GSERM - Oslo 2019
Panel Data Models for Binary and Count Responses

January 8, 2019 (afternoon session)

Logit/Probit Redux

Start with:

$$\begin{aligned} Y_{it}^* &= \mathbf{X}_{it}\beta + u_{it} \\ Y_{it} &= \begin{cases} 0 \text{ if } Y_{it}^* \leq 0 \\ 1 \text{ if } Y_{it}^* > 0 \end{cases} \end{aligned}$$

which is generically:

$$Y_{it} = f(\mathbf{X}_{it}\beta + u_{it})$$

e.g. f can be logit or probit
underlying data generating process is linear, but
observations are binary

What Can Go Wrong?

Suppose:

$$
\begin{aligned}
X_{it} &= \rho_X \mathbf{X}_{it-1} + \nu_{it} \\
u_{it} &= \rho_u u_{it-1} + \epsilon_{it}
\end{aligned}
$$

For high values of ρ, logit/probit:

- $\hat{\beta}$s are consistent, but s.e.s are biased, inefficient (Poirier and Ruud 1988);
- underestimate Var(β) by up to 50 percent (Beck and Katz 1997).

s.e. are too small

Unit Effects, Fixed

One-way unit effects:

$$Y_{it} = f(\mathbf{X}_{it}\beta + \alpha_i + u_{it})$$

for logit only, so:

$$\Pr(Y_{it} = 1) = \frac{\exp(\mathbf{X}_{it}\beta + \alpha_i)}{1 + \exp(\mathbf{X}_{it}\beta + \alpha_i)} \equiv \Lambda(\mathbf{X}_{it}\beta + \alpha_i)$$

big lambda denotes the function

Incidental Parameters

- Nonlinearity $\rightarrow$ inconsistency in both $\hat{\alpha}$s *and* $\hat{\beta}$.
- Anderson:

should be X_it*beta

$$L^U = \prod_{i=1}^{N} \prod_{t=1}^{T} \Lambda(\mathbf{X}_{it} + \alpha_i)^{Y_{it}} [1 - \Lambda(\mathbf{X}_{it} + \alpha_i)]^{1-Y_{it}}$$

- Chamberlain:

$$L^C = \prod_{i=1}^{N} \Pr\left(Y_{i1} = y_{i1}, Y_{i2} = y_{i2}, \ldots Y_{iT} = y_{iT} \mid \sum_{t=1}^{T} Y_{it} \right)$$

Intuition:

- $\Pr(Y_{i1} = 0 \text{ and } Y_{i2} = 0 \mid \sum_T Y_{it} = 0) = 1.0$
- $\Pr(Y_{i1} = 1 \text{ and } Y_{i2} = 1 \mid \sum_T Y_{it} = 2) = 1.0$

think for a simple T=2 panel

fixed effects within does not work if there is no variation within a unit (this was unlikely in continuous case, but can happen here in binary case.

Fixed-Effects (continued)

More intuition:

$$\Pr\left(Y_{i1} = 0 \text{ and } Y_{i2} = 1 \mid \sum_T Y_{it} = 1\right) = \frac{\Pr(0,1)}{\Pr(0,1) + \Pr(1,0)}$$

with a similar statement for $\Pr(Y_{i1} = 0 \text{ and } Y_{i2} = 1 \mid \sum_T Y_{it} = 1)$.

Points:

- Fixed effects = no estimates for $\boldsymbol{\beta}_b$
- Interpretation: per logit, but $\mid \hat{\alpha}_i$. see image, it depends on X...
- BTSCS in IR: Green et al. (2001) v. B&K (2001).

coz total combinations possible for Y outcomes is limited due to binary nature, we do not need one alpha for each unit, just for the possible combinations.
(reminder no intercept; cant estimate for data lacking within variance)

btscs = binary time series cross sectional data in international relations.

