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ADVANCED BAYESIAN DATA ANALYSIS

BAYESIAN DATA ANALYSIS ON SUICIDES IN INDIA

TU DORTMUND | DATA SCIENCE

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Supervisors

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Research Objective

How the number of suicides vary by gender, age group, cause and each state in India?

Specific Objectives:

- Investigate the relationship between different age groups and the number of suicides in India
- Analyze the differences in number of suicides between males and females in India
- Identify the suicide methods that pose the highest risk of suicide in India

Data Description

- **Total observations :** 2,37,520
- **Total columns** : 7
- **Data source:** https://data.world/rajanand/suicides-in-india

Column Name	Data Type	Description
State	Categorical	29 Indian states and 7 Union territories
Year	Numeric	From 2001 to 2012
Type_Code	Categorical	5 Category of Suicide
Type	Categorical	69 different reasons of suicide
Gender	Categorical	Male or Female
Age_group	Categorical	6 Groups: 0-14, 15-29, 30-44, 45-60, 60+, 0-100+(Total)
Total	Numeric	Total number of suicides

Table 1: Dataset description

Data Processing

- Selected one year i.e. 2012 (most recent)
- Remove age group 0-100+ as it contains total sum of all suicides for the other age groups
- Remove unwanted special characters present in Type column
- Map down 69 categories of suicide causes into 9 different categories

Type	Cause
"By_Consuming_Insecticides","Consuming_Insecticides", "By_Consuming_Other_Poison", "By_Over_Alcoholism", "By_Overdose_of_sleeping_pills", "Drug_Abuse_Addiction"	Drugs
"Ideological_Causes_Hero_Worshipping", "Love_Affairs", "Fall_in_Social_Reputation", "Physical_Abuse_Rape_Incest_Etc_"	Social
"Property_Dispute", "Family_Problems", "Cancellation_Non_Settlement_of_Marriage", "Married", "Never_Married", "Divorcee","Seperated","Dowry_Dispute", "Divorce", "Widowed_Widower", "Death_of_Dear_Person","Suspected_Illicit_Relation"	Family
"Insanity_Mental_Illness", "Illness_Aids_STD", "Not_having_Children_Barrenness_Impotency", "Other_Prolonged_Illness", "By_Self_Infliction_of_injury", "Illegitimate_Pregnancy", "Cancer", "Paralysis", "Insanity_Mental_Illness"	Health
"No_Education", "Student", "Hr__Secondary_Intermediate_Pre_Universit", "Failure_in_Examination", "Post_Graduate_and_Above", "Middle", "Primary", "Diploma", "Matriculate_Secondary", "Unemployed", "Graduate"	Educational
"Self_employed_Business_activity", "ServicePrivate", "Poverty", "Professional_Career_Problem", "Retired_Person", "House_Wife", "Bankruptcy_or_Sudden_change_in_Economic", "Unemployment", "Service_Government","Public_Sector_Undertaking","Self_employed_Business_activity"	Financial & Career
"By_Drowning", "By_touching_electric_wires", "Professional_Activity", "Farming_Agriculture_Activity","By_coming_under_running_vehicles_trains","By_Machine"	Accidental
"By_Hanging", "By_Jumping_from_Building", "By_Fire_Arms", "By_Fire_Self_Immolation","By_Jumping_from_Other_sites", "By_Jumping_off_Moving_Vehicles_Trains"	Intentional
Others_Please_Specify", "By_Other_means_please_specify","Other_Causes_Please_Specity", "Causes_Not_known", "Others_Please_Specify"	Others

Table 2: Mapping of all Type to Cause Categories

Cleaned dataset

	State	Year	Gender	Age_group	Cause	Total
1	ANDHRA PRADESH	2012	Female	0-14	Accidental	24
2	ANDHRA PRADESH	2012	Female	0-14	Drugs	70
3	ANDHRA PRADESH	2012	Female	0-14	Educational	65
4	ANDHRA PRADESH	2012	Female	0-14	Family	19
5	ANDHRA PRADESH	2012	Female	0-14	Financial & Career	1
6	ANDHRA PRADESH	2012	Female	0-14	Health	24
7	ANDHRA PRADESH	2012	Female	0-14	Intentional	45
8	ANDHRA PRADESH	2012	Female	0-14	Others	158
9	ANDHRA PRADESH	2012	Female	0-14	Social	23
10	ANDHRA PRADESH	2012	Female	15-29	Accidental	332
11	ANDHRA PRADESH	2012	Female	15-29	Drugs	912
12	ANDHRA PRADESH	2012	Female	15-29	Educational	368
13	ANDHRA PRADESH	2012	Female	15-29	Family	667
14	ANDHRA PRADESH	2012	Female	15-29	Financial & Career	1192
15	ANDHRA PRADESH	2012	Female	15-29	Health	672
16	ANDHRA PRADESH	2012	Female	15-29	Intentional	818
17	ANDHRA PRADESH	2012	Female	15-29	Others	1038
18	ANDHRA PRADESH	2012	Female	15-29	Social	139
19	ANDHRA PRADESH	2012	Female	30-44	Accidental	335
20	ANDHRA PRADESH	2012	Female	30-44	Drugs	712

Fig 1.1: Processed/Cleaned dataset

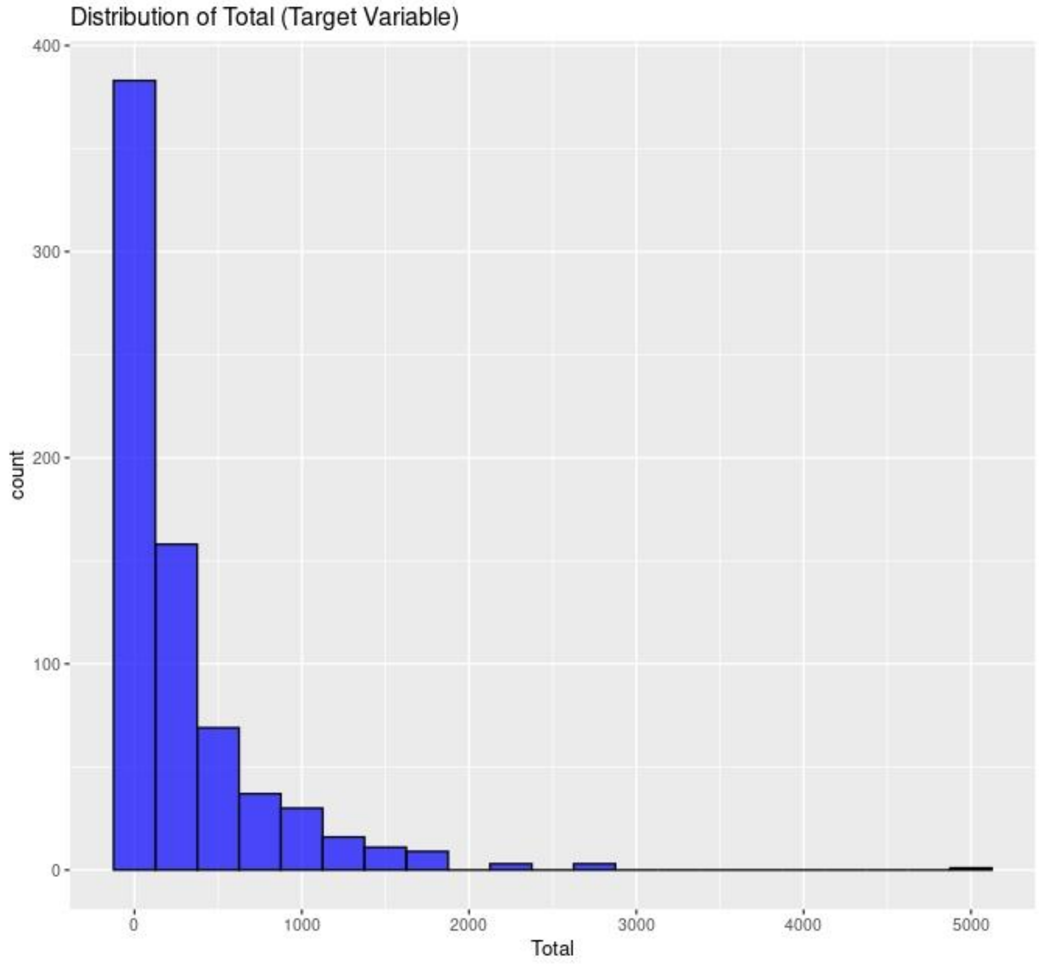

Fig 1.2:Distribution of Total

Models

Which model to choose ?

- Poisson Model
- Negative Binomial
- Zero Inflated Negative Binomial

*Source: brms: An R Package for Bayesian Multilevel Models using Stan By Paul-Christian Bürkner

Poisson | Neg Binomial | Zero inflated NB

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Family: Poisson
Links: mu = log ()
Response variable: Total
Group level Term: State, random intercept is for State variable with 8 unique levels.
sd(Intercept): represents standard deviation at group level which measure variability across different states.

Significant covariates:

- All covariates are significant.

ESS: captures how many independent draws contain the same amount of information as the dependent sample obtained by the MCMC algorithm.

- High Bulk_ESS*
- High Tail_ESS

*Bulk_ESS > num of chains * 100
- Source: Runtime warnings and convergence problems by Stan Development Team (link)

```
> summary(poisson_model)
 Family: poisson
  Links: mu = log
Formula: Total ~ Cause + Gender + Age_group + (1 | State)
   Data: subset_df1 (Number of observations: 720)
  Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
         total post-warmup draws = 4000

Group-Level Effects:
~State (Number of levels: 8)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.88      0.29     0.51     1.62 1.00     1015     1573

Population-Level Effects:
                      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                 2.34      0.30     1.71     2.93 1.01      828     1037
CauseDrugs                0.46      0.01     0.45     0.48 1.00     2023     2595
CauseEducational         -0.65      0.01    -0.68    -0.63 1.00     2565     2804
CauseFamily               0.11      0.01     0.09     0.13 1.00     2122     2541
CauseFinancial&Career     0.47      0.01     0.45     0.49 1.00     2104     2565
CauseHealth              -0.16      0.01    -0.18    -0.14 1.00     2240     2541
CauseIntentional          0.68      0.01     0.66     0.70 1.00     1836     2426
CauseOthers               0.96      0.01     0.95     0.98 1.00     1840     2257
CauseSocial              -1.87      0.02    -1.91    -1.83 1.00     2833     2674
GenderMale                0.64      0.00     0.63     0.65 1.00     2190     1805
Age_group15M29            3.05      0.02     3.02     3.09 1.00     1824     1865
Age_group30M44            3.04      0.02     3.00     3.07 1.00     1930     2095
Age_group45M59            2.53      0.02     2.50     2.57 1.00     1938     1993
Age_group60P              1.61      0.02     1.57     1.65 1.00     2019     2084

Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
and Tail_ESS are effective sample size measures, and Rhat is the potential
scale reduction factor on split chains (at convergence, Rhat = 1).
>
```

Fig 2(a) : Poisson Model Summary

Poisson | Neg Binomial | Zero inflated NB

Convergence Diagnostics:

- R-hat compares between and within chain estimates of model parameters.
- Rhat for the model parameters are less than 1.01.
- Chains have mixed well and he chains have converged to a common distribution.

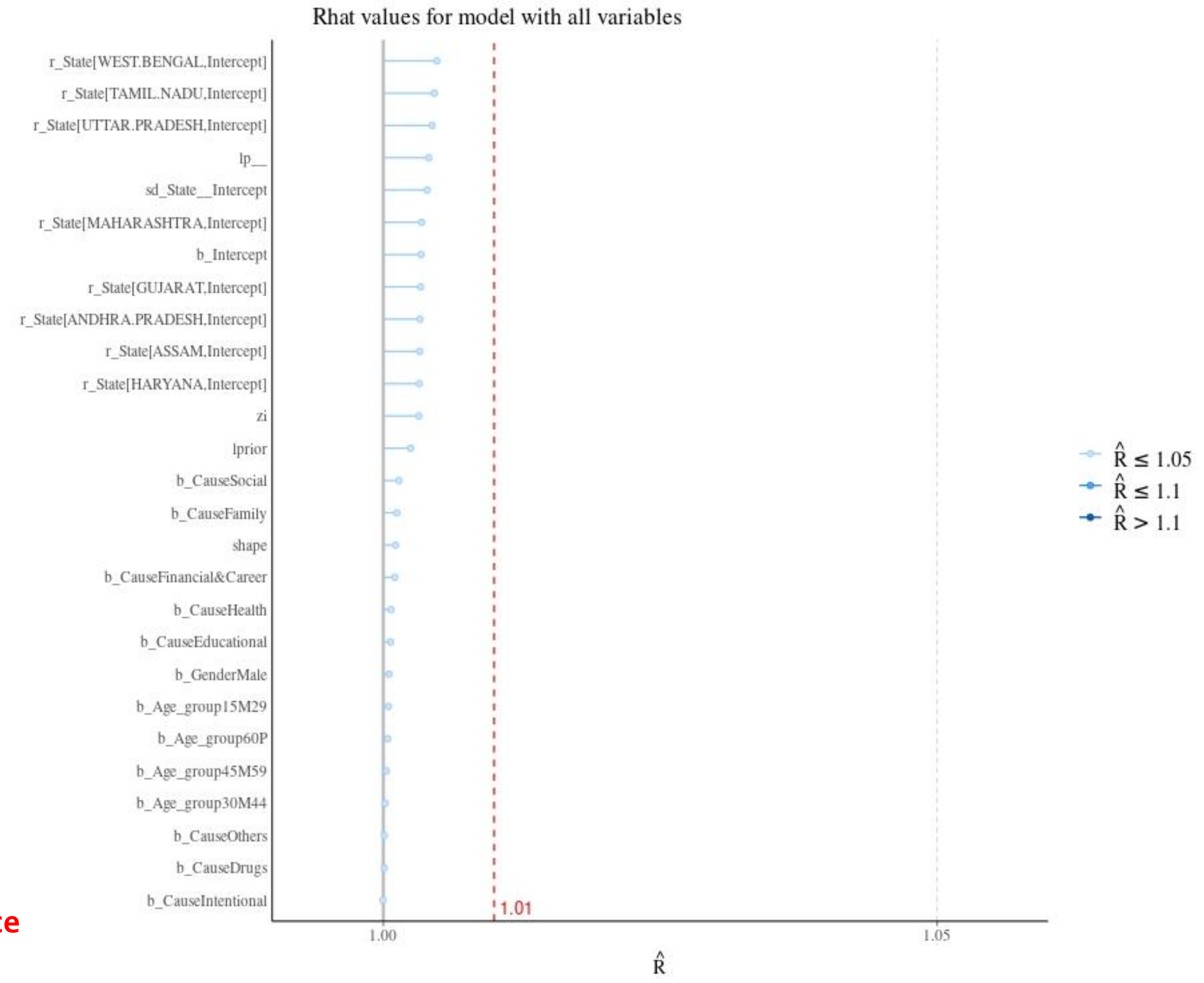

Fig2(b): R-hat values

* R-hat < 1.01
- Source: Runtime warnings and convergence problems by Stan Development (link)

