Replication study - [redacted]

Coalition mood in European parliamentary democracies

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EXPLAINING THE ORIGINAL STUDY

Abstract (extract)

“The success and longevity of coalition governments depends on the ability to keep conflicts between coalition members at bay. ... This article presents a new approach to measuring the atmosphere between government parties. The ‘coalition mood’ is a time-varying measure that draws on applause patterns between coalition partners during legislative debates.” (Imre et al., 2022)

EXPLAINING THE ORIGINAL STUDY

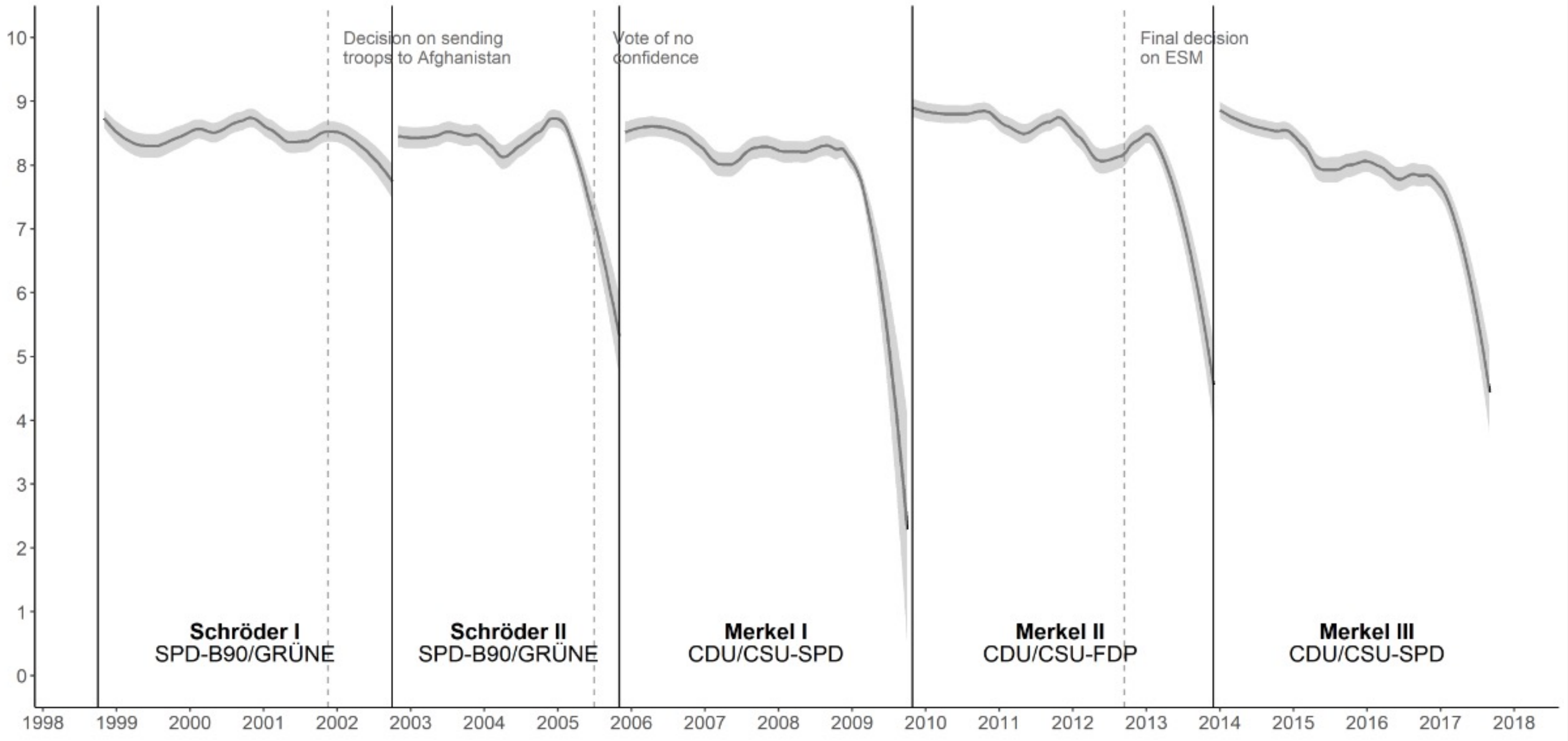
Details of the original study

- Define ‘coalition mood’ as level of conflict, both policy and non-policy based
- Identification of the gap in the literature: how changes in mood over time relate to the success of coalition governments
- Fundamental assumption: more applause is associated with better atmosphere
- 350,000 party-to-party interactions during 105,000 plenary debates (all members of all parties are to attend)
- Germany, 1998–2017; Austria, 2003–18

EXPLAINING THE ORIGINAL STUDY

Example of outputs of the study

One of the graphs presented in the original study shows that ‘Coalition Mood’, as measured by their definition of mood, follows electoral cycles.