Random Effects

Model is:

$$
\begin{aligned}
Y_{it}^* &= \mathbf{X}_{it}\beta + u_{it} \\
Y_{it} &= 0 \text{ if } Y_{it}^* \leq 0 \text{ ;} \\
&= 1 \text{ if } Y_{it}^* > 0
\end{aligned}
$$

with:

$$u_{it} = \alpha_i + \eta_{it}$$

with $\eta_{it} \sim$ i.i.d. N(0,1), and $\alpha_i \sim N(0, \sigma_\alpha^2)$.

Random Effects (continued)

Implies:

$$\text{Var}(u_{it}) = 1 + \sigma_\alpha^2$$

and so:

correlation, coz alpha is same within units and between units (?)

$$\text{Corr}(u_{it}, u_{is},\ t \neq s) \equiv \rho = \frac{\sigma_\alpha^2}{1 + \sigma_\alpha^2}$$

which means that we can write $\sigma_\alpha^2 = \left(\frac{\rho}{1-\rho}\right)$.

Random Effects Variants

Probit:

$$
\begin{aligned}
L_i &= \text{Prob}(Y_{i1} = y_{i1},\ Y_{i2} = y_{i2},\ ...Y_{iT} = y_{iT}) \\
&= \int_{-\infty}^{X_{i1}\beta} \int_{-\infty}^{X_{i2}\beta} ... \int_{-\infty}^{X_{iT}\beta} \phi(u_{i1}, u_{i2}...u_{iT}) du_{iT}...du_{i2}\ du_{i1}
\end{aligned}
$$

Logit:

$$
\begin{aligned}
L_i &= \text{Prob}(Y_{i1} = y_{i1},\ Y_{i2} = y_{i2},\ ...Y_{iT} = y_{iT}) \\
&= \int_{-\infty}^{X_{i1}\beta} \int_{-\infty}^{X_{i2}\beta} ... \int_{-\infty}^{X_{iT}\beta} \lambda(u_{i1}, u_{i2}...u_{iT}) du_{iT}...du_{i2}\ du_{i1}
\end{aligned}
$$

Solution?

$$
\phi(u_{i1}, u_{i2}, ...u_{iT}) = \int_{-\infty}^{\infty} \phi(u_{i1}, u_{i2}, ...u_{iT} \mid \alpha_i) \phi(\alpha_i) d\alpha_i
$$

- $\hat{\rho} =$ proportion of the variance due to the α_is.
- Implementation: Gauss-Hermite quadrature or MCMC.
  obsolete
  markov chain montecarlo (bayesian posterior)
- Best with N large and T small.
- Critically requires $\text{Cov}(\mathbf{X}, \alpha) = 0$ (see notes re: Chamberlain's CRE Estimator).

Software

R

- `glmmML` (Gauss-Hermite quadrature)
- `pglm` (panel GLMs) (maximum likelihood + quadrature)
- `MCMCpack` (`MCMChlogit`)
- Various user-generated functions (e.g., here).

Stata

- `xtprobit`, `xtlogit`, `xtcloglog`
- Plus `xttrans` (transition probabilities), `quadchk` (quadrature checking), `xtrho` / `xtrhoi` (estimation of within-unit covariances)

Example: Segal (1986) Search & Seizure Cases

$Y = 1$ (search allowed)

- `warrant`: Whether (=1) or not (=0) a warrant was issued,
- `house`: Whether (=1) or not (=0) the search was of a private home,
- `person`: Whether (=1) or not (=0) the search was of a person,
- `business`: Whether (=1) or not (=0) the search was of a business,
- `car`: Whether (=1) or not (=0) the search was of an automobile,
- `us`: Whether (=1) or not (=0) the U.S. government was the petitioner,
- `except`: The number of "exceptions" outlined by the Court under which the search fell, and
- `justideo`: The justice's Segal-Cover (1989) ideology score, ranging from zero (most conservative) to 1 (most liberal).