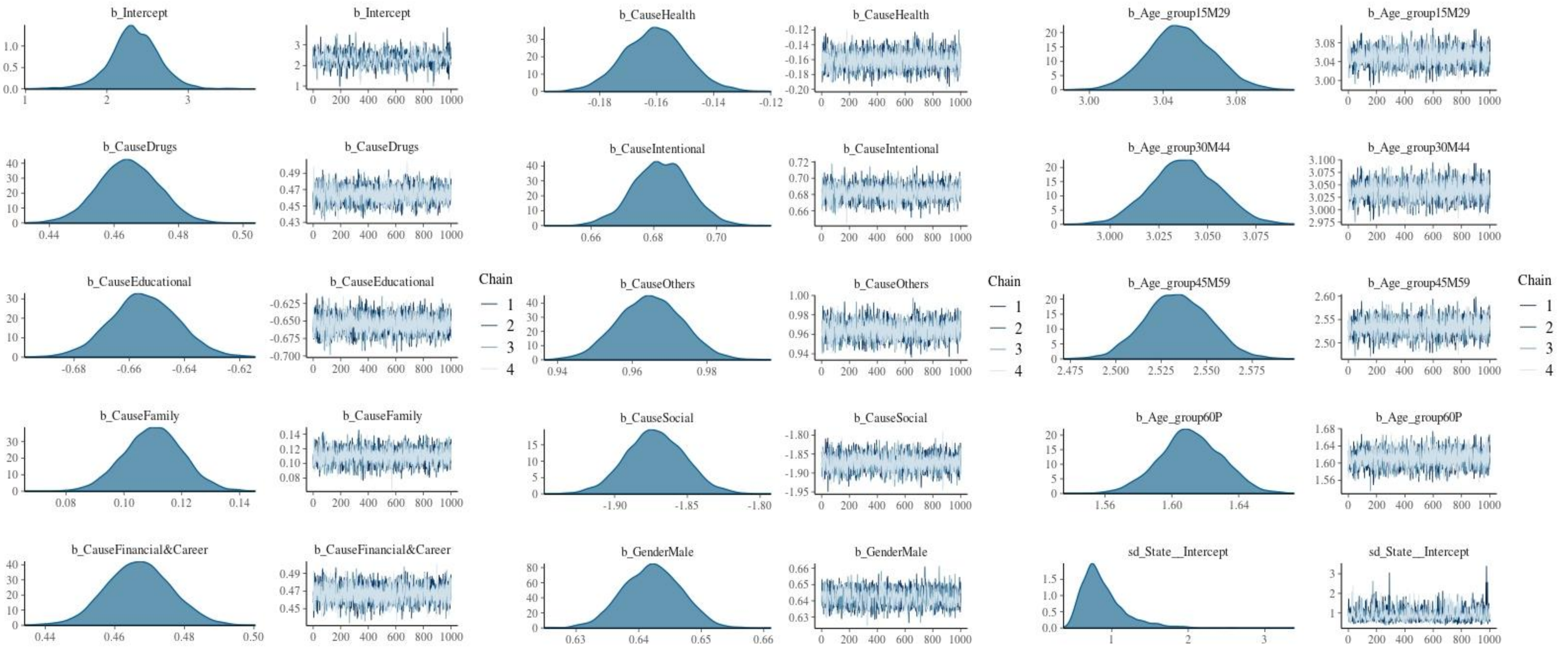

Fig 3: Trace and Density plots of all relevant parameters of the poisson model

- Trace plots shows that model has explored all the possible values it could look at so it converged well.
- Density plot shows the estimate found by model in Summary

Poisson | Neg Binomial | Zero inflated NB

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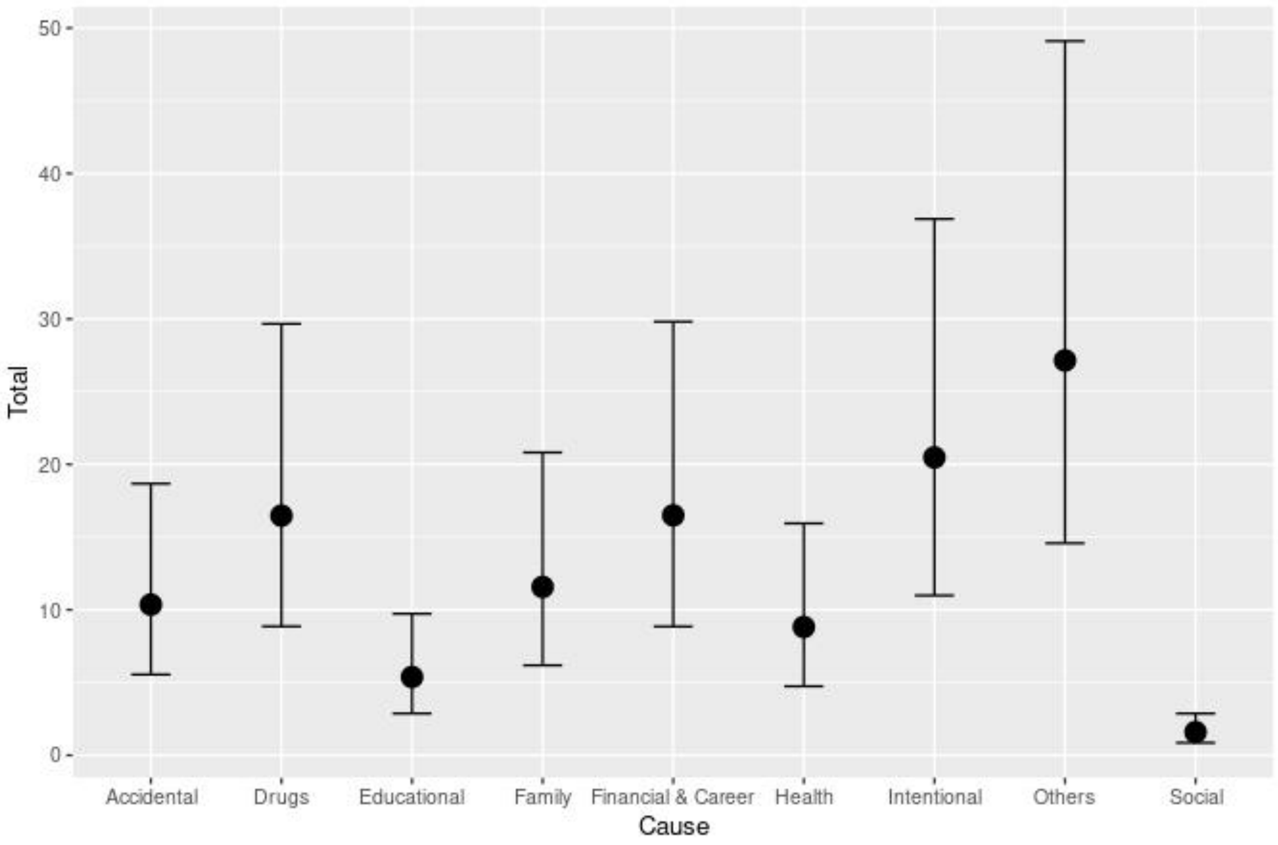

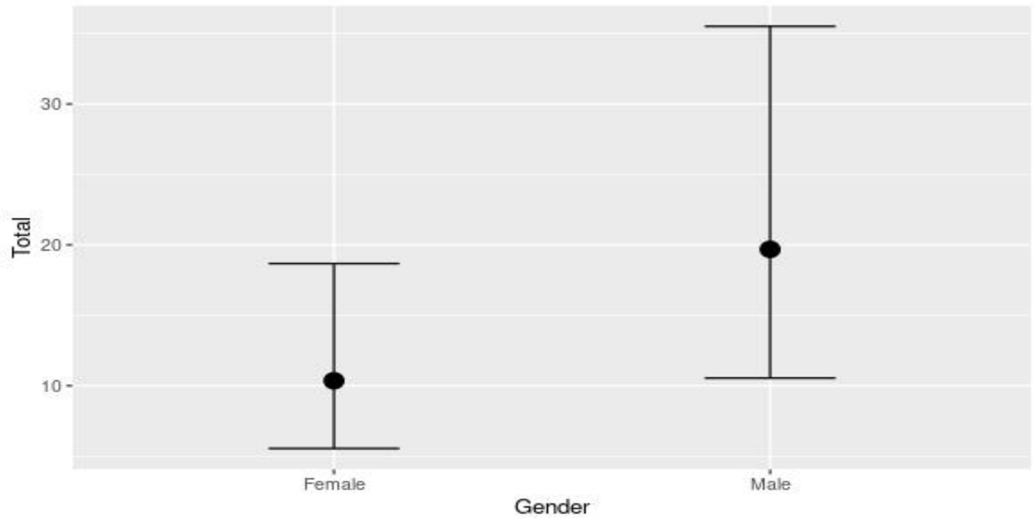

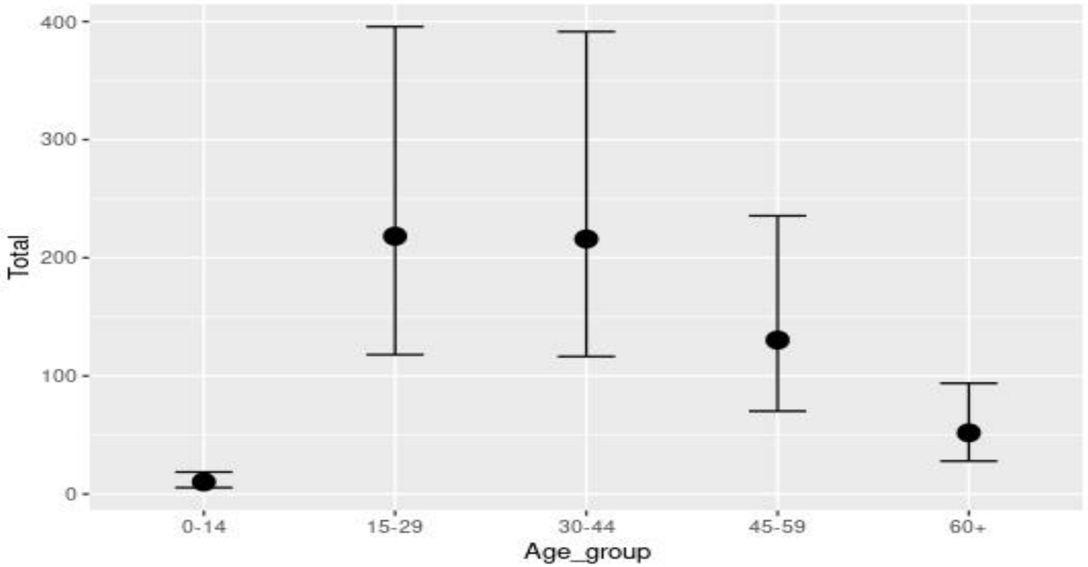

Fig 4: Conditional effects plots of all population-level predictors (fitted)