EXPLAINING THE ORIGINAL STUDY

Data

Data	
applause_austria	302 obs. of 4 variables
applause_germany	414 obs. of 4 variables

applause_austria

Filter

	party_from_to	date	applauseby10kwords	role
1	BZÖ for ÖVP	2006-05-01	25	Junior Party for PM Party
2	BZÖ for ÖVP	2006-06-01	23	Junior Party for PM Party
3	BZÖ for ÖVP	2006-07-01	26	Junior Party for PM Party
4	BZÖ for ÖVP	2006-09-01	33	Junior Party for PM Party
5	BZÖ for ÖVP	2006-10-01	24	Junior Party for PM Party
6	BZÖ for ÖVP	2006-11-01	15	Junior Party for PM Party
7	BZÖ for ÖVP	2006-12-01	9	Junior Party for PM Party
8	FPÖ for ÖVP	2003-06-01	40	Junior Party for PM Party
9	FPÖ for ÖVP	2003-07-01	30	Junior Party for PM Party

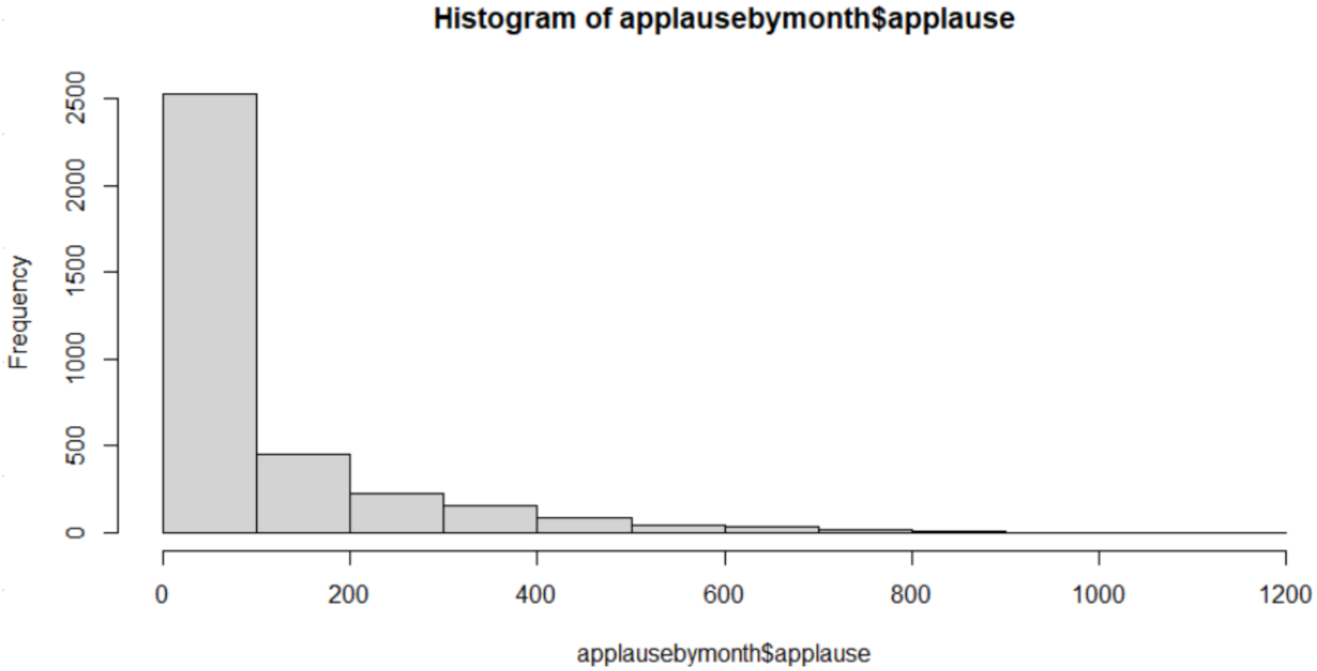
MY CONTRIBUTION

"To measure the coalition mood, we model applause for government parties in the legislature as a negative binomial process […] the negative binomial model is based on the log-transformed applause patterns (rather than raw frequencies) to account for the fact that additional applause should have a higher impact on the mood if the overall frequency of applause is rather low."