$N = 14, \;\; \bar{T} = 74.1.$

```
> summary(Segal)
     justid          caseid           year          vote         warrant    
 Min.   : 1.0   Min.   :  1   Min.   :63   Min.   :0.00   Min.   :0.00  
 1st Qu.: 6.0   1st Qu.: 34   1st Qu.:69   1st Qu.:0.00   1st Qu.:0.00  
 Median : 8.0   Median : 64   Median :73   Median :1.00   Median :0.00  
 Mean   : 8.1   Mean   : 64   Mean   :73   Mean   :0.53   Mean   :0.15  
 3rd Qu.:11.0   3rd Qu.: 94   3rd Qu.:78   3rd Qu.:1.00   3rd Qu.:0.00  
 Max.   :14.0   Max.   :123   Max.   :81   Max.   :1.00   Max.   :1.00  
     house          person        business         car            us       
 Min.   :0.00   Min.   :0.00   Min.   :0.00   Min.   :0.0   Min.   :0.00  
 1st Qu.:0.00   1st Qu.:0.00   1st Qu.:0.00   1st Qu.:0.0   1st Qu.:0.00  
 Median :0.00   Median :0.00   Median :0.00   Median :0.0   Median :0.00  
 Mean   :0.23   Mean   :0.31   Mean   :0.15   Mean   :0.2   Mean   :0.45  
 3rd Qu.:0.00   3rd Qu.:1.00   3rd Qu.:0.00   3rd Qu.:0.0   3rd Qu.:1.00  
 Max.   :1.00   Max.   :1.00   Max.   :1.00   Max.   :1.0   Max.   :1.00  
     except        justideo   
 Min.   :0.00   Min.   :0.05  
 1st Qu.:0.00   1st Qu.:0.17  
 Median :0.00   Median :0.73  
 Mean   :0.35   Mean   :0.59  
 3rd Qu.:1.00   3rd Qu.:0.88  
 Max.   :3.00   Max.   :1.00  
```

Plain-Vanilla Logit

```
> SegalLogit<-glm(vote~warrant+house+person+business+car+us+
                   except+justideo,data=Segal,family="binomial")
> summary(SegalLogit)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.3147  -0.9405   0.3898   0.9348   1.9032

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   1.9419     0.2799   6.938 3.97e-12 ***
warrant       0.5335     0.2083   2.561 0.010440 *
house        -1.0840     0.2756  -3.934 8.36e-05 ***
person       -0.9438     0.2569  -3.674 0.000239 ***
business     -1.4722     0.2975  -4.949 7.46e-07 ***
car          -1.0066     0.2816  -3.574 0.000351 ***
us            0.4824     0.1482   3.254 0.001136 **
except        0.8640     0.1384   6.243 4.29e-10 ***
justideo     -2.4026     0.2158 -11.134  < 2e-16 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1434.9  on 1036  degrees of freedom
Residual deviance: 1196.7  on 1028  degrees of freedom
AIC: 1214.7

Number of Fisher Scoring iterations: 4
```

```
> library(glmmML)
> SegalFE<-glmmboot(vote~warrant+house+person+business+car+us+
           except,data=Segal,family="binomial",
           cluster=justid)
> summary(SegalFE)

Call:  glmmboot(formula = vote ~ warrant + house + person + business +
        car + us + except, family = "binomial", data = Segal, cluster = justid)


           coef se(coef)     z Pr(>|z|)
warrant   0.599    0.228  2.63  8.7e-03
house    -1.473    0.305 -4.82  1.4e-06
person   -1.124    0.282 -3.99  6.7e-05
business -1.837    0.326 -5.63  1.8e-08
car      -1.202    0.308 -3.90  9.6e-05
us        0.537    0.162  3.32  9.1e-04
except    1.093    0.155  7.03  2.1e-12

Residual deviance: 1050 on 1016 degrees of freedom  AIC: 1090
```

```
> SegalRE<-glmmML(vote~warrant+house+person+business+car+us+
                  except+justideo,data=Segal,family="binomial",
                  cluster=justid)
> summary(SegalRE)

Call:  glmmML(formula = vote ~ warrant + house + person + business +
car + us + except + justideo, family = "binomial", data = Segal, cluster = justid)

              coef se(coef)     z Pr(>|z|)
(Intercept)  2.016    0.565  3.57  3.6e-04
warrant      0.594    0.226  2.63  8.5e-03
house       -1.434    0.303 -4.73  2.2e-06
person      -1.104    0.280 -3.95  7.9e-05
business    -1.799    0.324 -5.56  2.7e-08
car         -1.181    0.306 -3.86  1.1e-04
us           0.531    0.160  3.31  9.3e-04
except       1.070    0.154  6.95  3.6e-12
justideo    -2.344    0.737 -3.18  1.5e-03

Scale parameter in mixing distribution:  0.926 gaussian
Std. Error:                              0.195

        LR p-value for H_0: sigma = 0:  4.63e-24

Residual deviance: 1100 on 1027 degrees of freedom  AIC: 1120
```