Poisson | Neg Binomial | Zero inflated NB

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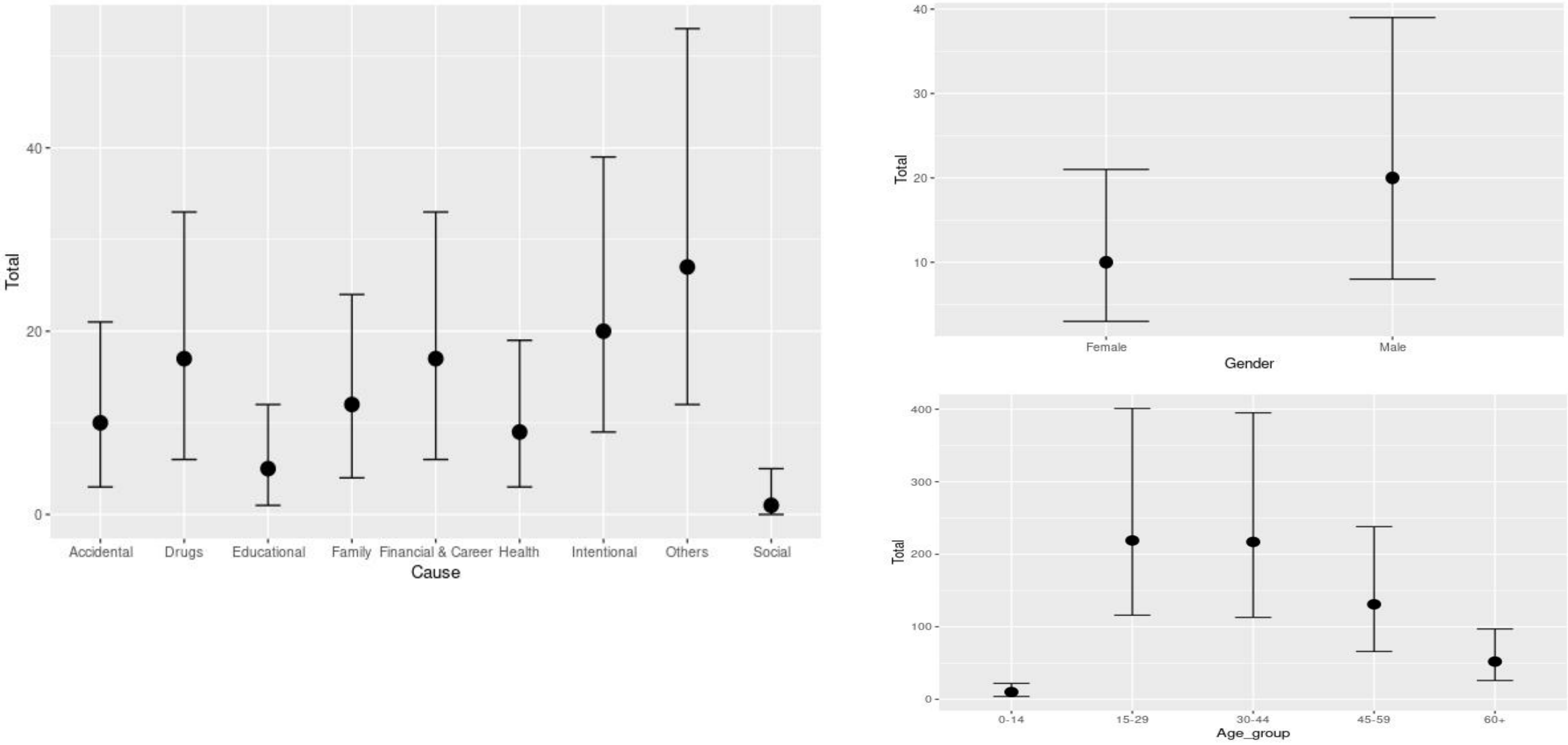
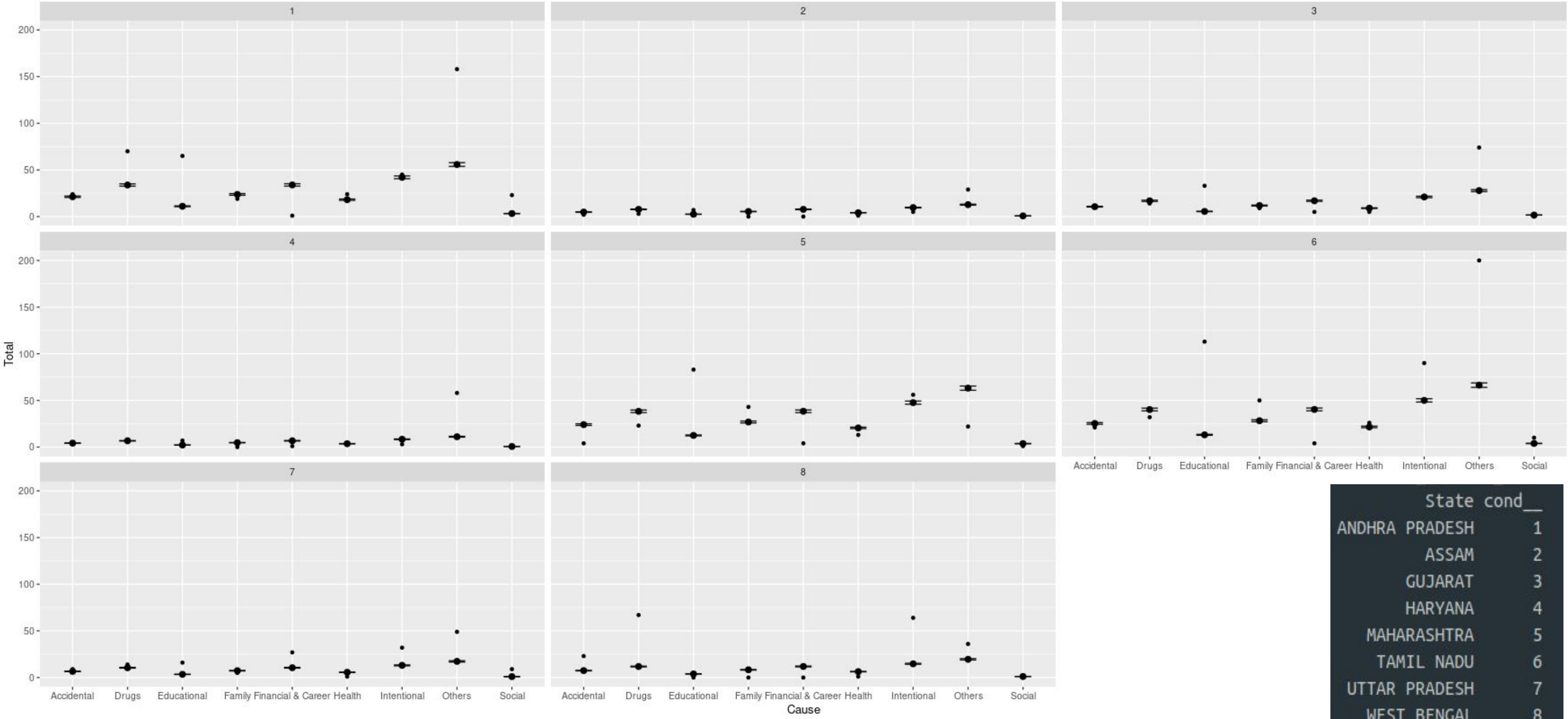


Fig 4(b): Conditional effects plots of all population-level predictors (Predict)

Poisson | Neg Binomial | Zero inflated NB



State	cond__
ANDHRA PRADESH	1
ASSAM	2
GUJARAT	3
HARYANA	4
MAHARASHTRA	5
TAMIL NADU	6
UTTAR PRADESH	7
WEST BENGAL	8

Fig 5(a): Conditional effects plots of all population-level predictors across the states (fitted)

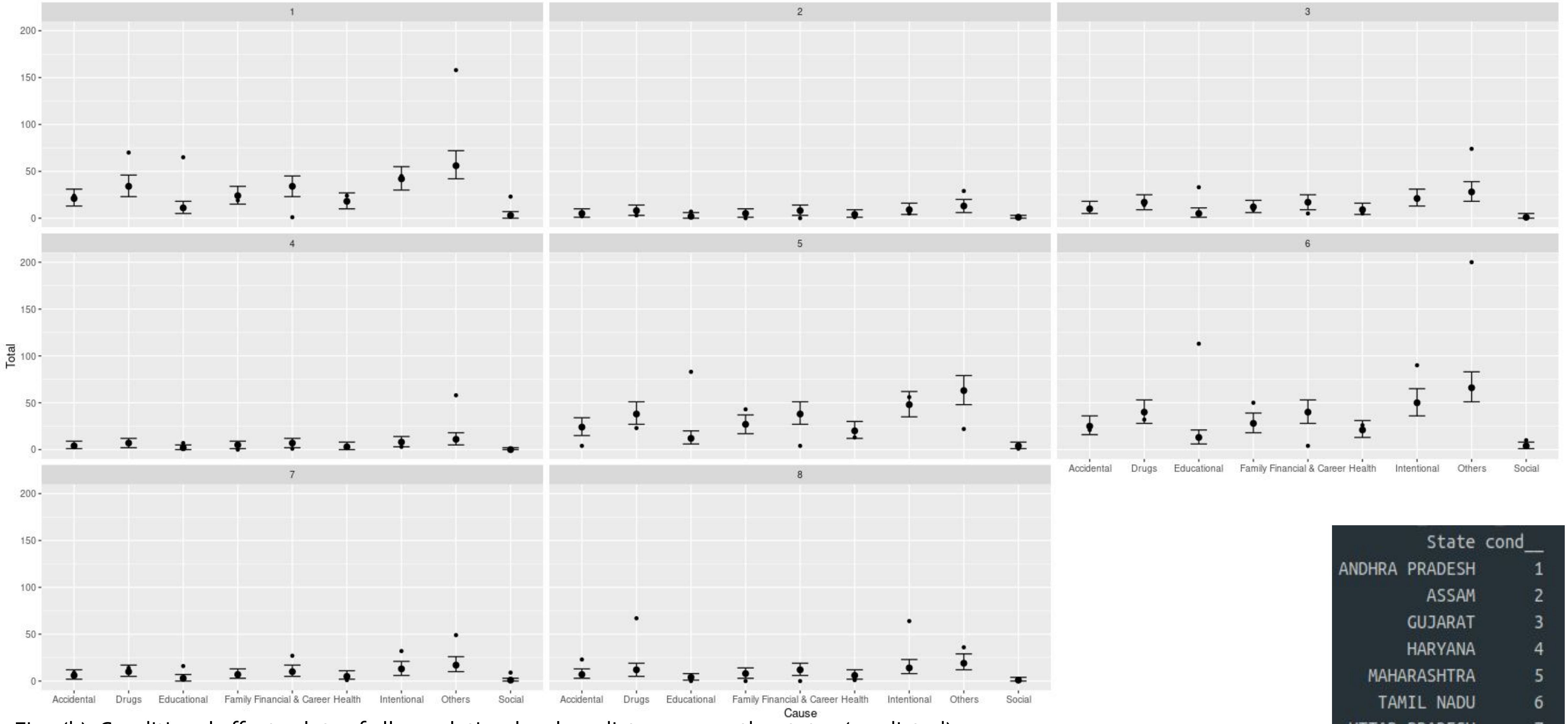


Fig 5(b): Conditional effects plots of all population-level predictors across the states (predicted)

State	cond__
ANDHRA PRADESH	1
ASSAM	2
GUJARAT	3
HARYANA	4
MAHARASHTRA	5
TAMIL NADU	6
UTTAR PRADESH	7
WEST BENGAL	8

Poisson | **Neg Binomial** | Zero inflated NB

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Significant covariates:

- Drugs
- Educational
- Intentional
- Social
- Others

Convergence diagnostics:

- Values of Rhat close to 1.00 suggest that the chains have converged to a common distribution.

ESS:

- Relatively high Bulk_ESS*.
- High Tail_ESS

Shape:

- Under Dispersion as Estimate(0.98) < 1
- observed counts have less variability in counts than would be expected under a Poisson distribution, although the deviation from 1 is relatively small.

***Bulk_ESS > num of chains * 100**

- **Source: Runtime warnings and convergence problems by Stan Development Team (link)**

```
> summary(negBinomial_model)
 Family: negbinomial
  Links: mu = log; shape = identity
Formula: Total ~ Cause + Gender + Age_group + (1 | State)
   Data: subset_df1 (Number of observations: 720)
  Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
         total post-warmup draws = 4000

Group-Level Effects:
~State (Number of levels: 8)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.98      0.32     0.56     1.77 1.00      917     1655

Population-Level Effects:
                      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                 2.52      0.39     1.74     3.30 1.00     1009     1434
CauseDrugs                0.57      0.17     0.25     0.90 1.00     1958     2919
CauseEducational         -0.49      0.17    -0.83    -0.15 1.00     1811     2808
CauseFamily              -0.18      0.17    -0.51     0.14 1.00     2106     2897
CauseFinancial&Career     0.31      0.17    -0.01     0.63 1.00     2093     2724
CauseHealth              -0.21      0.17    -0.53     0.12 1.00     2027     2794
CauseIntentional          0.85      0.16     0.53     1.18 1.00     1936     2580
CauseOthers               1.31      0.17     0.98     1.65 1.00     2120     2597
CauseSocial              -1.75      0.18    -2.09    -1.40 1.00     2058     2789
GenderMale                0.62      0.08     0.46     0.77 1.00     4048     3184
Age_group15M29            3.06      0.13     2.81     3.31 1.00     2559     2772
Age_group30M44            2.82      0.13     2.57     3.08 1.00     2611     3043
Age_group45M59            2.18      0.13     1.92     2.44 1.00     2556     2992
Age_group60P              1.06      0.13     0.79     1.31 1.00     2654     2870

Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape     0.98      0.05     0.88     1.08 1.00     4474     2757

Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
and Tail_ESS are effective sample size measures, and Rhat is the potential
scale reduction factor on split chains (at convergence, Rhat = 1).
```