My contribution: Confirm that a negative binomial model is more appropriate than a Poisson model, i.e. over-dispersion is present (variance > mean).

MY CONTRIBUTION Poisson or Negative Binomial?

Distribution of applause



Conclusion: Clearly a Poisson/negative binomial model will be appropriate here

MY CONTRIBUTION Poisson or Negative Binomial?

Poisson and negative binomial models

```
# Calculate poisson model
p_model <- glm(applause ~ date*dyad2*country +
                  words_party_to, family = 'poisson', data = applausebymonth)

# Calculate negative binomial model
nb_model <- glm.nb(applause ~ date*dyad2*country +
                  words_party_to, data = applausebymonth)
```

MY CONTRIBUTION Poisson or Negative Binomial?

Likelihood ratio test using Chi-squared

```
p_value <- pchisq(2 * (logLik(nb_model) - logLik(p_model)), df = 1, lower.tail = FALSE)
```

```
'log Lik.' 0 (df=1067)
```

Conclusion: negative binomial is better, but can I get a p-value?

MY CONTRIBUTION Poisson or Negative Binomial?

Likelihood Ratio test using lrtest

```
library("lmtest")

lrtest(p_model, nb_model)
        Likelihood ratio test

        Model 1: applause ~ date * dyad2 * country + words_party_to
        Model 2: applause ~ date * dyad2 * country + words_party_to
          #Df LogLik Df Chisq Pr(>Chisq)
        1 1066 -22241
        2 1067 -14399  1 15683  < 2.2e-16 ***
        ---
        Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

MY CONTRIBUTION Poisson or Negative Binomial?

Dispersion test

```
library(AER)

