PLSC 504 - Fall 2017
Event Counts, II

September 14, 2017

What We're About

- Truncated Count Models
- Censored Count Models
- "Zero-Inflated" / "Hurdle" Count Models

Running Example: International Conflict(s)

- `conflicts` $= N$ of violent conflicts/year
- `polity` $=$ Rescaled POLITY IV democracy score
- `logPopulation` $= \ln(\text{population})$
- `logGDP` $= \ln(\text{GDP per capita})$
- `GDPGrowth` $=$ growth in GDP
- `logOpenness` $= \ln\left(\frac{\text{Imports} + \text{Exports}}{\text{GDP}}\right)$
- `govshareGDP` $=$ government's % of GDP

Conflict Data

```
> summary(wars)
     ccode          year        conflicts    conflicts_no_zeros
 Min.   :  2   Min.   :1951   Min.   :0.000   Min.   :1
 1st Qu.:211   1st Qu.:1970   1st Qu.:0.000   1st Qu.:1
 Median :439   Median :1981   Median :0.000   Median :1
 Mean   :439   Mean   :1980   Mean   :0.304   Mean   :1
 3rd Qu.:640   3rd Qu.:1991   3rd Qu.:0.000   3rd Qu.:1
 Max.   :950   Max.   :2000   Max.   :8.000   Max.   :8
                                              NA's   :4075
     polity          politysq        population          GDP
 Min.   :0.000   Min.   :0.0000   Min.   :    122   Min.   :  171
 1st Qu.:0.150   1st Qu.:0.0225   1st Qu.:   3054   1st Qu.: 1401
 Median :0.450   Median :0.2025   Median :   7725   Median : 3777
 Mean   :0.527   Mean   :0.4278   Mean   :  33615   Mean   : 6641
 3rd Qu.:0.950   3rd Qu.:0.9025   3rd Qu.:  21979   3rd Qu.: 9032
 Max.   :1.000   Max.   :1.0000   Max.   :1262474   Max.   :84408

    openness       govshareGDP      GDPGrowth       logPopulation
 Min.   :  3.7   Min.   : 2.97   Min.   :-63.32   Min.   : 4.80
 1st Qu.: 30.9   1st Qu.:14.64   1st Qu.: -0.90   1st Qu.: 8.02
 Median : 50.0   Median :18.94   Median :  2.08   Median : 8.95
 Mean   : 62.2   Mean   :20.95   Mean   :  1.92   Mean   : 8.99
 3rd Qu.: 81.1   3rd Qu.:24.85   3rd Qu.:  4.84   3rd Qu.:10.00
 Max.   :986.5   Max.   :83.68   Max.   :125.96   Max.   :14.05

     logGDP        logOpenness    conflicts_censored    censored
 Min.   : 5.14   Min.   :1.31   Min.   :0.000       Min.   :-1.00
 1st Qu.: 7.25   1st Qu.:3.43   1st Qu.:0.000       1st Qu.: 1.00
 Median : 8.24   Median :3.91   Median :0.000       Median : 1.00
 Mean   : 8.23   Mean   :3.87   Mean   :0.299       Mean   : 0.99
 3rd Qu.: 9.11   3rd Qu.:4.40   3rd Qu.:0.000       3rd Qu.: 1.00
 Max.   :11.34   Max.   :6.89   Max.   :4.000       Max.   : 1.00
```

Basic Model: Poisson

```
> wars.poisson<-glm(conflicts~polity+politysq+logPopulation+logGDP+
  GDPGrowth+logOpenness+govshareGDP,family="poisson",data=wars)
> summary.glm(wars.poisson)

Call:
glm(formula = conflicts ~ polity + politysq + logPopulation +
    logGDP + GDPGrowth + logOpenness + govshareGDP, family = "poisson",
    data = wars)

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -4.88565    0.36284  -13.47  < 2e-16 ***
polity         1.05866    0.39129    2.71   0.0068 **
politysq      -0.95432    0.37292   -2.56   0.0105 *
logPopulation  0.39809    0.01626   24.48  < 2e-16 ***
logGDP        -0.05919    0.02919   -2.03   0.0426 *
GDPGrowth     -0.01579    0.00345   -4.58  4.6e-06 ***
logOpenness   -0.15187    0.03691   -4.11  3.9e-05 ***
govshareGDP    0.03632    0.00235   15.48  < 2e-16 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1
```