Fig 6: Negative Binomial Model Summary

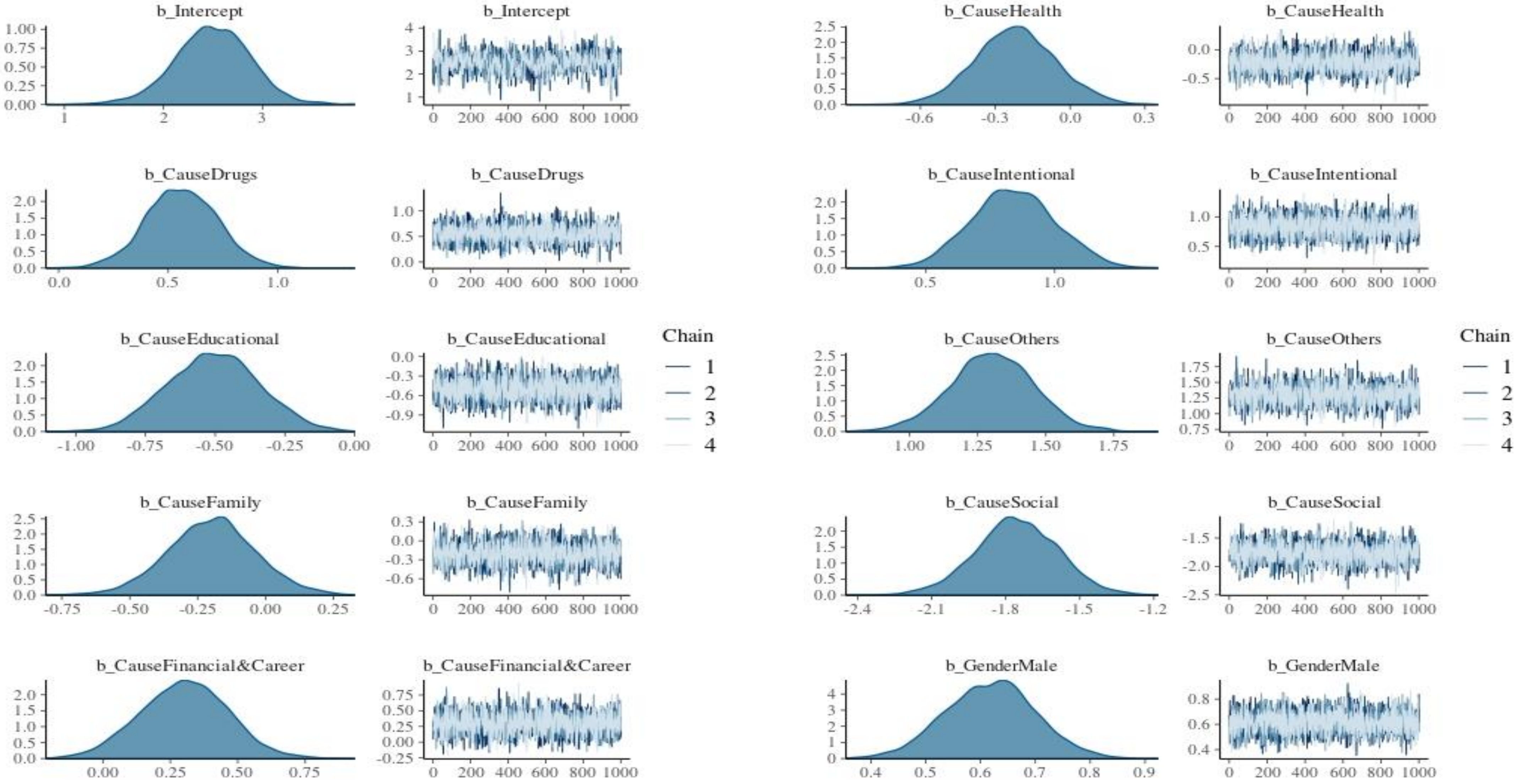
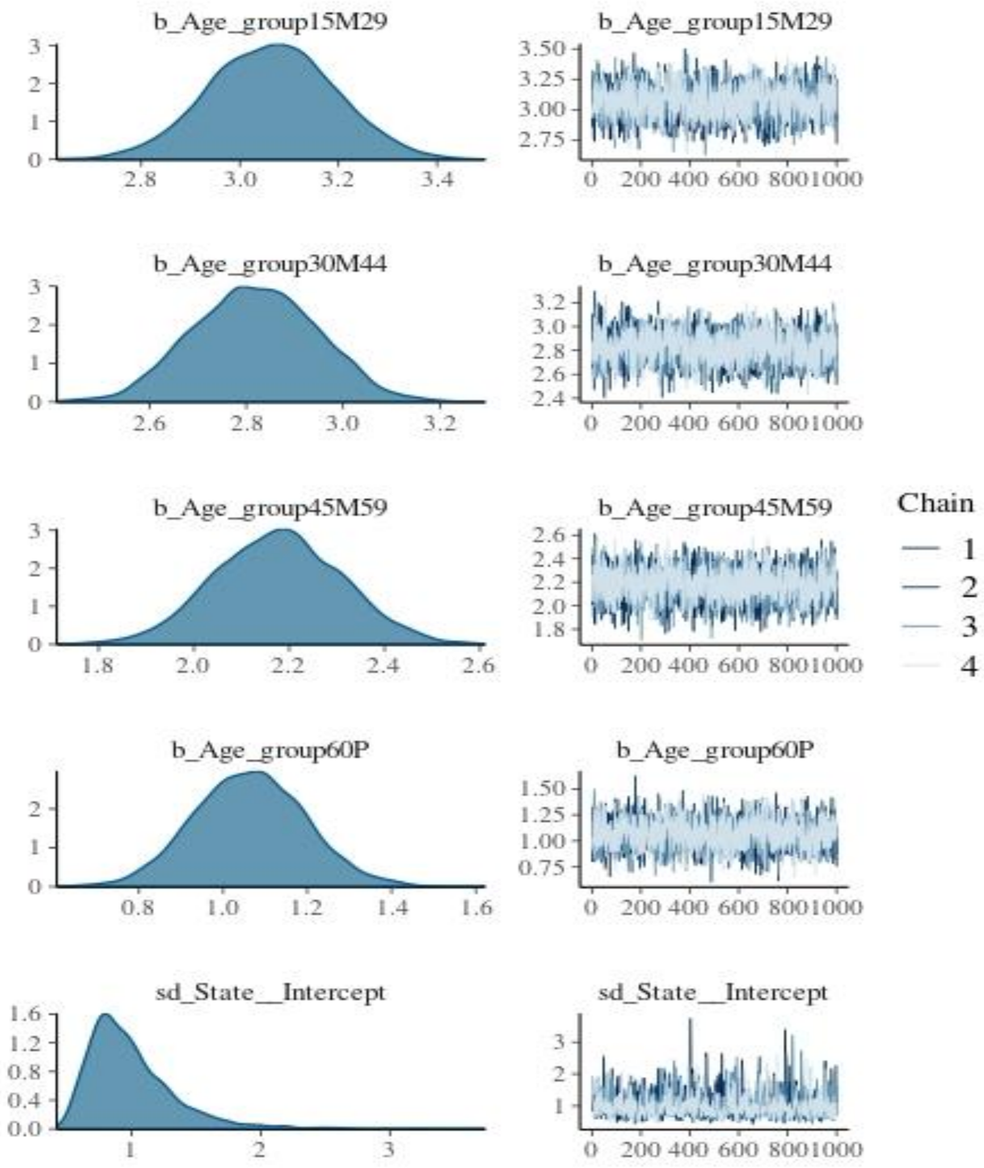
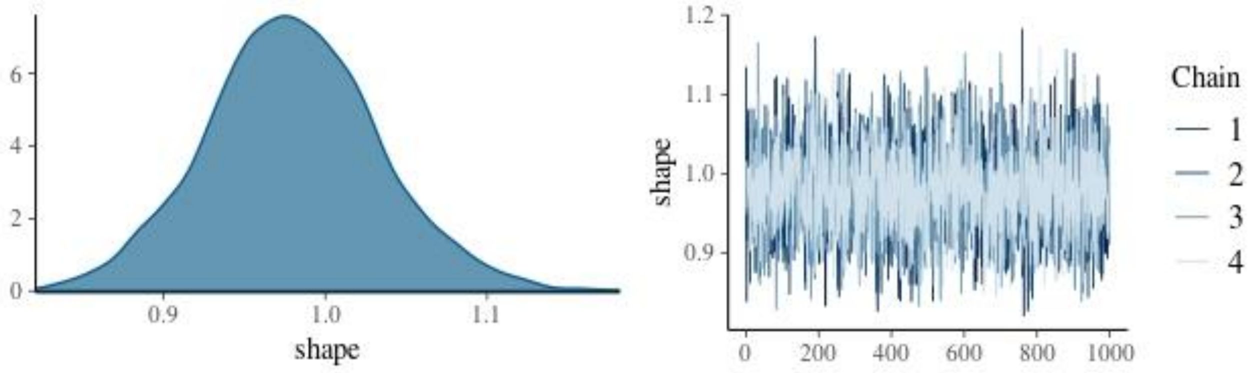


Fig 7: Trace and Density plots of all relevant parameters of the Negative Binomial model

Poisson | **Neg Binomial** | Zero inflated NB

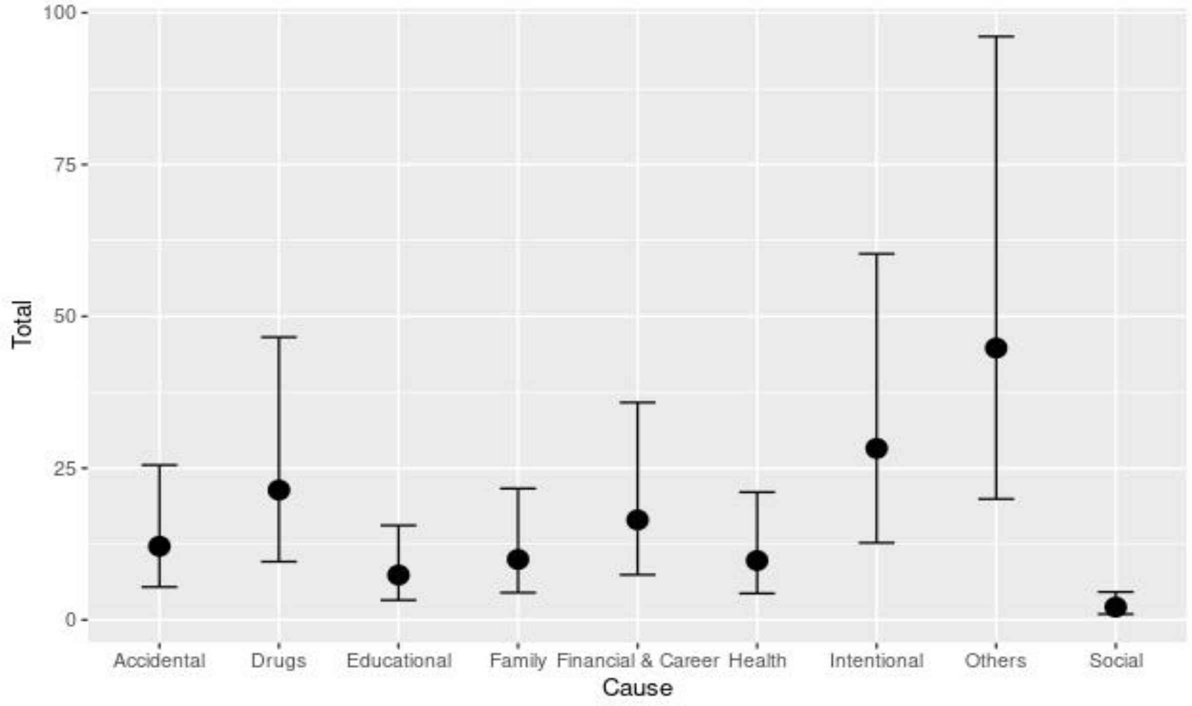


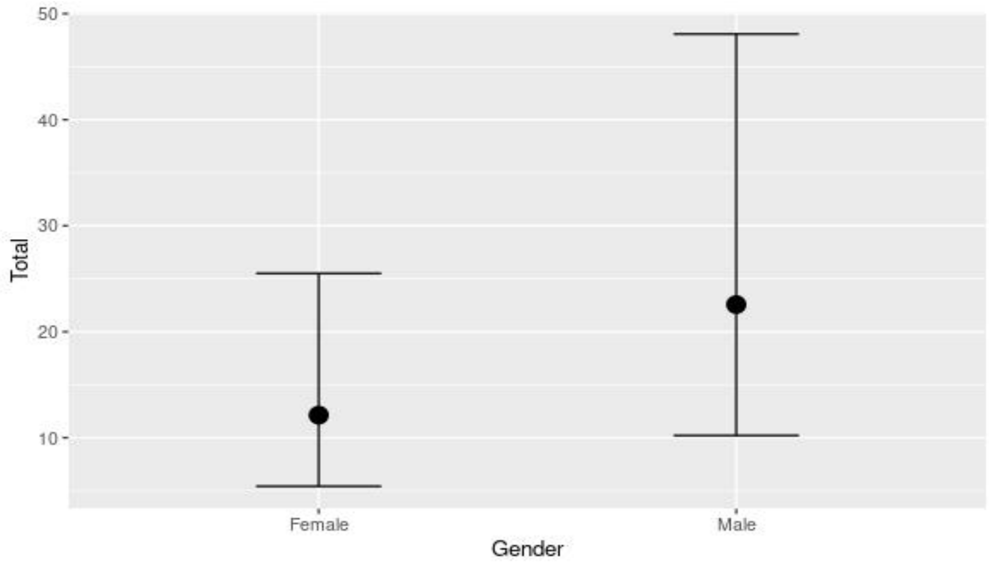
Extra Parameter for over dispersion Shape



- Trace plots shows that model has explored all the possible values it could look at so it converged well.
- Density plot shows the estimate found by model in Summary

Fig 7: Trace and Density plots of all relevant parameters of the Negative Binomial model





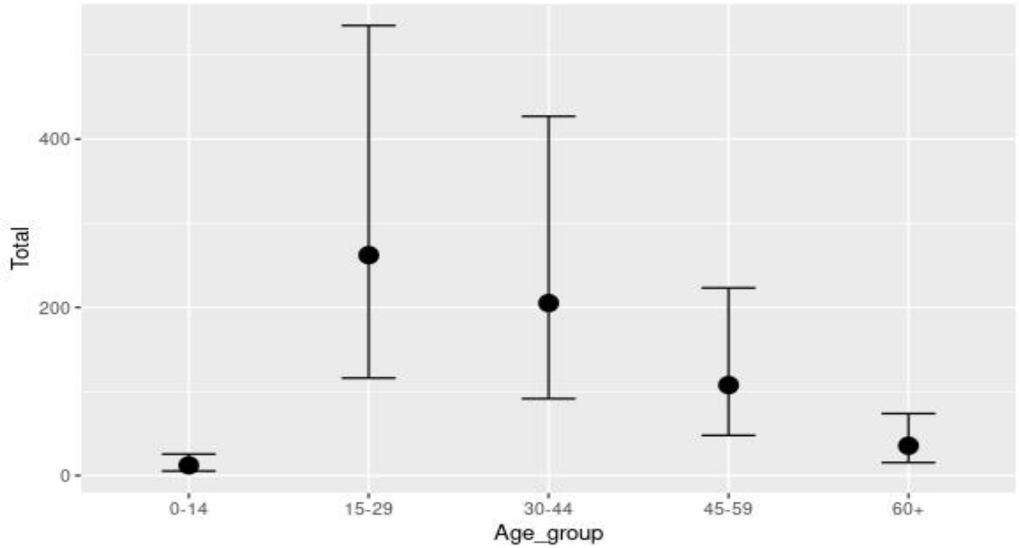


Fig 8(a): Conditional effects plots of all population-level predictors (fitted) technische universität dortmund

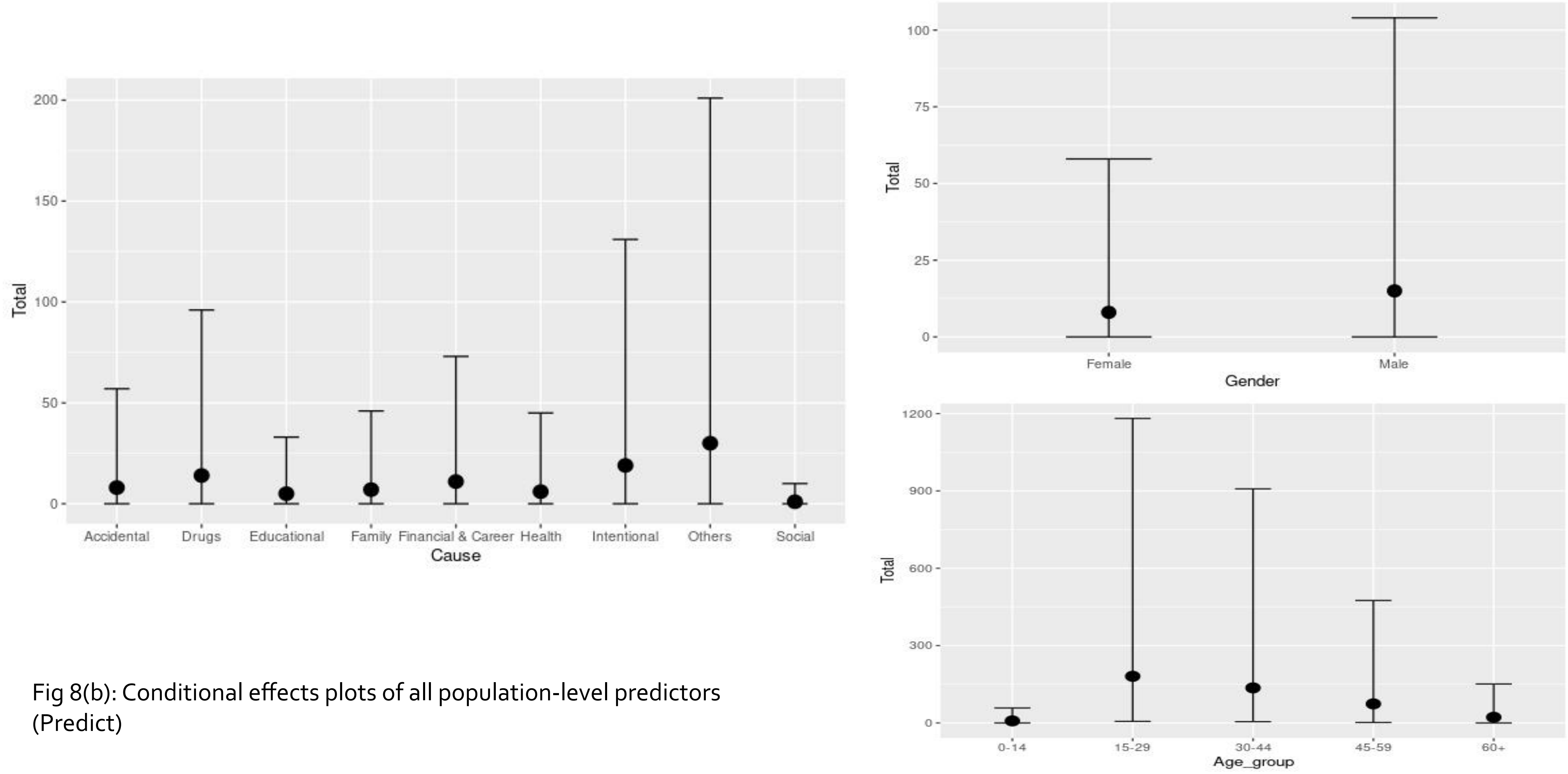


Fig 8(b): Conditional effects plots of all population-level predictors (Predict)