Models for Event Counts

Things That Are Not Counts

- Ordinal scales/variables
- Grouped Binary Data
  - $\frac{N \text{ of "successes"}}{N \text{ of "trials"}}$
  - Binomial data
  - $=$ counts only if Pr("success") is small

Count Properties

- Discrete / integer-values
- Non-negative
- “Cumulative”

for 3, you need 1 and 2 before

Count Data: Motivation

$$\text{Arrival Rate} = \lambda$$

constant arrival rate

$$\Pr(\text{Event})_{t,t+h} = \lambda h$$

$$\Pr(\text{No Event})_{t,t+h} = 1 - \lambda h$$

$$\begin{aligned} \Pr(Y_t = y) &= \frac{\exp(-\lambda h)\lambda h^y}{y!} \\ &= \frac{\exp(-\lambda)\lambda^y}{y!} \end{aligned}$$

if h=1 it reduces to below.

Poisson Assumptions

- No Simultaneous Events
- Constant Arrival Rate
- Independent Event Arrivals

Poisson: Other Motivations

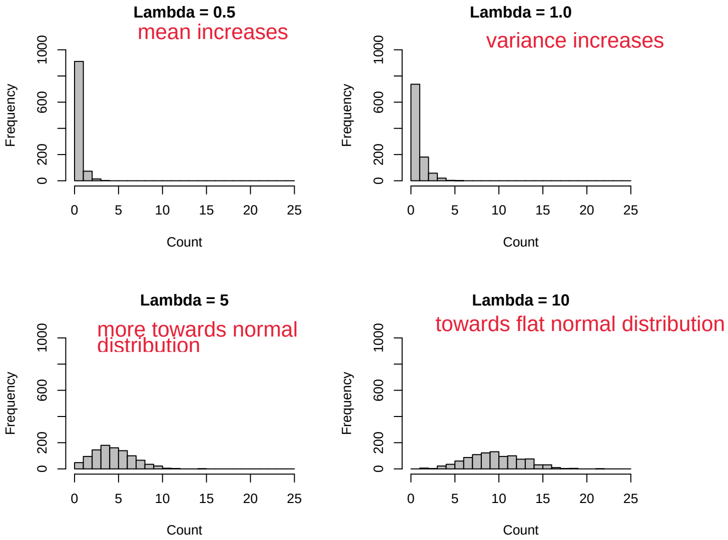
For M independent Bernoulli trials with (sufficiently small) probability of success π and where $M\pi \equiv \lambda > 0$,

$$\begin{aligned}
\Pr(Y_i = y) &= \lim_{M\to\infty} \left[\binom{M}{y} \left(\frac{\lambda}{M}\right)^{y} \left(1 - \frac{\lambda}{M}\right)^{M-y} \right] \\
&= \frac{\lambda^{y} \exp(-\lambda)}{y!}
\end{aligned}$$