Basic Model: Negative Binomial

```
> wars.nb<-glm.nb(conflicts~polity+politysq+logPopulation+logGDP+GDPGrowth+
  logOpenness+govshareGDP,data=wars)
> summary(wars.nb)

Call:
glm.nb(formula = conflicts ~ polity + politysq + logPopulation +
    logGDP + GDPGrowth + logOpenness + govshareGDP, data = wars,
    init.theta = 2.10281397427423, link = log)

Coefficients:
               Estimate Std. Error z value Pr(>|z|)
(Intercept)   -4.987258   0.403221 -12.369  < 2e-16 ***
polity         1.031445   0.429147   2.403 0.016240 *
politysq      -1.006861   0.409911  -2.456 0.014038 *
logPopulation  0.419436   0.019065  22.000  < 2e-16 ***
logGDP        -0.062318   0.032646  -1.909 0.056276 .
GDPGrowth     -0.014965   0.003964  -3.775 0.000160 ***
logOpenness   -0.164250   0.041114  -3.995 6.47e-05 ***
govshareGDP    0.036494   0.002672  13.657  < 2e-16 ***
---
              Theta:  2.103
          Std. Err.:  0.322
```

Zero Truncation

$$\begin{aligned}\Pr(Y_i = 0) &= \frac{\exp(-\lambda_i)\lambda_i^0}{0!} \\ &= \exp(-\lambda_i)\end{aligned}$$

$$\Pr(Y_i > 0) = 1 - \exp(-\lambda_i).$$

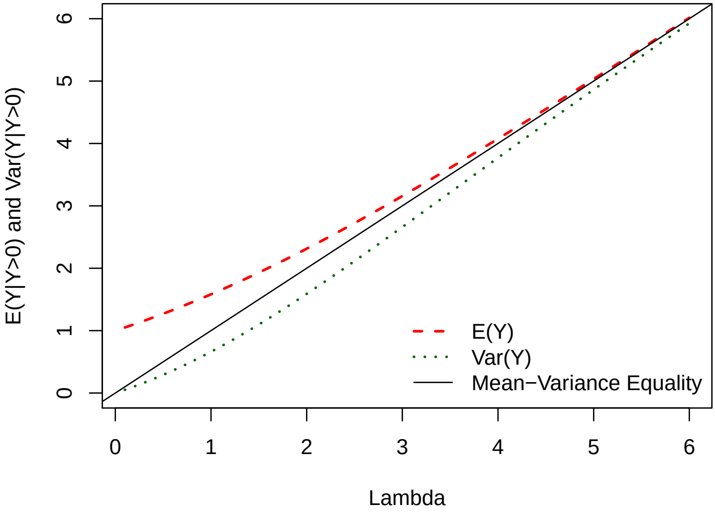
$$\begin{aligned}\Pr(Y_i = y | Y_i > 0) &= \frac{\Pr(Y_i = y)}{\Pr(Y_i > 0)} \\ &= \frac{\exp(-\lambda_i)\lambda_i^y}{y![1 - \exp(-\lambda_i)]}\end{aligned}$$

Zero Truncation (continued)

$$\mathsf{E}(Y|Y>0)=\frac{\lambda}{1-\exp(-\lambda)}$$

$$\begin{aligned}\mathsf{Var}(Y|Y>0) &= \mathsf{E}(Y|Y>0)\times\{[1-\mathsf{Pr}(Y=0)]\,\mathsf{E}(Y|Y>0)\}\\ &= \frac{\lambda}{1-\exp(-\lambda)}\left[1-\frac{\lambda}{\exp(\lambda)-1}\right]\end{aligned}$$