Poisson | **Neg Binomial** | Zero inflated NB

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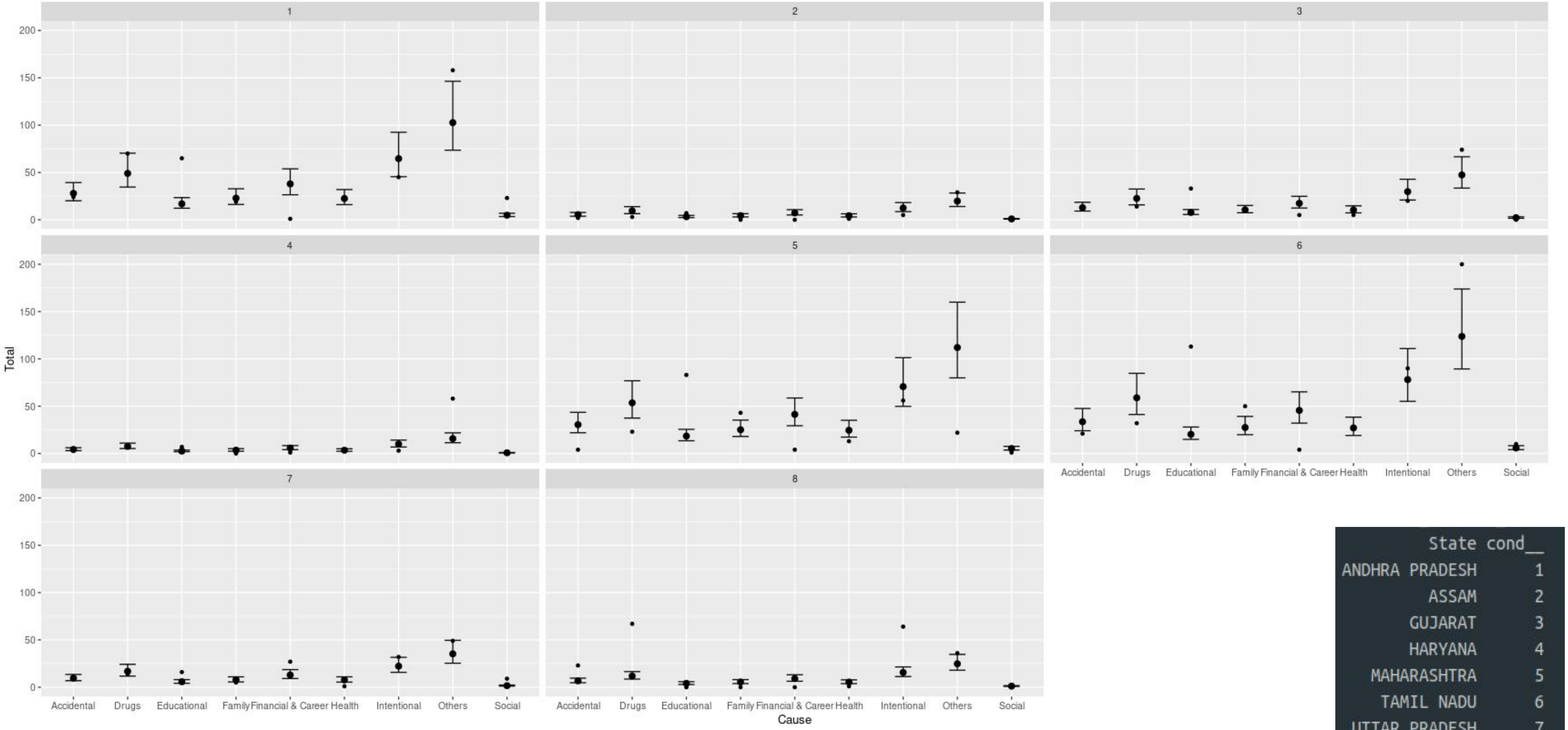
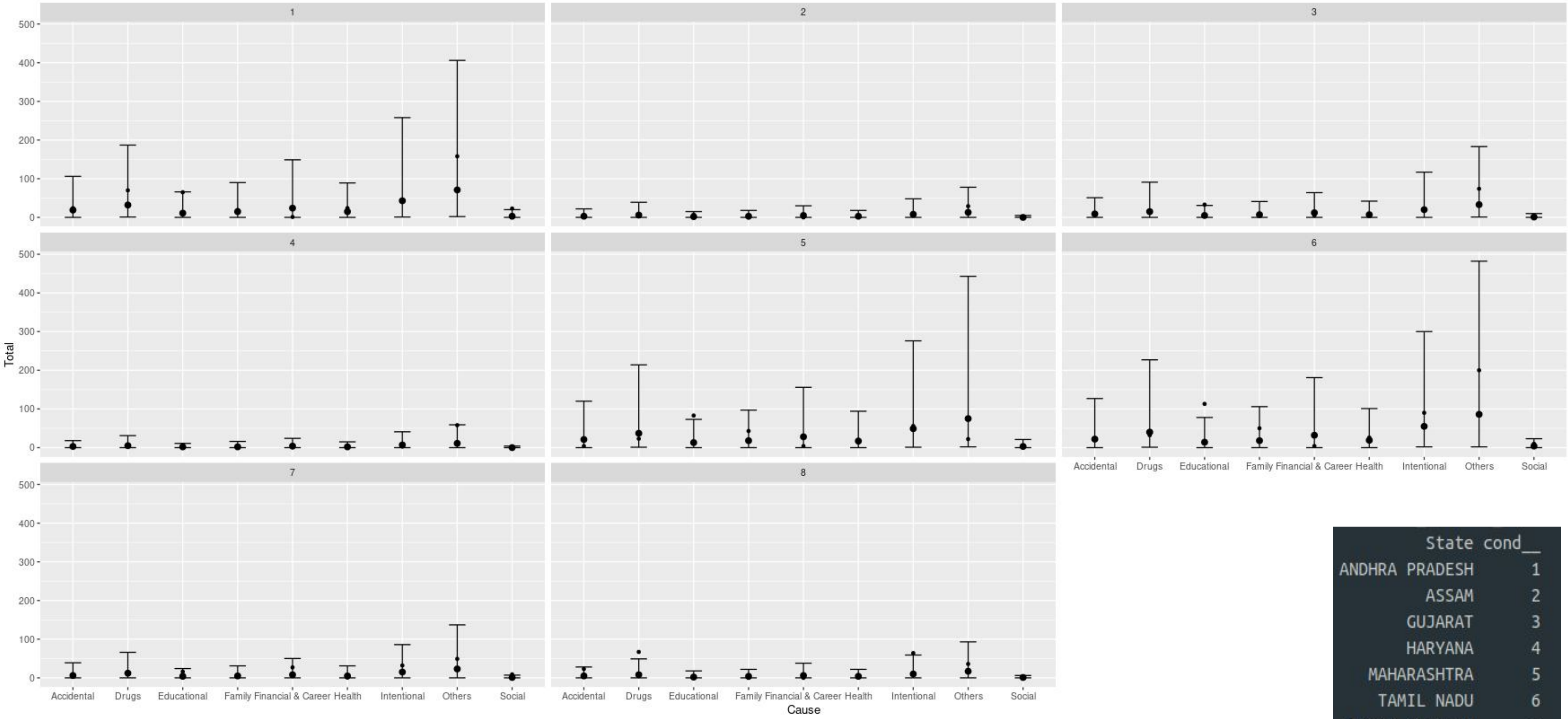


Fig 9(a) : Conditional effects plots of all population-level predictors across the states (fitted)

State	cond__
ANDHRA PRADESH	1
ASSAM	2
GUJARAT	3
HARYANA	4
MAHARASHTRA	5
TAMIL NADU	6
UTTAR PRADESH	7
WEST BENGAL	8

Poisson | **Neg Binomial** | Zero inflated NB



State	cond__
ANDHRA PRADESH	1
ASSAM	2
GUJARAT	3
HARYANA	4
MAHARASHTRA	5
TAMIL NADU	6
UTTAR PRADESH	7
WEST BENGAL	8

Fig 9(a) : Conditional effects plots of all population-level predictors across the states (predicted)

Poisson | Neg Binomial | **Zero inflated NB**

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Significant covariates:
- Drugs
- Financial & Career
- Intentional
- Social
- Others

Convergence diagnostics:
- Values of Rhat close to 1.00 suggest that the chains have converged to a common distribution.

ESS:
- High Bulk_ESS*.
- High Tail_ESS

Shape (Dispersion parameter):
- Over Dispersion as Estimate(1.54) > 1
- observed counts have more variability in the counts than would be expected under a Poisson distribution.

Zi (zero-inflation parameter):
- probability of excess zeros in the data
- small probability of observing excess zeros

***Bulk_ESS > num of chains * 100**
- **Source: Runtime warnings and convergence problems by Stan Development Team (link)**

```
> summary(zi_nbm)
 Family: zero_inflated_negbinomial
  Links: mu = log; shape = identity; zi = identity
Formula: Total ~ Cause + Gender + Age_group + (1 | State)
   Data: subset_df1 (Number of observations: 720)
  Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
         total post-warmup draws = 4000

Group-Level Effects:
~State (Number of levels: 8)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.94      0.29     0.55     1.67 1.00     1136     1891

Population-Level Effects:
                      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                 2.46      0.35     1.75     3.18 1.01      805     1329
CauseDrugs                0.45      0.13     0.20     0.71 1.00     1841     2042
CauseEducational         -0.26      0.14    -0.55     0.02 1.00     2050     2484
CauseFamily               0.03      0.14    -0.24     0.29 1.00     1943     2608
CauseFinancial&Career     0.56      0.14     0.30     0.84 1.00     1845     2394
CauseHealth              -0.15      0.13    -0.41     0.10 1.00     1909     2263
CauseIntentional          0.74      0.13     0.48     1.01 1.00     1904     2351
CauseOthers               1.29      0.13     1.04     1.55 1.00     1944     2436
CauseSocial              -1.52      0.15    -1.82    -1.24 1.00     2205     2607
GenderMale                0.66      0.07     0.53     0.79 1.00     3790     3013
Age_group15M29            3.07      0.11     2.85     3.28 1.00     1896     2577
Age_group30M44            2.83      0.11     2.61     3.04 1.00     1900     2786
Age_group45M59            2.20      0.11     1.98     2.41 1.00     1757     2580
Age_group60P              1.13      0.11     0.90     1.34 1.00     1938     2710

Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape     1.54      0.09     1.37     1.73 1.00     4290     2898
zi        0.06      0.01     0.05     0.08 1.00     4405     2492

Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
and Tail_ESS are effective sample size measures, and Rhat is the potential
scale reduction factor on split chains (at convergence, Rhat = 1).
```