dispersiontest(p_model)
```

```
        Overdispersion test

data:  p_model
z = 25.65, p-value < 2.2e-16
alternative hypothesis: true dispersion is greater than 1
sample estimates:
dispersion
   7.50158
```

Conclusion: Overdispersion, response variance is greater than the mean, so don't use Poisson.

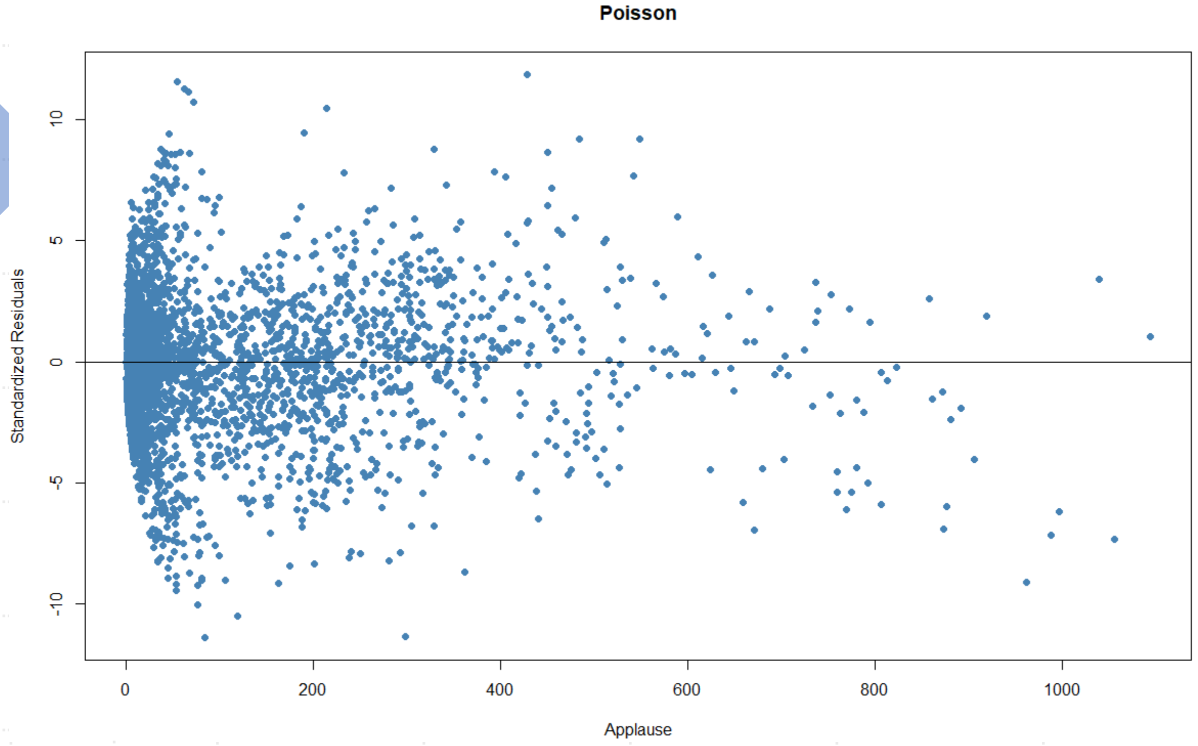
MY CONTRIBUTION Poisson or Negative Binomial?

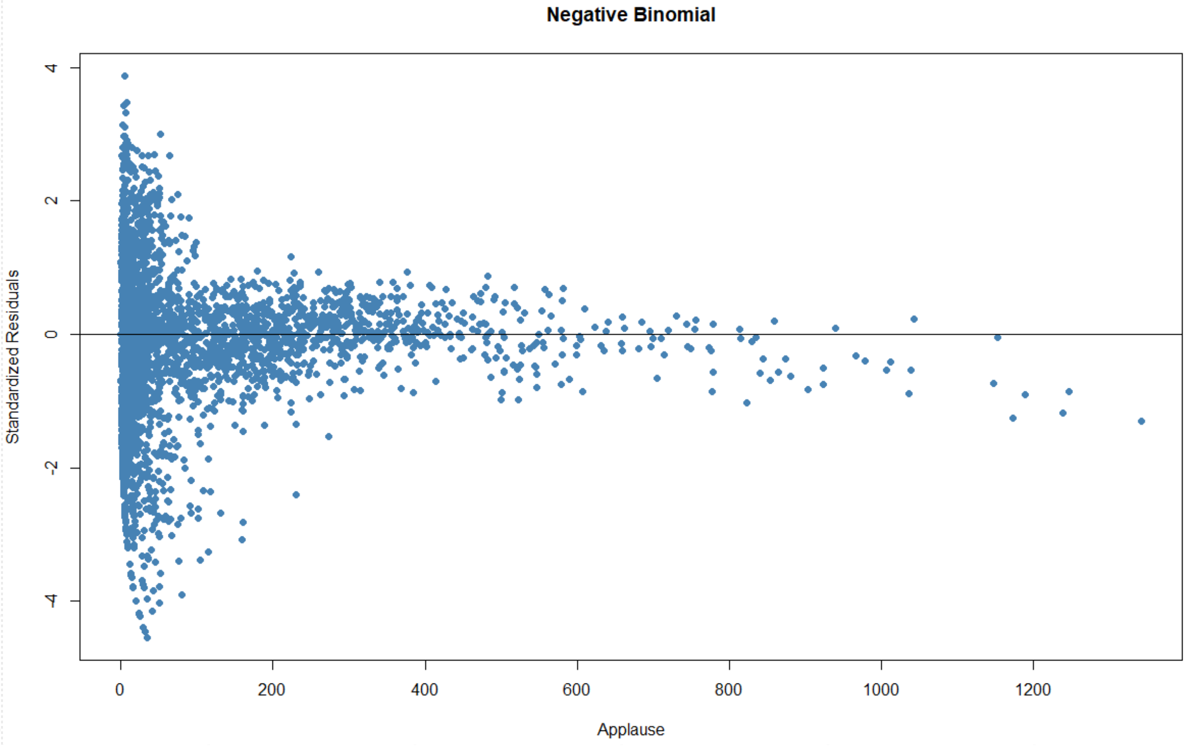
Plot residuals for both models

```r
#Residual plot for Poisson regression
p_res <- resid(p_model)
plot(fitted(p_model), p_res, col='steelblue', pch=16,
     xlab='Applause', ylab='Standardized Residuals', main='Poisson')
abline(0,0)