Zero Truncation Illustrated



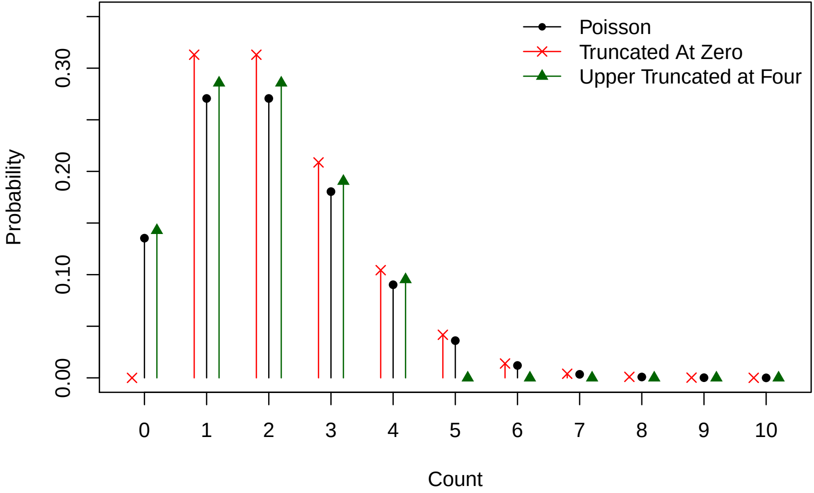
Upper Truncation

$$Y_i = \begin{cases} Y_i^* \text{ if } Y_i^* \leq \tau \\ \text{unobserved if } Y_i^* > \tau \end{cases}$$

$$\Pr(Y_i^* \leq \tau) = \sum_{y=0}^{\tau} \frac{\exp(-\lambda_i)\lambda_i^y}{y!}$$

$$\Pr(Y_i = y | Y_i \leq \tau) = \frac{\exp(-\lambda_i)\lambda_i^y}{y! \sum_{y=0}^{\tau} \frac{\exp(-\lambda_i)\lambda_i^y}{y!}}$$

Truncation Illustrated



Truncated Models: Estimation and Interpretation

$$\lambda_i = \exp(\mathbf{X}_i\boldsymbol{\beta})$$

- IRRs, predicted probabilities, etc. as usual
- Using formulae above

Zero-Truncated Models: (Incorrect/Poisson) Example

```
> wars.poisNo0s<-glm(conflicts_no_zeros~polity+politysq+logPopulation+
  logGDP+GDPGrowth+logOpenness+govshareGDP,family="poisson",data=wars)
> summary(wars.poisNo0s)

Coefficients:
               Estimate Std. Error z value Pr(>|z|)
(Intercept)   -1.4940523  0.3799176  -3.933 8.40e-05 ***
polity        -0.3508331  0.3858776  -0.909    0.363
politysq       0.4273003  0.3734399   1.144    0.253
logPopulation  0.1317254  0.0181912   7.241 4.45e-13 ***
logGDP         0.0389308  0.0320827   1.213    0.225
GDPGrowth     -0.0005765  0.0031788  -0.181    0.856
logOpenness   -0.0387960  0.0401573  -0.966    0.334
govshareGDP    0.0135720  0.0023168   5.858 4.68e-09 ***
---
    Null deviance: 396.43  on 1179  degrees of freedom
Residual deviance: 300.56  on 1172  degrees of freedom
  (11870 observations deleted due to missingness)
AIC: 2891.2

Number of Fisher Scoring iterations: 4
```

Zero-Truncated Models: Example

```
> library(VGAM)
> wars.0tpois<-vglm(conflicts_no_zeros~polity+politysq+logPopulation+
  logGDP+GDPGrowth+logOpenness+govshareGDP,pospoisson,data=wars)
> summary(wars.0tpois)

Coefficients:
                  Value Std. Error  t value
(Intercept)   -6.9985662  0.7802697 -8.96942
polity        -1.3061668  0.8185705 -1.59567
politysq       1.3202509  0.7876759  1.67613
logPopulation  0.3997250  0.0331791 12.04749
logGDP         0.2326896  0.0608548  3.82369
GDPGrowth     -0.0018478  0.0064828 -0.28503
logOpenness   -0.1045685  0.0779237 -1.34193
govshareGDP    0.0409683  0.0038646 10.60102

Number of linear predictors:  1
Name of linear predictor: log(lambda)
Dispersion Parameter for pospoisson family:   1
Log-likelihood: -806.6696 on 1172 degrees of freedom
Number of Iterations: 5
```