Fig 10 :Zero Inflated Negative Binomial Model Summary

Poisson | Neg Binomial | **Zero inflated NB**

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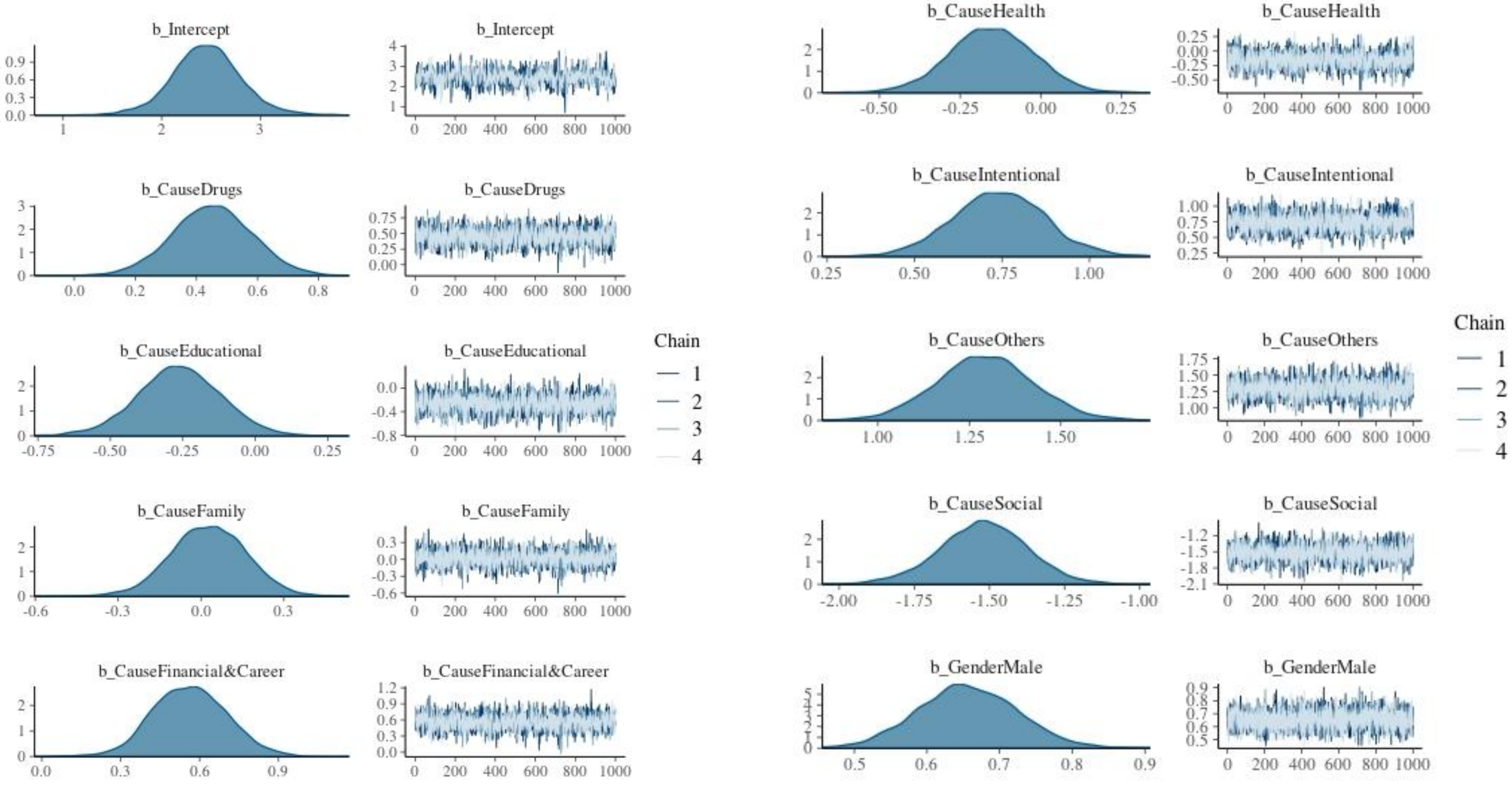
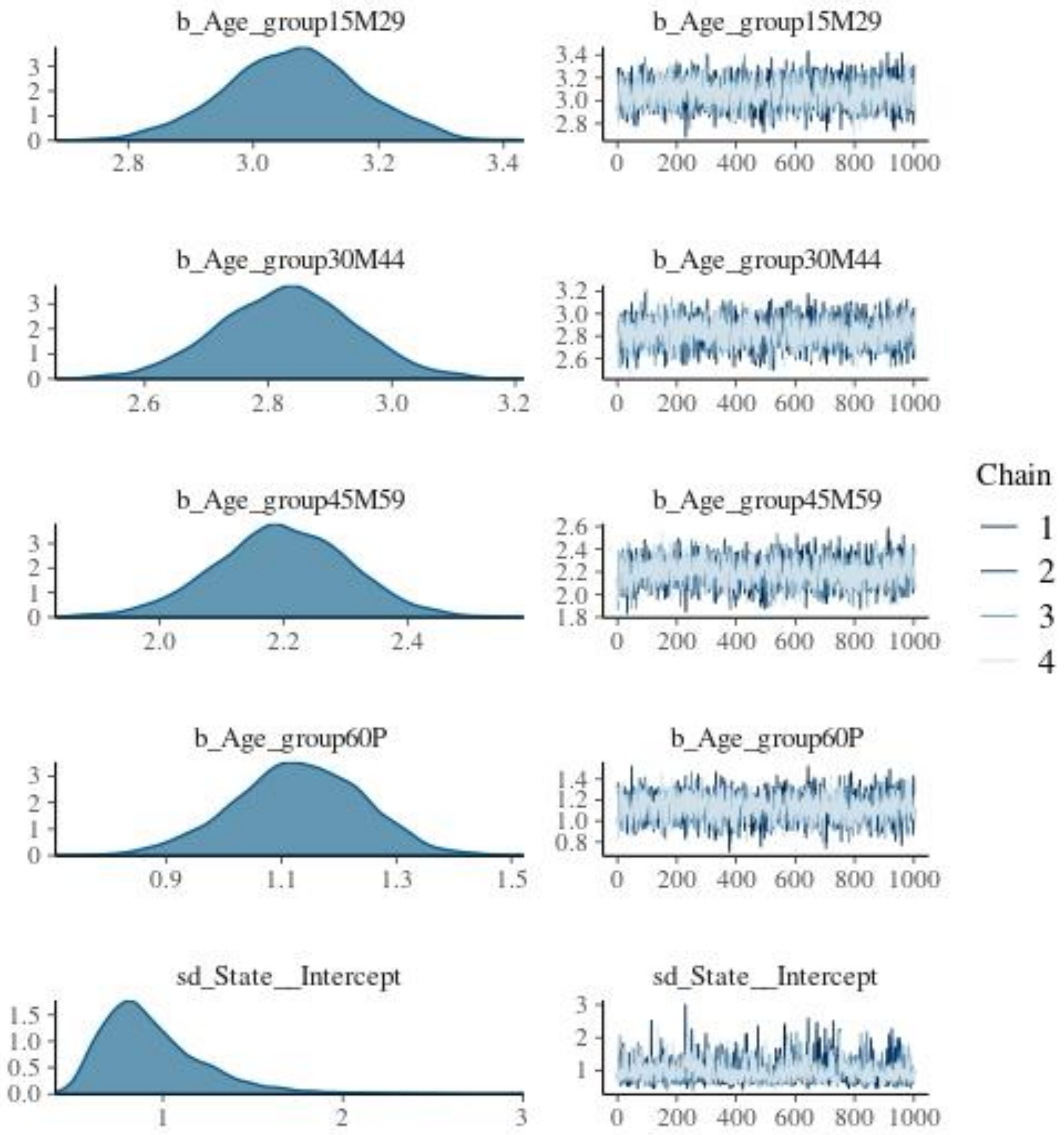


Fig 11: Trace and Density plots of all relevant parameters of Zero inflated Negative Binomial model



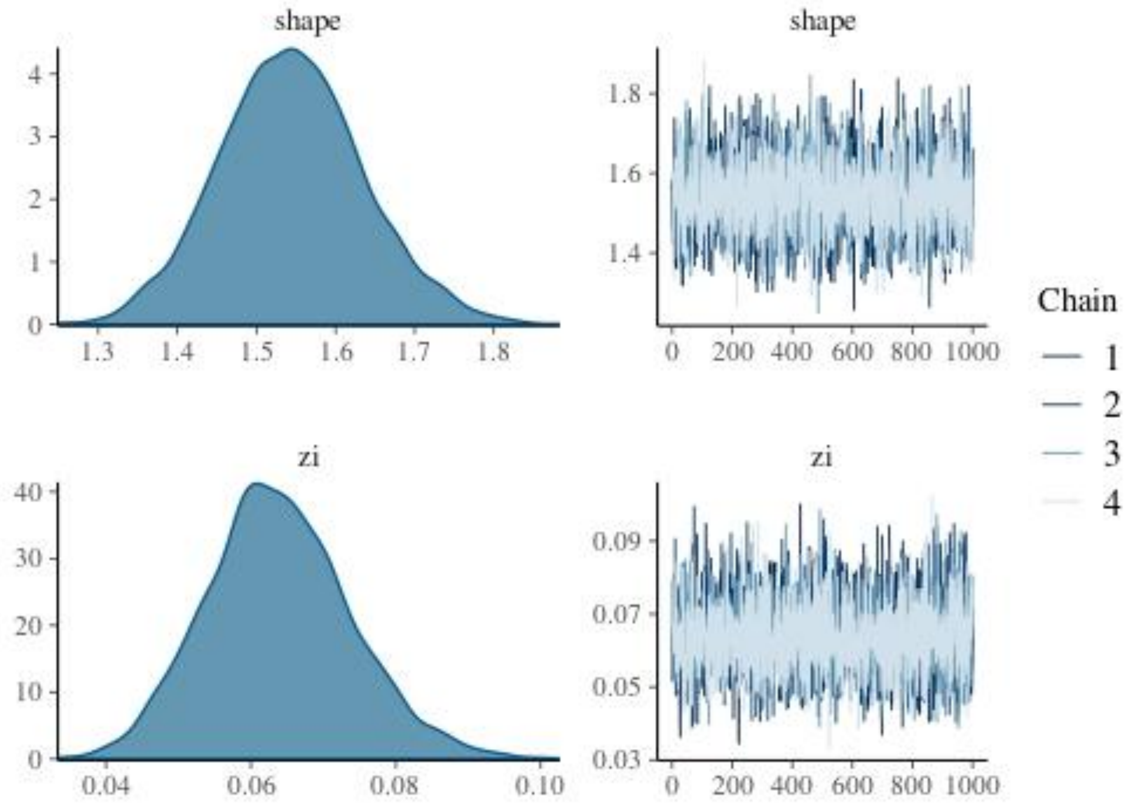


Fig 11: Trace and Density plots of all relevant parameters of Zero inflated Negative Binomial model

Poisson | Neg Binomial | **Zero inflated NB**

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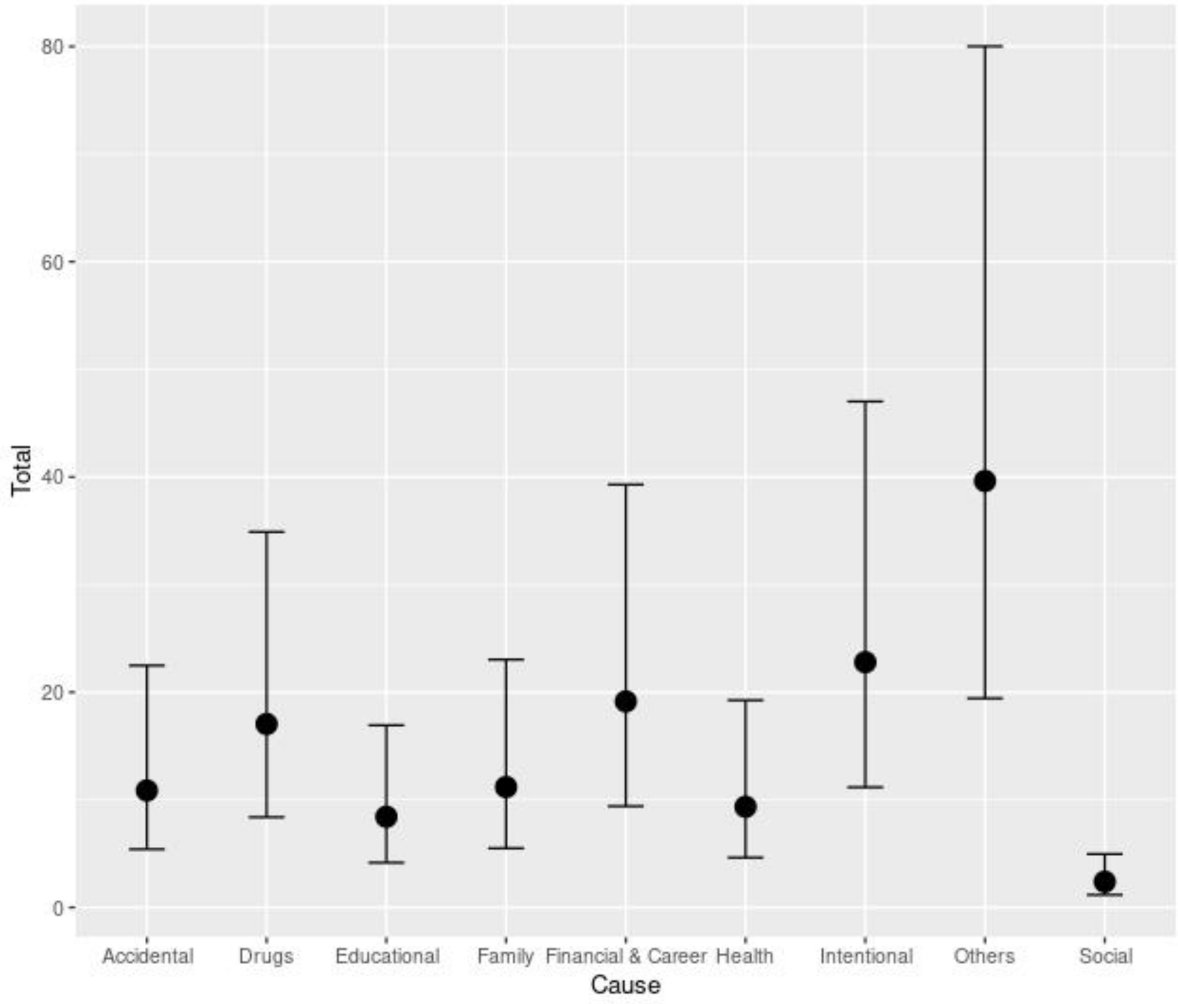
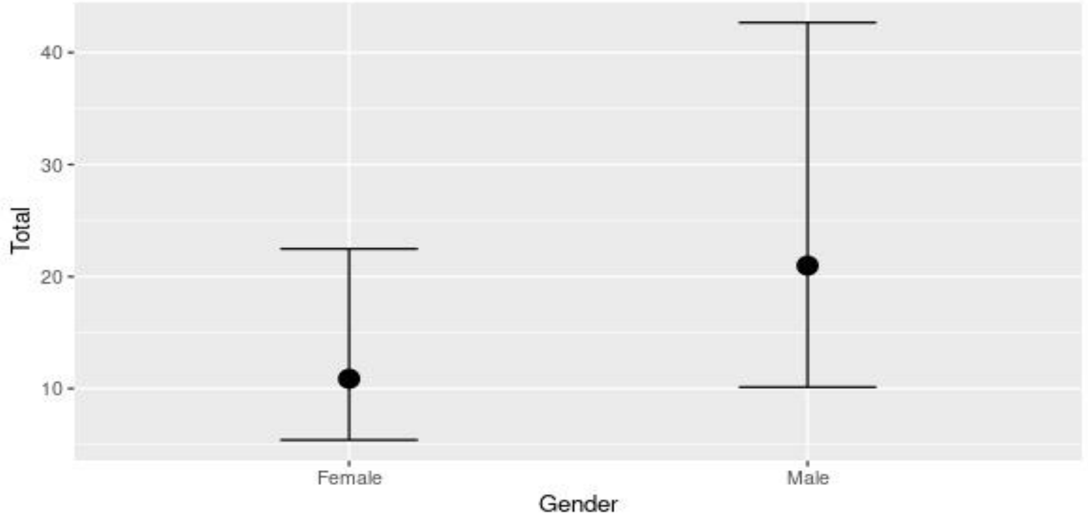
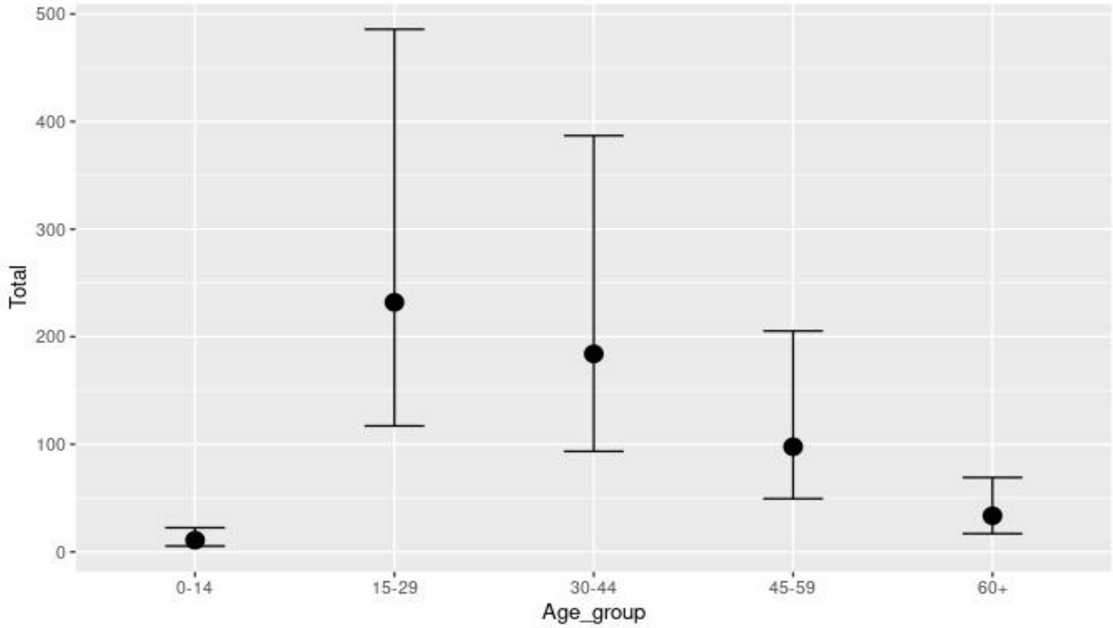
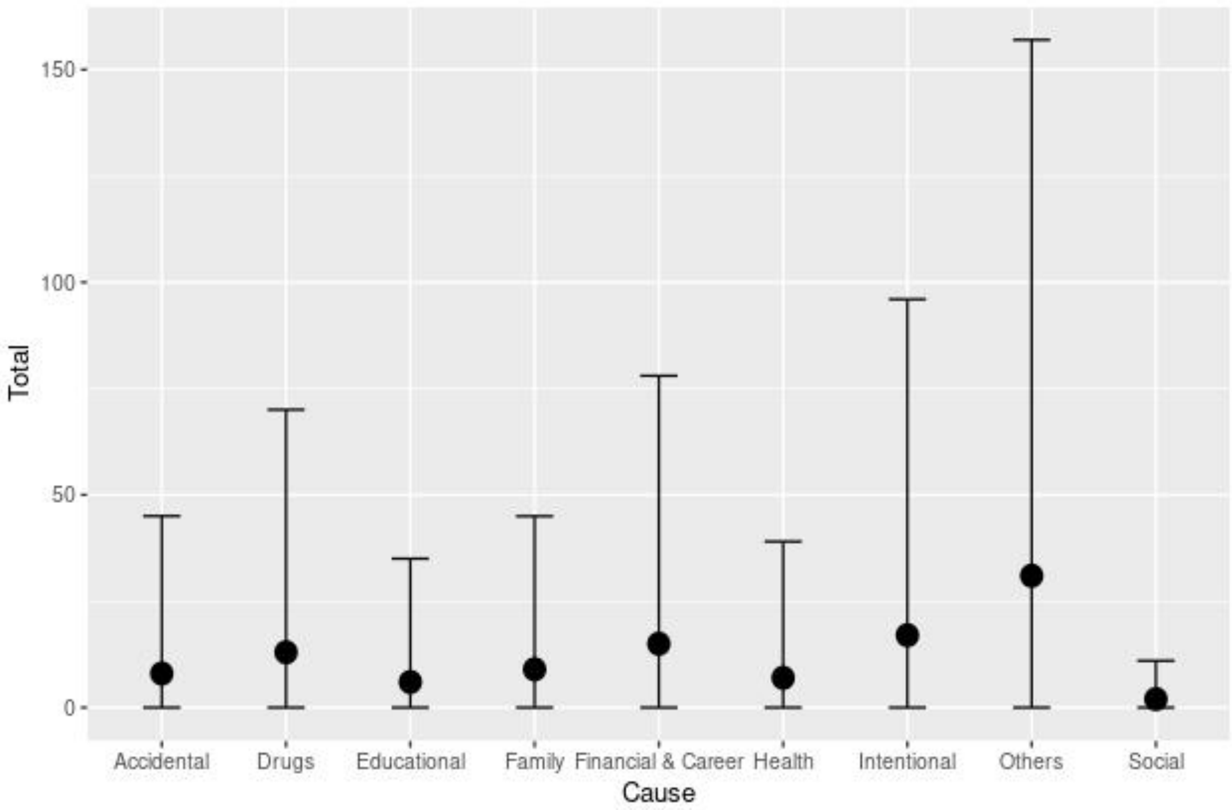