Poisson: Characteristics

- Discrete
- $\mathrm{E}(Y) = \mathrm{Var}(Y) = \lambda$
- Is not preserved under affine transformations...
- For $X \sim \text{Poisson}(\lambda_X)$ and $Y \sim \text{Poisson}(\lambda_Y)$,
  $Z = X + Y \sim \text{Poisson}(\lambda_{X+Y})$ *iff* X and Y are *independent* but
- ...same is not true for differences. (you can get negatives)
- $\lambda \to \infty \iff Y \sim N$

Poissons: Examples



Suppose

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

then

$$\Pr(Y_i = y|\mathbf{X}_i, \boldsymbol{\beta}) = \frac{\exp[-\exp(\mathbf{X}_i\boldsymbol{\beta})][\exp(\mathbf{X}_i\boldsymbol{\beta})]^y}{y!}$$

$$L = \prod_{i=1}^{N} \frac{\exp[-\exp(\mathbf{X}_i\boldsymbol{\beta})][\exp(\mathbf{X}_i\boldsymbol{\beta})]^{Y_i}}{Y_i!}$$

$$\ln L = \sum_{i=1}^{N} [-\exp(\mathbf{X}_i\boldsymbol{\beta}) + Y_i\mathbf{X}_i\boldsymbol{\beta} - \ln(Y_i!)]$$

Event Counts: Unit Effects

alpha*lambda is multiplicative and not additive to not get negative Expected value

$$Y_{it} \sim \text{Poisson}(\mu_{it} = \alpha_i \lambda_{it})$$

alpha scales the count

with $\lambda_{it} = \exp(\mathbf{X}_{it}\boldsymbol{\beta})$ implies:

$$\begin{aligned} \mathrm{E}(Y_{it} \mid \mathbf{X}_{it}, \alpha_i) &= \mu_{it} \\ &= \alpha_i \exp(\mathbf{X}_{it}\boldsymbol{\beta}) \\ &= \exp(\delta_i + \mathbf{X}_{it}\boldsymbol{\beta}) \end{aligned}$$

where $\delta_i = \ln(\alpha_i)$.

Fixed-Effects Poisson

- No "incidental parameters" problem (see e.g. Cameron and Trivedi, pp. 281-2)
- Means "brute force" approach works
- Via `xtpoisson` (and `xtnbreg`) in Stata, `glmmML` in R

Random-Effects Models

$$\begin{aligned}
\Pr(Y_{i1} = y_{i1}, \dots Y_{iT} = y_{iT}) &= \int_0^\infty \Pr(Y_{i1} = y_{i1}, \dots Y_{iT} = y_{iT}) f(\alpha_i) d\alpha_i \\
&= \int_0^\infty \left[\prod_{t=1}^{T} \Pr(Y_{it} \mid \alpha_i) \right] f(\alpha_i) d\alpha_i
\end{aligned}$$

- Simplest to assume $\alpha_i \sim \Gamma(\theta)$
- Yields a model with $\mathrm{E}(Y_{it}) = \lambda_{it}$ and $\mathrm{Var}(Y_{it}) = \lambda_{it} + \frac{\lambda_{it}^2}{\theta}$
- Via `xtpois, re` in Stata and `glmmML` or `glmer` in R
- $\exists$ random effects negative binomial too...

var not only lambad anymore, but scaled

Panel Models: Software

R:

- Tobit = `censReg` (in **censReg**)
- Poisson (random effects) = `glmmML` in **glmmML** or `glmer` in **lme4**
- Poisson (fixed effects) = `glmmML` or "brute force"

Stata:

- Tobit = `xttobit` (`re` only)
- Poisson / negative binomial = `xtpoisson`, `xtnbreg` (both with `fe`, `re` options)
- See notes for more details / examples