Censoring

$$Y_i = \begin{cases} Y_i^* \text{ if } Y_i^* < k \\ k \text{ if } Y_i^* \geq k \end{cases}$$

$$\Pr(Y = y | Y^* < k) = \frac{\exp(-\lambda_i)\lambda_i^y}{y!},$$

$$\Pr(Y = k) = 1 - \sum_{y=0}^{k-1} \frac{\exp(-\lambda_i)\lambda_i^y}{y!}$$

Censored Models

Right Censoring

$$c_i = \begin{cases} 1 \text{ if } Y_i = k \\ 0 \text{ if } Y_i < k \end{cases}$$

$$\ln L = \sum_{i=1}^{N} (1 - c_i) \ln \left[\frac{\exp(-\lambda_i)\lambda_i^y}{y!} \right] + c_i \ln \left[1 - \sum_{y=0}^{k-1} \frac{\exp(-\lambda_i)\lambda_i^y}{y!} \right]$$

Left Censoring

$$Y_i = \begin{cases} \ell \text{ if } Y_i^* \leq \ell \\ Y_i^* \text{ if } Y_i^* > \ell \end{cases}$$

Double Censoring

$$Y_i = \begin{cases} \ell \text{ if } Y_i^* \leq \ell \\ Y_i^* \text{ if } \ell < Y_i^* < k \\ k \text{ if } Y_i^* \geq k \end{cases}$$

Software

- R :
  - `vglm, pospoisson` (in `VGAM`) (zero truncation)
  - `vglm, cens.poisson` (in `VGAM`) (censored Poisson)

- Stata :
  - `ztp` / `ztnb` (zero truncation)
  - `trpoisson` (general truncation)
  - `cenpois` (censored Poisson)

Example, Again

$$c_i = \begin{cases} 1 \text{ if the observation's count is } \textit{uncensored}, \\ 0 \text{ if the observation's count is } \textit{left-censored}, \text{ and} \\ -1 \text{ if the observation's count is } \textit{right-censored}. \end{cases}$$

```
wars$censoredconflicts<-wars$conflicts
wars$censoredconflicts<-ifelse(wars$conflicts>3,4,wars$censoredconflicts)
wars$censindicator<-ifelse(wars$censoredconflicts==4,1,0)
```

Censored Example: (Incorrect) Poisson

```
> wars.poisCensored<-glm(censoredconflicts~polity+politysq+logPopulation+
  logGDP+GDPGrowth+logOpenness+govshareGDP,family="poisson",data=wars)
> summary(wars.poisCensored)

Coefficients:
               Estimate Std. Error z value Pr(>|z|)
(Intercept)   -4.743385   0.364843 -13.001  < 2e-16 ***
polity         1.070801   0.392156   2.731  0.00632 **
politysq      -1.025014   0.374139  -2.740  0.00615 **
logPopulation  0.381121   0.016491  23.111  < 2e-16 ***
logGDP        -0.049747   0.029444  -1.690  0.09111 .
GDPGrowth     -0.015869   0.003469  -4.574 4.78e-06 ***
logOpenness   -0.150489   0.037176  -4.048 5.16e-05 ***
govshareGDP    0.034396   0.002373  14.495  < 2e-16 ***
---
    Null deviance: 5007.5  on 5254  degrees of freedom
Residual deviance: 4059.2  on 5247  degrees of freedom
  (7795 observations deleted due to missingness)
AIC: 6644.6
Number of Fisher Scoring iterations: 6
```