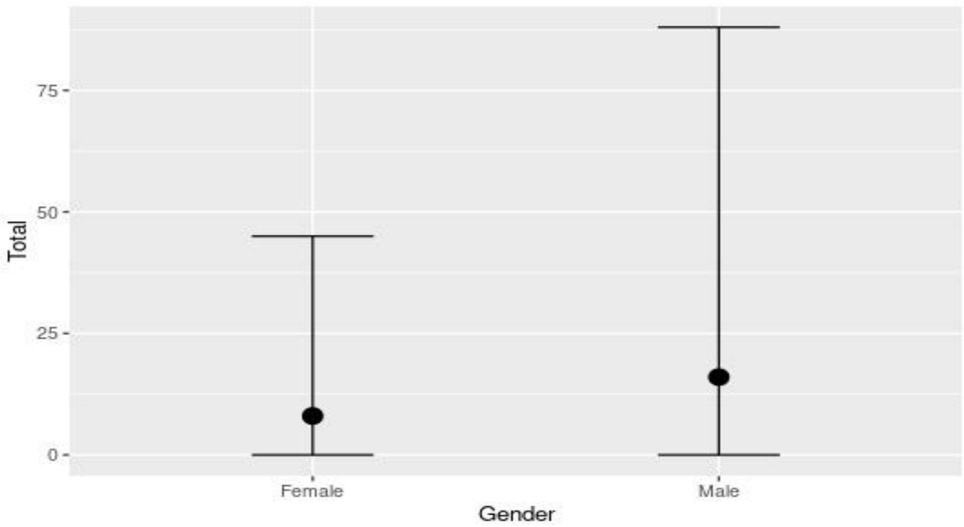
Fig 12(a): Conditional effects plots of all population-level predictors (fitted)





Poisson | Neg Binomial | **Zero inflated NB**





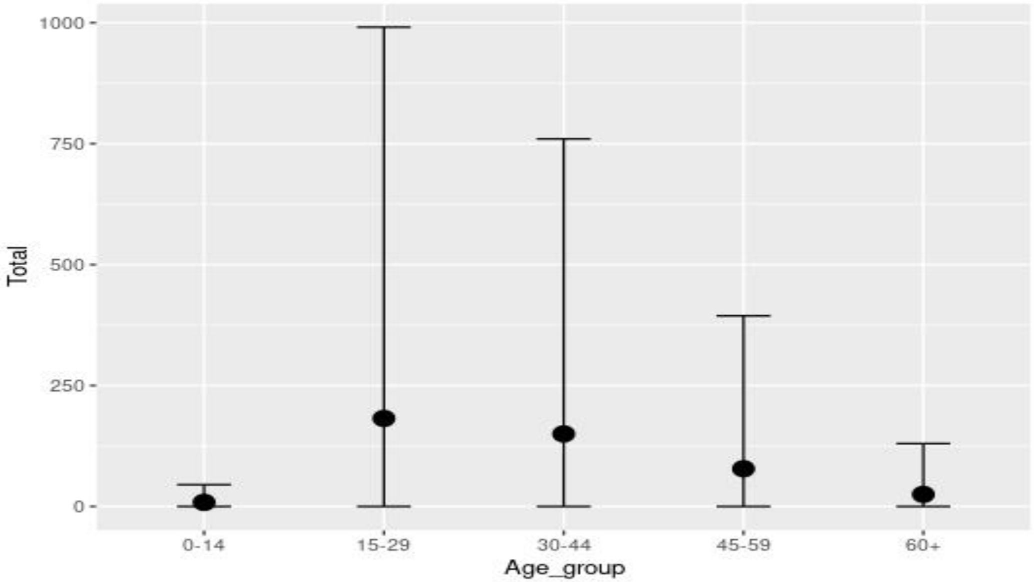


Fig 12(b): Conditional effects plots of all population-level predictors (predicted)

Poisson | Neg Binomial | **Zero inflated NB**

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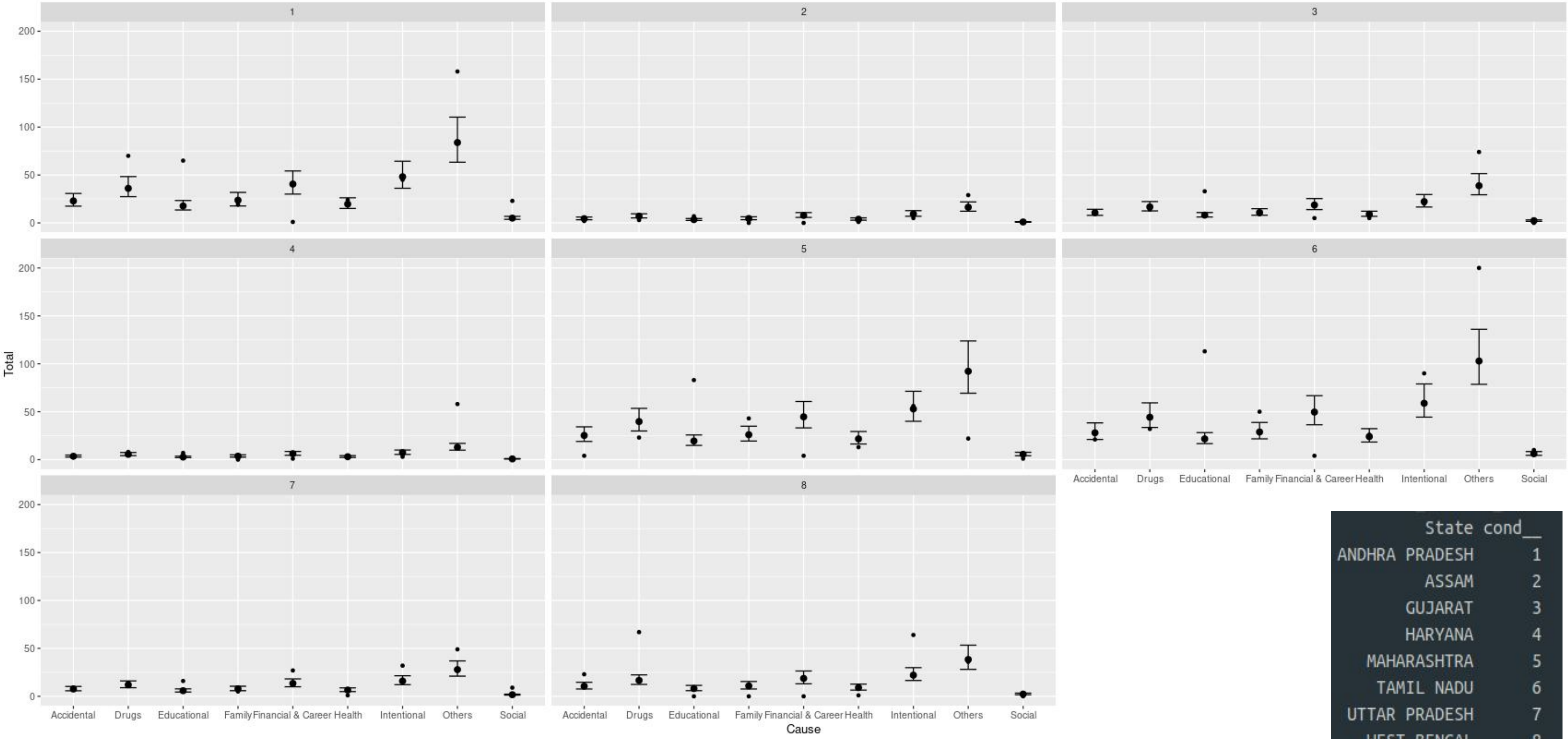
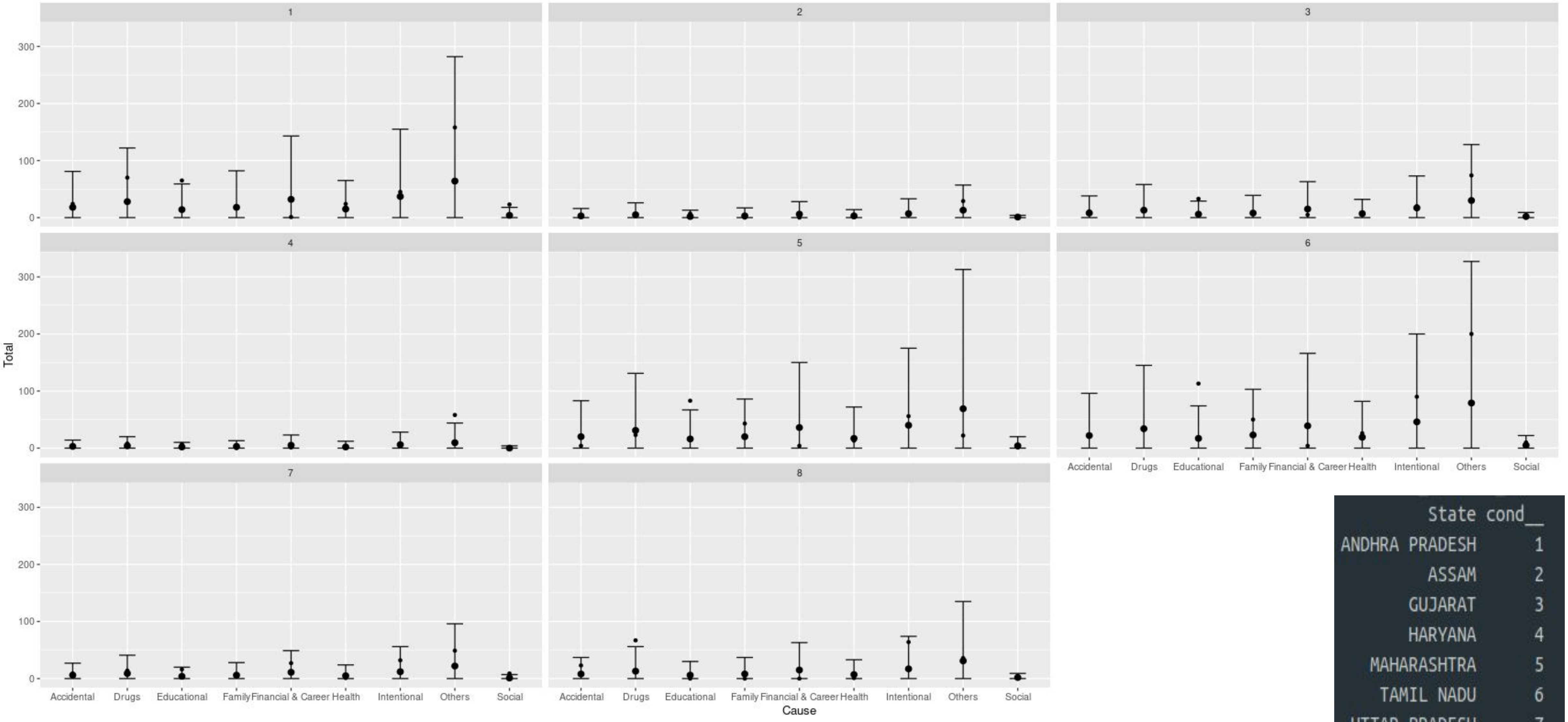


