:medicaidyes ## -17.689119 -0.242715 ## ## Degrees of Freedom: 4405 Total (i.e. Null); 4374 Residual## Null Deviance: 5749 ## Residual Deviance: 5039 AIC: 24400

nb\_with\_onlychron = **glm.nb**(ofp **~** health **+** adldiff **+** privins **+** numchron **+**  medicaid **+** region **+** gender **+** school **+** health**:**privins **+** health**:**medicaid **+**  adldiff**:**numchron **+** privins**:**medicaid,data=Medi\_data3)**summary**(nb\_with\_onlychron)

## ## Call:## glm.nb(formula = ofp ~ health + adldiff + privins + numchron + ## medicaid + region + gender + school + health:privins + health:medicaid + ## adldiff:numchron + privins:medicaid, data = Medi\_data3, init.theta = 1.208322365, ## link = log)## ## Deviance Residuals: ## Min 1Q Median 3Q Max ## -2.5133 -0.9713 -0.2941 0.2946 5.1888 ## ## Coefficients:## Estimate Std. Error z value Pr(>|z|) ## (Intercept) 6.184e-01 7.575e-02 8.164 3.24e-16 \*\*\*## healthpoor 2.875e-01 1.056e-01 2.724 0.00646 \*\* ## healthexcellent -7.295e-01 1.794e-01 -4.065 4.80e-05 \*\*\*## adldiffyes 3.233e-01 1.153e-01 2.805 0.00503 \*\* ## privinsyes 3.355e-01 5.203e-02 6.448 1.14e-10 \*\*\*## numchron1 3.958e-01 4.575e-02 8.652 < 2e-16 \*\*\*## numchron2 6.199e-01 5.150e-02 12.038 < 2e-16 \*\*\*## numchron3 7.559e-01 6.282e-02 12.032 < 2e-16 \*\*\*## numchron4 9.321e-01 9.327e-02 9.994 < 2e-16 \*\*\*## numchron5 9.953e-01 1.261e-01 7.896 2.87e-15 \*\*\*## numchron6 1.227e+00 2.364e-01 5.192 2.08e-07 \*\*\*## numchron7 9.266e-01 9.818e-01 0.944 0.34524 ## numchron8 6.037e-01 9.983e-01 0.605 0.54534 ## medicaidyes 2.090e-01 8.116e-02 2.576 0.01001 \* ## regionnoreast 1.059e-01 4.605e-02 2.300 0.02146 \* ## regionother -9.161e-03 3.979e-02 -0.230 0.81792 ## regionwest 1.311e-01 4.720e-02 2.778 0.00546 \*\* ## gendermale -7.878e-02 3.172e-02 -2.484 0.01301 \* ## school 2.845e-02 4.528e-03 6.282 3.34e-10 \*\*\*## healthpoor:privinsyes -8.976e-03 1.147e-01 -0.078 0.93761 ## healthexcellent:privinsyes 4.146e-01 1.891e-01 2.193 0.02833 \* ## healthpoor:medicaidyes 2.672e-01 1.418e-01 1.884 0.05955 . ## healthexcellent:medicaidyes 4.958e-01 3.136e-01 1.581 0.11385 ## adldiffyes:numchron1 -1.981e-01 1.349e-01 -1.469 0.14192 ## adldiffyes:numchron2 -1.974e-01 1.367e-01 -1.444 0.14884 ## adldiffyes:numchron3 -4.379e-01 1.491e-01 -2.937 0.00332 \*\* ## adldiffyes:numchron4 -3.033e-01 1.762e-01 -1.721 0.08524 . ## adldiffyes:numchron5 -3.072e-01 2.063e-01 -1.490 0.13635 ## adldiffyes:numchron6 -8.456e-01 3.537e-01 -2.391 0.01682 \* ## adldiffyes:numchron7 -1.344e-02 1.074e+00 -0.013 0.99002 ## adldiffyes:numchron8 -2.121e+01 6.641e+03 -0.003 0.99745 ## privinsyes:medicaidyes -2.427e-01 1.467e-01 -1.654 0.09810 . ## ---## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1## ## (Dispersion parameter for Negative Binomial(1.2083) family taken to be 1)## ## Null deviance: 5749.2 on 4405 degrees of freedom## Residual deviance: 5038.9 on 4374 degrees of freedom## AIC: 24397## ## Number of Fisher Scoring iterations: 1## ## ## Theta: 1.2083 ## Std. Err.: 0.0336 ## ## 2 x log-likelihood: -24330.7810

org\_mod = **glm**(ofp**~**.,data=Medi\_data,family = 'poisson')**pchisq**(2**\***(**logLik**(new\_nb\_wout\_numfac\_mod) **-** **logLik**(org\_mod)),df=1,lower.tail = FALSE)

## 'log Lik.' 0 (df=20)

this chisq test shows that nb model is strongly suggested.