Censored Example: Poisson

```
> wars.censpois<-vglm(SurvS4(censoredconflicts,censindicator)~polity+politysq+logPopulation
                     +logGDP+GDPGrowth+logOpenness+govshareGDP, cens.poisson,data=wars)
> summary(wars.censpois)

Call:
vglm(formula = SurvS4(censoredconflicts, censindicator) ~ polity +
    politysq + logPopulation + logGDP + GDPGrowth + logOpenness +
    govshareGDP, family = cens.poisson, data = wars)

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    1.90350    1.22197    1.56    0.119
polity         1.65054    1.75924    0.94    0.348
politysq      -1.96215    1.67550   -1.17    0.242
logPopulation -0.05184    0.05040   -1.03    0.304
logGDP         0.07472    0.09577    0.78    0.435
GDPGrowth      0.00248    0.00809    0.31    0.759
logOpenness    0.09201    0.14403    0.64    0.523
govshareGDP   -0.01267    0.00741   -1.71    0.088 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Number of linear predictors:  1
Name of linear predictor: loge(mu)
Dispersion Parameter for cens.poisson family:   1
Log-likelihood: -51.72 on 5247 degrees of freedom
Number of iterations: 12
```

“Zero-Modified” Count Models

- “Zero-Inflated” Models
- “Hurdle” Models

"Zero-Inflated" Count Models

$$Y_i = p_i \times Y_i^*$$

$$\begin{aligned} \Pr(Y_i = 0) &= \Pr(p_i = 0) + [\Pr(p_i = 1) \times \Pr(Y_i^* = 0)] \\ &= (1 - p_i^*) + p_i^*[\exp(-\lambda_i)] \end{aligned}$$

$$\begin{aligned} \Pr(Y_i = y) &= \Pr(p_i = 1) \times \Pr(Y_i^* = y) \\ &= p_i^* \times \frac{\exp(-\lambda_i)\lambda_i^y}{y!} \end{aligned}$$

More on "Zero-Inflated" Models

$$E(Y_i^*) \equiv \lambda_i = \exp(\mathbf{X}_i\boldsymbol{\beta})$$

$$\Pr(p_i = 1) \equiv p_i^* = \frac{1}{1 + \exp(-\mathbf{Z}_i\gamma)} \text{ or } \Phi(\mathbf{Z}_i\gamma)$$

- $\lambda_0 = \Pr(\text{No War}) = \exp(-\lambda)$
- $\lambda_+ = \Pr(Y \in \{1, 2, 3, ...\})$

$$\lambda_{0i} = \exp(\mathbf{X}_{0i}\boldsymbol{\beta}_0)$$

$$\lambda_{+i} = \exp(\mathbf{X}_{+i}\boldsymbol{\beta}_+)$$

"Hurdle" Count Models

Define:

$$\delta_i = \begin{cases} 0 \text{ if } Y_i = 0 \\ 1 \text{ if } Y_i > 0 \end{cases}$$

$$\begin{aligned} \ln L \;\; = \;\; & -\sum_{i=1}^{N} \delta_i \exp(\mathbf{X}_{0i}\boldsymbol{\beta}_0) + \sum_{i=1}^{N}(1-\delta_i)\{\ln[1-\exp(-\exp(\mathbf{X}_{0i}\boldsymbol{\beta}_0))] + \\ & Y_i(\mathbf{X}_{+i}\boldsymbol{\beta}_+) - \ln[\exp(\exp(\mathbf{X}_{+i}\boldsymbol{\beta}_+)) - 1]\} \end{aligned}$$

$$\Pr(Y_i = 0) = 1 - \exp[-\exp(\mathbf{X}_{0i}\beta_0)]$$

- λ_+ defines a *truncated* Poisson process
- Y may be overdispersed, Poisson, or underdispersed