Fig 13(a): Conditional effects plots of all population-level predictors across the states (fitted)

State	cond__
ANDHRA PRADESH	1
ASSAM	2
GUJARAT	3
HARYANA	4
MAHARASHTRA	5
TAMIL NADU	6
UTTAR PRADESH	7
WEST BENGAL	8

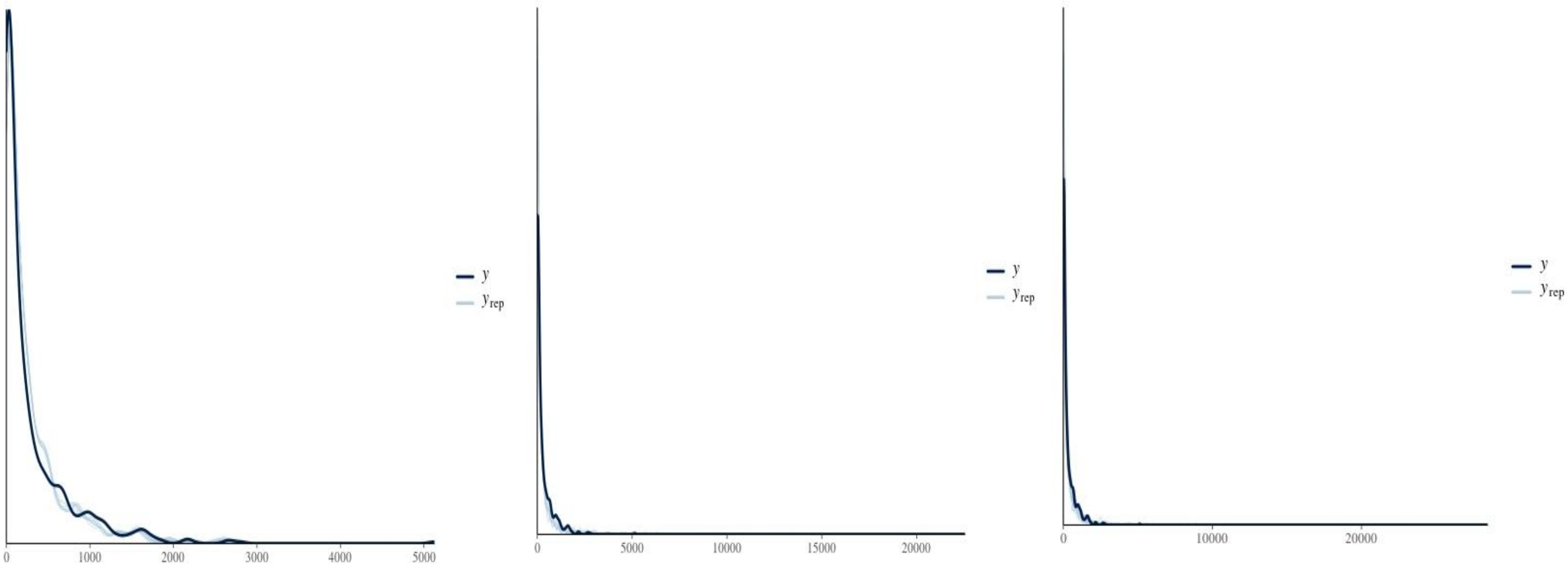
Poisson | Neg Binomial | **Zero inflated NB**



State	cond__
ANDHRA PRADESH	1
ASSAM	2
GUJARAT	3
HARYANA	4
MAHARASHTRA	5
TAMIL NADU	6
UTTAR PRADESH	7
WEST BENGAL	8

Fig 13(b): Conditional effects plots of all population-level predictors across the states (predicted)

Posterior Check



Poisson

Negative Binomial

Zero inflated negative binomial

Fig 14 : Posterior Predictive Check Graph for all models

Model Comparison

Models	elpd_diff	se_diff
Zero-inflated Negative Binomial Model	0.0	0.0
Negative Binomial Model	-55.2	12.9
Poisson Model	-34573.2	2687.0

Table 3: Model comparison using "loo()" function

- Higher the ELPD score the more well model fits the data.
- Zero-inflated negative binomial model performs best as it has highest ELPD (Expected log predictive density) score.
- It is taken as a base model for comparison.

Prior Sensitivity Check

```
> prior_summary(zi_nbm)
               prior     class                 coef group resp dpar nlpar lb ub       source
              (flat)         b                                                       default
              (flat)         b        Age_group15M29                            (vectorized)
              (flat)         b        Age_group30M44                            (vectorized)
              (flat)         b        Age_group45M59                            (vectorized)
              (flat)         b          Age_group60P                            (vectorized)
              (flat)         b            CauseDrugs                            (vectorized)
              (flat)         b       CauseEducational                           (vectorized)
              (flat)         b           CauseFamily                            (vectorized)
              (flat)         b CauseFinancial&Career                            (vectorized)
              (flat)         b           CauseHealth                            (vectorized)
              (flat)         b      CauseIntentional                            (vectorized)
              (flat)         b           CauseOthers                            (vectorized)
              (flat)         b           CauseSocial                            (vectorized)
              (flat)         b            GenderMale                            (vectorized)
 student_t(3, 4.6, 2.5) Intercept                                                    default
   student_t(3, 0, 2.5)        sd                                          0         default
   student_t(3, 0, 2.5)        sd                      State               0    (vectorized)
   student_t(3, 0, 2.5)        sd            Intercept State               0    (vectorized)
      gamma(0.01, 0.01)     shape                                          0         default
            beta(1, 1)        zi                                           0  1      default
```

Fig 15: Default Prior Settings

Prior Sensitivity Check

(a)

```
priors_set1<- c(
  set_prior("normal(0, 5)", class = "b"),
  set_prior("normal(0, 10)", class = "Intercept"),
  set_prior("cauchy(0, 2)", class = "sd"),
  set_prior("beta(1, 1)", class = "zi"),
  set_prior("gamma(2, 0.5)", class = "shape")
)
```

(b)

```
priors_set2 <- c(
  set_prior("normal(0, 2)", class = "b"),
  set_prior("normal(0, 5)", class = "Intercept"),
  set_prior("cauchy(0, 1)", class = "sd"),
  set_prior("beta(2, 2)", class = "zi"),
  set_prior("gamma(2, 0.1)", class = "shape")
)
```

Fig 16):Different Prior Settings (a) Prior Setting-1, (b) Prior Setting-2

Prior Sensitivity Check

Fig 17: Prior Summary of Two models fitted with different Prior settings

```
> prior_summary(PSA_zi_nbm1)
        prior     class                 coef group resp dpar nlpar lb ub       source
  normal(0, 5)        b                                                          user
  normal(0, 5)        b      Age_group15M29                                (vectorized)
  normal(0, 5)        b      Age_group30M44                                (vectorized)
  normal(0, 5)        b      Age_group45M59                                (vectorized)
  normal(0, 5)        b        Age_group60P                                (vectorized)
  normal(0, 5)        b          CauseDrugs                                (vectorized)
  normal(0, 5)        b     CauseEducational                               (vectorized)
  normal(0, 5)        b         CauseFamily                                (vectorized)
  normal(0, 5)        b CauseFinancial&Career                              (vectorized)
  normal(0, 5)        b         CauseHealth                                (vectorized)
  normal(0, 5)        b     CauseIntentional                               (vectorized)
  normal(0, 5)        b         CauseOthers                                (vectorized)
  normal(0, 5)        b         CauseSocial                                (vectorized)
  normal(0, 5)        b          GenderMale                                (vectorized)
 normal(0, 10) Intercept                                                         user
  cauchy(0, 2)       sd                                          0               user
  cauchy(0, 2)       sd                       State              0         (vectorized)
  cauchy(0, 2)       sd             Intercept State              0         (vectorized)
 gamma(2, 0.5)    shape                                          0               user
    beta(1, 1)       zi                                          0  1            user
```

Fig 17(a): Prior setting-1

```
> prior_summary(PSA_zi_nbm2)
        prior     class                 coef group resp dpar nlpar lb ub       source
  normal(0, 2)        b                                                          user
  normal(0, 2)        b      Age_group15M29                                (vectorized)
  normal(0, 2)        b      Age_group30M44                                (vectorized)
  normal(0, 2)        b      Age_group45M59                                (vectorized)
  normal(0, 2)        b        Age_group60P                                (vectorized)
  normal(0, 2)        b          CauseDrugs                                (vectorized)
  normal(0, 2)        b     CauseEducational                               (vectorized)
  normal(0, 2)        b         CauseFamily                                (vectorized)
  normal(0, 2)        b CauseFinancial&Career                              (vectorized)
  normal(0, 2)        b         CauseHealth                                (vectorized)
  normal(0, 2)        b     CauseIntentional                               (vectorized)
  normal(0, 2)        b         CauseOthers                                (vectorized)
  normal(0, 2)        b         CauseSocial                                (vectorized)
  normal(0, 2)        b          GenderMale                                (vectorized)
  normal(0, 5) Intercept                                                         user
  cauchy(0, 1)       sd                                          0               user
  cauchy(0, 1)       sd                       State              0         (vectorized)
  cauchy(0, 1)       sd             Intercept State              0         (vectorized)
 gamma(2, 0.1)    shape                                          0               user
    beta(2, 2)       zi                                          0  1            user
```

Fig 17(b): Prior setting-2

Prior Sensitivity Check

```
> summary(PSA_zi_nbm1)
 Family: zero_inflated_negbinomial
  Links: mu = log; shape = identity; zi = identity
Formula: Total ~ Cause + Gender + Age_group + (1 | State)
   Data: subset_df1 (Number of observations: 720)
  Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
         total post-warmup draws = 4000

Group-Level Effects:
~State (Number of levels: 8)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.93      0.31     0.52     1.69 1.00      801     1224

Population-Level Effects:
                      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                 2.48      0.38     1.76     3.24 1.00      782      877
CauseDrugs                0.45      0.13     0.20     0.70 1.00     1631     1888
CauseEducational         -0.26      0.14    -0.55     0.01 1.00     1922     2532
CauseFamily               0.03      0.13    -0.24     0.29 1.00     1929     2635
CauseFinancial&Career     0.56      0.14     0.30     0.83 1.00     1853     2224
CauseHealth              -0.15      0.13    -0.41     0.10 1.00     1814     2223
CauseIntentional          0.74      0.13     0.48     0.99 1.00     1761     1755
CauseOthers               1.29      0.13     1.04     1.54 1.00     1570     2427
CauseSocial              -1.52      0.15    -1.81    -1.23 1.00     1826     2128
GenderMale                0.66      0.07     0.52     0.79 1.00     3454     3294
Age_group15M29            3.06      0.11     2.85     3.27 1.00     2237     2679
Age_group30M44            2.83      0.11     2.61     3.05 1.00     2166     2491
Age_group45M59            2.19      0.11     1.98     2.41 1.00     2086     2703
Age_group60P              1.13      0.11     0.90     1.34 1.00     2175     2564

Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape     1.55      0.09     1.37     1.73 1.00     4221     2654
zi        0.06      0.01     0.05     0.08 1.00     3484     2834

Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
and Tail_ESS are effective sample size measures, and Rhat is the potential
scale reduction factor on split chains (at convergence, Rhat = 1).
```

Fig 18 (a): Model summary of prior settings-1

```
> summary(PSA_zi_nbm2)
 Family: zero_inflated_negbinomial
  Links: mu = log; shape = identity; zi = identity
Formula: Total ~ Cause + Gender + Age_group + (1 | State)
   Data: subset_df1 (Number of observations: 720)
  Draws: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
         total post-warmup draws = 4000

Group-Level Effects:
~State (Number of levels: 8)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.89      0.27     0.53     1.54 1.00      972     1614

Population-Level Effects:
                      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                 2.47      0.34     1.79     3.13 1.00     1065     1487
CauseDrugs                0.45      0.13     0.19     0.70 1.00     1911     2632
CauseEducational         -0.27      0.15    -0.55     0.02 1.00     1816     2761
CauseFamily               0.03      0.13    -0.24     0.29 1.00     1997     2827
CauseFinancial&Career     0.57      0.14     0.30     0.84 1.00     1716     2511
CauseHealth              -0.15      0.13    -0.41     0.11 1.00     1766     2462
CauseIntentional          0.74      0.13     0.48     0.99 1.00     2010     2742
CauseOthers               1.29      0.13     1.03     1.55 1.00     1853     2658
CauseSocial              -1.51      0.15    -1.79    -1.23 1.00     1983     2761
GenderMale                0.66      0.07     0.53     0.78 1.00     3230     2613
Age_group15M29            3.05      0.11     2.84     3.25 1.00     2142     2502
Age_group30M44            2.81      0.11     2.59     3.02 1.00     1934     2564
Age_group45M59            2.18      0.11     1.97     2.40 1.00     1950     2338
Age_group60P              1.12      0.11     0.89     1.33 1.00     1954     2191

Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape     1.56      0.09     1.39     1.74 1.00     3928     2524
zi        0.07      0.01     0.05     0.09 1.00     3822     2700

Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
and Tail_ESS are effective sample size measures, and Rhat is the potential
scale reduction factor on split chains (at convergence, Rhat = 1).
```

Fig 18 (b): Model summary of prior settings-2

Prior Sensitivity Check

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Model Comparison

Zero-inflated Negative Binomial Model	**elpd_diff**	**se_diff**
with default settings	0.0	0.0
with Prior settings 2	-0.2	0.4
with Prior settings 1	-0.5	0.2

Table 4: Model comparison with different priors

- Zero inflated Negative binomial model is not sensitive to priors as the difference in the elpd score is quite small.

Results

- The number of suicides tend to be lower among children and older adults compared to middle-aged adults.
- Suicide is a more prevalent issue among males compareda to females in India.
- The main cause of suicides in India are intentional and financial & career-related problems.

Summary

- Cleaned Dataset contains 720 rows and 4 covariates
- Different Models like Poisson Model, Negative Binomial and Zero-inflated negative binomial models are fitted and variation of number of suicides based on gender, age groups, cause and each state in India is discussed
- Models are compared and Zero-inflated negative binomial model is the best fit
- Prior Sensitivity Analysis is performed on the best model.
- The model is not sensitive to priors as elpd_diff is quite small.

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