Example: State Failure Task Force

```
> summary(SFTF)
   countryid         year         sftprev       sftpeth        sftpreg
 AFG    :   9   Min.   :1957   Min.   :0.0   Min.   :0.00   Min.   :0.00
 ALB    :   9   1st Qu.:1967   1st Qu.:0.0   1st Qu.:0.00   1st Qu.:0.00
 ARG    :   9   Median :1977   Median :0.0   Median :0.00   Median :0.00
 AUL    :   9   Mean   :1979   Mean   :0.1   Mean   :0.13   Mean   :0.12
 AUS    :   9   3rd Qu.:1992   3rd Qu.:0.0   3rd Qu.:0.00   3rd Qu.:0.00
 BEL    :   9   Max.   :1997   Max.   :1.0   Max.   :1.00   Max.   :1.00
 (Other):1149
    sftpgen        poldurab      unuurbpc         ciob          cioc
 Min.   :0.00   Min.   : 0   Min.   :  2   Min.   : 0   Min.   : 0.0
 1st Qu.:0.00   1st Qu.: 4   1st Qu.: 23   1st Qu.:14   1st Qu.: 2.0
 Median :0.00   Median :12   Median : 41   Median :19   Median : 5.0
 Mean   :0.08   Mean   :21   Mean   : 43   Mean   :19   Mean   : 5.6
 3rd Qu.:0.00   3rd Qu.:30   3rd Qu.: 62   3rd Qu.:24   3rd Qu.: 8.0
 Max.   :1.00   Max.   :97   Max.   :100   Max.   :38   Max.   :24.0
                NA's   :5    NA's   :57
     POLITY        SumEvents
 Min.   :-10.0   Min.   : 0
 1st Qu.: -7.0   1st Qu.: 0
 Median : -4.0   Median : 0
 Mean   : -0.7   Mean   : 6
 3rd Qu.:  8.0   3rd Qu.: 5
 Max.   : 10.0   Max.   :61
 NA's   :14      NA's   :9

> pdim(SFTF)
Unbalanced Panel: n=170, T=1-9, N=1203
```

Panel Tobit: R (see here)

```
> library(plm)
> SFTF.panel<-pdata.frame(SFTF,i="countryid")
> library(censReg)
> Tobit.panel<-censReg(SumEvents~POLITY+unuurbpc+poldurab+year,
+                      data=SFTF.panel,method="BHHH")
> summary(Tobit.panel)

Call:
censReg(formula = SumEvents ~ POLITY + unuurbpc + poldurab +
    year, data = SFTF.panel, method = "BHHH")

Observations:
         Total  Left-censored     Uncensored Right-censored
          1132            707            425              0

Coefficients:
               Estimate  Std. error t value  Pr(> t)
(Intercept) -1385.21151    60.10481 -23.047  < 2e-16 ***
POLITY         -0.58977     0.09008  -6.547 5.87e-11 ***
unuurbpc       -0.31374     0.03263  -9.616  < 2e-16 ***
poldurab       -0.34628     0.02624 -13.198  < 2e-16 ***
year            0.70470     0.03048  23.121  < 2e-16 ***
logSigmaMu      2.83694     0.05035  56.341  < 2e-16 ***
logSigmaNu      2.58187     0.02160 119.522  < 2e-16 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

BHHH maximisation, 40 iterations
Return code 2: successive function values within tolerance limit
Log-likelihood: -2020 on 7 Df
```