ZIP/ZINB and Hurdle Models: R

Command	Package	Count Distribution(s)	Transition Link(s)
Zero-Inflated Models			
`zeroinfl`	`pscl`	Poisson, NB, geometric	probit, logit, cloglog, log, Cauchy
`vglm,zipoisson`	`VGAM`	Poisson	logit, probit, cloglog, Cauchy, others
`vglm,zinegbinomial`	`VGAM`	Negative Binomial	logit, probit, cloglog, Cauchy, others
`cozigam`	`COZIGAM`	various	Various (see documentation)
Hurdle Models			
`hurdle`	`pscl`	Poisson, NB, geometric	binomial, Poisson, NB, geometric
`vglm,zapoisson`	`VGAM`	Poisson	logit, probit, cloglog, Cauchy, others

ZIP/ZINB and Hurdle Models: Stata

Command	Count Distribution	Transition Link(s)
Zero-Inflated Models		
`zip`	Poisson	probit or logit
`zinb`	Negative Binomial	probit or logit
Hurdle Models		
`hplogit`	Poisson	logit
`hpclg`	Poisson	complementary log-log
`hnblogit`	Negative Binomial	logit
`hnbclg`	Negative Binomial	complementary log-log

ZIP Example

```
wars.ZIP<-zeroinfl(conflicts~polity+politysq+logPopulation+logGDP+GDPGrowth+logOpenness+govshareGDP,
                   data=wars,dist="poisson",link="logit")
summary(wars.ZIP)

Call:
zeroinfl(formula = conflicts ~ polity + politysq + logPopulation +
    logGDP + GDPGrowth + logOpenness + govshareGDP, data = wars,
    dist = "poisson", link = "logit")

Pearson residuals:
    Min      1Q  Median      3Q     Max
-1.4061 -0.5113 -0.3391 -0.0859 31.5392

Count model coefficients (poisson with log link):
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -3.79438    0.50297   -7.54  4.6e-14 ***
polity        -0.34467    0.52364   -0.66  0.51040
politysq       0.85585    0.50196    1.71  0.08819 .
logPopulation  0.27385    0.02336   11.72  < 2e-16 ***
logGDP        -0.14271    0.03993   -3.57  0.00035 ***
GDPGrowth     -0.00931    0.00405   -2.30  0.02138 *
logOpenness    0.20226    0.04963    4.08  4.6e-05 ***
govshareGDP    0.03138    0.00288   10.88  < 2e-16 ***
.
.
.
```

ZIP Example (continued)

```
.
.
.
Zero-inflation model coefficients (binomial with logit link):
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.47668    1.80620    0.26  0.79185
polity        -3.97446    1.56375   -2.54  0.01103 *
politysq       5.34458    1.49540    3.57  0.00035 ***
logPopulation -0.62737    0.09152   -6.86  7.1e-12 ***
logGDP        -0.20497    0.13193   -1.55  0.12026
GDPGrowth      0.01898    0.01117    1.70  0.08933 .
logOpenness    1.73322    0.21124    8.21  2.3e-16 ***
govshareGDP   -0.03454    0.00889   -3.88  0.00010 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Number of iterations in BFGS optimization: 31
Log-likelihood: -3.26e+03 on 16 Df
```

Example: Prose

- `polity`'s effect on the probability of being in the "zeros-only" state is curvilinear: it first decreases (as a country goes from being strongly autocratic to transitional) then increases (as it becomes more democratic).
- Growth and openness increase the probability of being in the zeros-only state, while government spending decreases it. e.g.:
  - A one-unit increase in `logOpenness` increases $\Pr(p_i = 0)$ by $(\exp(1.733)) \times 100 = 566$ percent.
  - Similarly, a one-unit (in this case, one-percent) increase in `govshareGDP` decreases $\Pr(p_i = 0)$ by $[1 - (\exp(-0.0345)) \times 100] = 3.4$ percent.
- A one-unit increase in `logOpenness` increases the incidence of armed conflicts by $(\exp(0.202)) \times 100 = 122$ percent.
- A one-unit increase in `logGDP`, by contrast, decreases the incidence of armed conflicts by $(1 - \exp(-0.1427)) \times 100 = 13.3$ percent.