**summary**(new\_nb\_wout\_numfac\_mod)

## ## Call:## glm.nb(formula = ofp ~ health + adldiff + privins + medicaid + ## numchron + region + gender + school + health:adldiff + health:privins + ## health:medicaid + privins:medicaid, data = Medi\_data2, init.theta = 1.187718812, ## link = log)## ## Deviance Residuals: ## Min 1Q Median 3Q Max ## -2.6090 -0.9965 -0.3064 0.3026 5.3623 ## ## Coefficients:## Estimate Std. Error z value Pr(>|z|) ## (Intercept) 0.7611331 0.0716414 10.624 < 2e-16 \*\*\*## healthpoor 0.3632915 0.1146425 3.169 0.00153 \*\* ## healthexcellent -0.7945670 0.1806520 -4.398 1.09e-05 \*\*\*## adldiffyes 0.1355241 0.0481997 2.812 0.00493 \*\* ## privinsyes 0.3552711 0.0521678 6.810 9.75e-12 \*\*\*## medicaidyes 0.2119929 0.0815837 2.598 0.00936 \*\* ## numchron 0.1887790 0.0121773 15.503 < 2e-16 \*\*\*## regionnoreast 0.1112991 0.0462836 2.405 0.01618 \* ## regionother 0.0001412 0.0399776 0.004 0.99718 ## regionwest 0.1414739 0.0474186 2.984 0.00285 \*\* ## gendermale -0.0849036 0.0318058 -2.669 0.00760 \*\* ## school 0.0278128 0.0045477 6.116 9.61e-10 \*\*\*## healthpoor:adldiffyes -0.1968948 0.0975629 -2.018 0.04358 \* ## healthexcellent:adldiffyes -0.0033642 0.2344541 -0.014 0.98855 ## healthpoor:privinsyes -0.0111370 0.1145663 -0.097 0.92256 ## healthexcellent:privinsyes 0.4565848 0.1895609 2.409 0.01601 \* ## healthpoor:medicaidyes 0.3260183 0.1431869 2.277 0.02279 \* ## healthexcellent:medicaidyes 0.5323253 0.3179477 1.674 0.09408 . ## privinsyes:medicaidyes -0.2798753 0.1474234 -1.898 0.05764 . ## ---## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1## ## (Dispersion parameter for Negative Binomial(1.1877) family taken to be 1)## ## Null deviance: 5683.2 on 4405 degrees of freedom## Residual deviance: 5040.4 on 4387 degrees of freedom## AIC: 24429## ## Number of Fisher Scoring iterations: 1## ## ## Theta: 1.1877 ## Std. Err.: 0.0328 ## ## 2 x log-likelihood: -24388.8370

Here is 95% confidence interval.

ci = **cbind**(Estimate=**coef**(new\_nb\_wout\_numfac\_mod), **confint**(new\_nb\_wout\_numfac\_mod))

Figure 3

## Waiting for profiling to be done...

ci

## Estimate 2.5 % 97.5 %## (Intercept) 0.7611330909 0.62101333 0.902013507## healthpoor 0.3632914857 0.14002766 0.591057913## healthexcellent -0.7945670376 -1.15182859 -0.435061174## adldiffyes 0.1355241076 0.04211984 0.230101369## privinsyes 0.3552711113 0.25236749 0.457017591## medicaidyes 0.2119928548 0.05229346 0.373122914## numchron 0.1887790344 0.16429424 0.213445387## regionnoreast 0.1112991050 0.02075678 0.202123290## regionother 0.0001411787 -0.07859805 0.078692093## regionwest 0.1414738565 0.04854337 0.234739766## gendermale -0.0849035674 -0.14735828 -0.022308954## school 0.0278127557 0.01899755 0.036618026## healthpoor:adldiffyes -0.1968948156 -0.38994680 -0.004675679## healthexcellent:adldiffyes -0.0033642064 -0.44435280 0.464930790## healthpoor:privinsyes -0.0111369865 -0.23871659 0.213751185## healthexcellent:privinsyes 0.4565847895 0.07988559 0.831799388## healthpoor:medicaidyes 0.3260183086 0.04369789 0.610348090## healthexcellent:medicaidyes 0.5323253370 -0.07657452 1.180006558## privinsyes:medicaidyes -0.2798753394 -0.56405960 0.014999667

**exp**(**coef**(new\_nb\_wout\_numfac\_mod))

## (Intercept) healthpoor ## 2.1407005 1.4380550 ## healthexcellent adldiffyes ## 0.4517768 1.1451368 ## privinsyes medicaidyes ## 1.4265674 1.2361391 ## numchron regionnoreast ## 1.2077740 1.1177292 ## regionother regionwest ## 1.0001412 1.1519704 ## gendermale school ## 0.9186009 1.0282031 ## healthpoor:adldiffyes healthexcellent:adldiffyes ## 0.8212770 0.9966414 ## healthpoor:privinsyes healthexcellent:privinsyes ## 0.9889248 1.5786733 ## healthpoor:medicaidyes healthexcellent:medicaidyes ## 1.3854407 1.7028875 ## privinsyes:medicaidyes ## 0.7558780

**plot**(**fitted**(new\_nb\_wout\_numfac\_mod),**residuals**(new\_nb\_wout\_numfac\_mod,"pearson"))

Chart, scatter chart

Description automatically generated