Panel Poisson (Random Effects)

```
> library(lme4)
> Poisson.RE<-glmer(ciob~POLITY+unuurbpc+poldurab+I(year-1900)+(1|countryid),
                    data=SFTF,family="poisson")
> summary(Poisson.RE)
Generalized linear mixed model fit by maximum likelihood (Laplace
  Approximation) [glmerMod]
 Family: poisson  ( log )
Formula:
ciob ~ POLITY + unuurbpc + poldurab + I(year - 1900) + (1 | countryid)
   Data: SFTF

     AIC      BIC   logLik deviance df.resid
    6811     6841    -3399     6799     1126

Random effects:
 Groups    Name        Variance Std.Dev.
 countryid (Intercept) 0.159    0.399
Number of obs: 1132, groups:  countryid, 160

Fixed effects:
                Estimate Std. Error z value    Pr(>|z|)
(Intercept)     1.200274   0.063085   19.03     < 2e-16 ***
POLITY         -0.003484   0.001812   -1.92       0.055 .
unuurbpc        0.005996   0.001064    5.64 0.000000017 ***
poldurab        0.001167   0.000672    1.74       0.082 .
I(year - 1900)  0.016385   0.000855   19.16     < 2e-16 ***
---
Signif. codes:  0  ***  0.001  **  0.01 * 0.05 . 0.1   1

Correlation of Fixed Effects:
            (Intr) POLITY unrbpc poldrb
POLITY       0.354
unuurbpc    -0.075 -0.139
poldurab     0.224  0.348 -0.087
I(yer-1900) -0.628 -0.273 -0.589 -0.313
convergence code: 0
Model failed to converge with max|grad| = 0.00158426 (tol = 0.001, component 1)
Model is nearly unidentifiable: very large eigenvalue
 - Rescale variables?
```

Panel Poisson (Random Effects – Alternative)

```
> library(glmmML)
> Poisson.RE.alt<-glmmML(ciob~POLITY+unuurbpc+poldurab+I(year-1900),
                         data=SFTF,cluster=countryid,
                         family="poisson")
> summary(Poisson.RE.alt)

Call:  glmmML(formula = ciob ~ POLITY + unuurbpc + poldurab + I(year - 1900),
       family = "poisson", data = SFTF, cluster = countryid)

                   coef se(coef)     z    Pr(>|z|)
(Intercept)     1.20027 0.063120 19.02 0.000000000
POLITY         -0.00348 0.001814 -1.92 0.055000000
unuurbpc        0.00600 0.001064  5.63 0.000000018
poldurab        0.00117 0.000672  1.74 0.082000000
I(year - 1900)  0.01639 0.000856 19.15 0.000000000

Scale parameter in mixing distribution:  0.399 gaussian
Std. Error:                              0.0263

        LR p-value for H_0: sigma = 0:  2.28e-289

Residual deviance: 1590 on 1126 degrees of freedom  AIC: 1600
```

is random effects better than FE?

Panel Poisson (Fixed Effects – "brute force")

```
> Poisson.FE<-glm(ciob~POLITY+unuurbpc+poldurab+I(year-1900)+
              as.factor(countryid),data=SFTF,family="poisson")
> summary(Poisson.FE)

Call:
glm(formula = ciob ~ POLITY + unuurbpc + poldurab + I(year -
    1900) + as.factor(countryid), family = "poisson", data = SFTF)

Deviance Residuals:
   Min      1Q  Median      3Q     Max
-4.806  -0.312   0.069   0.364   2.863

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)              1.040769   0.117296    8.87  < 2e-16 ***
POLITY                  -0.007437   0.001939   -3.84  0.00013 ***
unuurbpc                 0.005011   0.001580    3.17  0.00151 **
poldurab                -0.000477   0.000749   -0.64  0.52386
I(year - 1900)           0.018411   0.001115   16.51  < 2e-16 ***
as.factor(countryid)ALB -0.376632   0.142587   -2.64  0.00826 **
as.factor(countryid)ALG  0.200591   0.131453    1.53  0.12702
.
.
.
as.factor(countryid)ZAM  0.094994   0.132209    0.72  0.47244
as.factor(countryid)ZIM -0.053680   0.137511   -0.39  0.69627
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 4453.85  on 1131  degrees of freedom
Residual deviance:  942.45  on  968  degrees of freedom
  (71 observations deleted due to missingness)
AIC: 6483

Number of Fisher Scoring iterations: 5
```