Example: ZINB

```
wars.ZINB<-zeroinfl(conflicts~polity+politysq+logPopulation+logGDP+GDPGrowth+logOpenness+govshareGDP,
                    data=wars,dist="negbin",link="logit")
summary(wars.ZINB)

Call:
zeroinfl(formula = conflicts ~ polity + politysq + logPopulation +
    logGDP + GDPGrowth + logOpenness + govshareGDP, data = wars,
    dist = "negbin", link = "logit")

Pearson residuals:
    Min      1Q  Median      3Q     Max
-1.2273 -0.5056 -0.3405 -0.0845 34.0184

Count model coefficients (negbin with log link):
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -3.86793    0.51463   -7.52  5.7e-14 ***
polity        -0.14355    0.54078   -0.27  0.79067
politysq       0.59083    0.52442    1.13  0.25990
logPopulation  0.28574    0.02491   11.47  < 2e-16 ***
logGDP        -0.14299    0.04100   -3.49  0.00049 ***
GDPGrowth     -0.00957    0.00416   -2.30  0.02151 *
logOpenness    0.17351    0.05298    3.28  0.00106 **
govshareGDP    0.03204    0.00313   10.24  < 2e-16 ***
Log(theta)     1.89010    0.37315    5.07  4.1e-07 ***
.
.
.
```

Example: ZINB (continued)

```
.
.
.
Zero-inflation model coefficients (binomial with logit link):
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    0.38441    1.98351    0.19  0.84633
polity        -3.66869    1.73171   -2.12  0.03413 *
politysq       5.05129    1.64892    3.06  0.00219 **
logPopulation -0.65973    0.09735   -6.78  1.2e-11 ***
logGDP        -0.23621    0.14249   -1.66  0.09737 .
GDPGrowth      0.01975    0.01181    1.67  0.09457 .
logOpenness    1.82769    0.22375    8.17  3.1e-16 ***
govshareGDP   -0.03515    0.00987   -3.56  0.00037 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Theta = 6.62
Number of iterations in BFGS optimization: 31
Log-likelihood: -3.25e+03 on 17 Df.
```

Example: Hurdle Poisson

```
> wars.hurdle<-hurdle(conflicts~polity+politysq+logPopulation+logGDP+GDPGrowth+
   logOpenness+govshareGDP,data=wars,dist=c("poisson"),zero.dist=c("poisson"),
   link=c("log"))
> summary(wars.hurdle)

Call:
hurdle(formula = conflicts ~ polity + politysq + logPopulation + logGDP + GDPGrowth +
    logOpenness + govshareGDP, data = wars, dist = c("poisson"), zero.dist = c("poisson"),
    link = c("log"))

Count model coefficients (truncated poisson with log link):
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -6.99856    0.78028   -8.97  < 2e-16 ***
polity        -1.30617    0.81861   -1.60  0.11058
politysq       1.32026    0.78772    1.68  0.09373 .
logPopulation  0.39973    0.03318   12.05  < 2e-16 ***
logGDP         0.23269    0.06085    3.82  0.00013 ***
GDPGrowth     -0.00185    0.00648   -0.29  0.77559
logOpenness   -0.10457    0.07793   -1.34  0.17963
govshareGDP    0.04097    0.00386   10.61  < 2e-16 ***

.
.
.
```

Example: Hurdle Poisson (continued)

```
.
.
.
Zero hurdle model coefficients (censored poisson with log link):
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -3.92477    0.41815   -9.39  < 2e-16 ***
polity         1.68586    0.44729    3.77  0.00016 ***
politysq      -1.61143    0.42744   -3.77  0.00016 ***
logPopulation  0.36963    0.01983   18.64  < 2e-16 ***
logGDP        -0.14103    0.03409   -4.14  3.5e-05 ***
GDPGrowth     -0.02152    0.00422   -5.09  3.5e-07 ***
logOpenness   -0.14945    0.04261   -3.51  0.00045 ***
govshareGDP    0.02909    0.00293    9.91  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Number of iterations in BFGS optimization: 27
Log-likelihood: -3.27e+03 on 16 Df
```