#Residual plot for negative binomial regression
nb_res <- resid(nb_model)
plot(fitted(nb_model), nb_res, col='steelblue', pch=16,
     xlab='Applause', ylab='Standardized Residuals', main='Negative Binomial')
abline(0,0)
```

MY CONTRIBUTION Poisson or Negative Binomial?





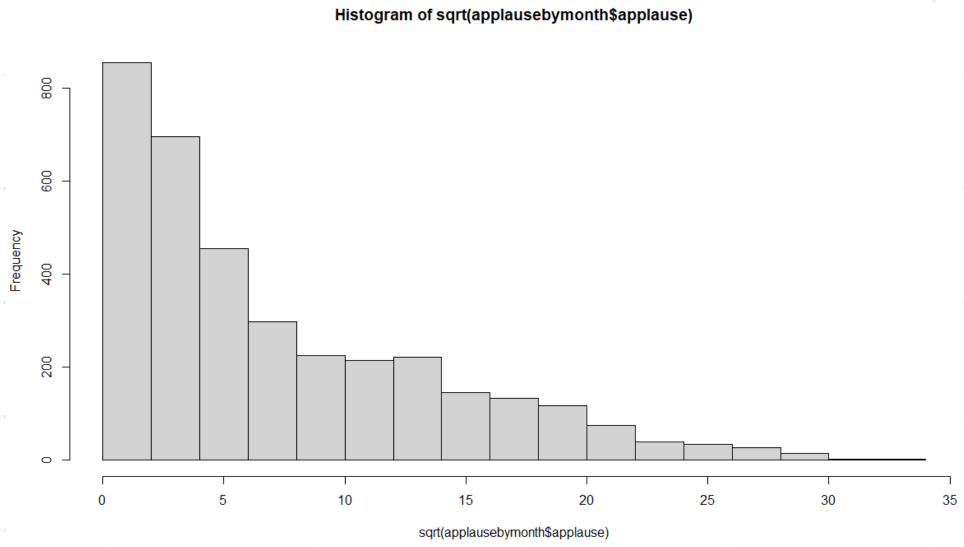
Conclusion: residuals are smaller for Negative Binomial model, therefore it is a better model than Poisson for this data.

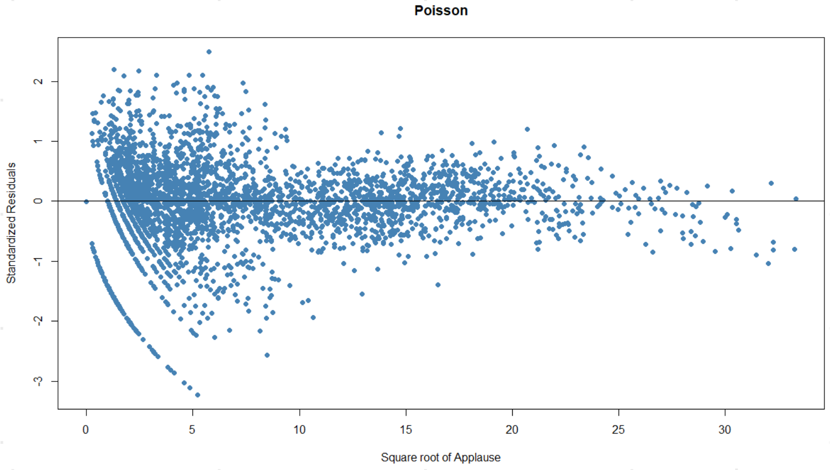
The non-random nature of the residuals reflects the heteroskedasticity predicted by the author of the original paper.

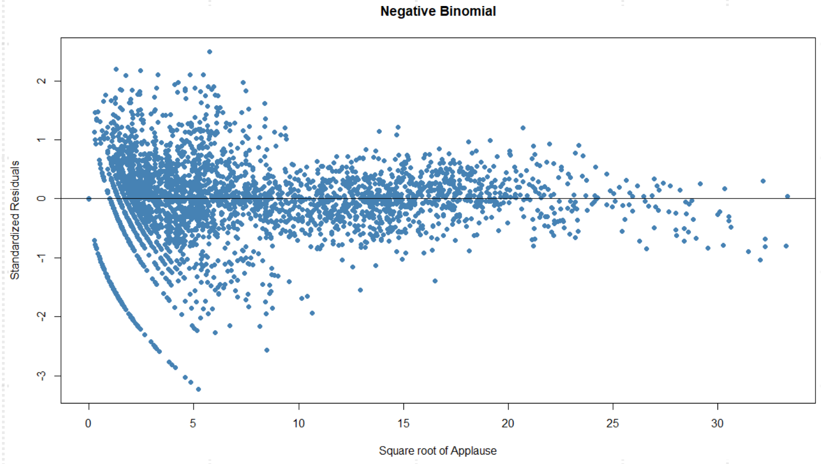
DISCOUNTED EXPLORATION

Square root of Applause

```
data:  srp_model
z = -42.1, p-value = 1
alternative hypothesis: true dispersion is greater than 1
sample estimates:
dispersion
 0.4259452
```





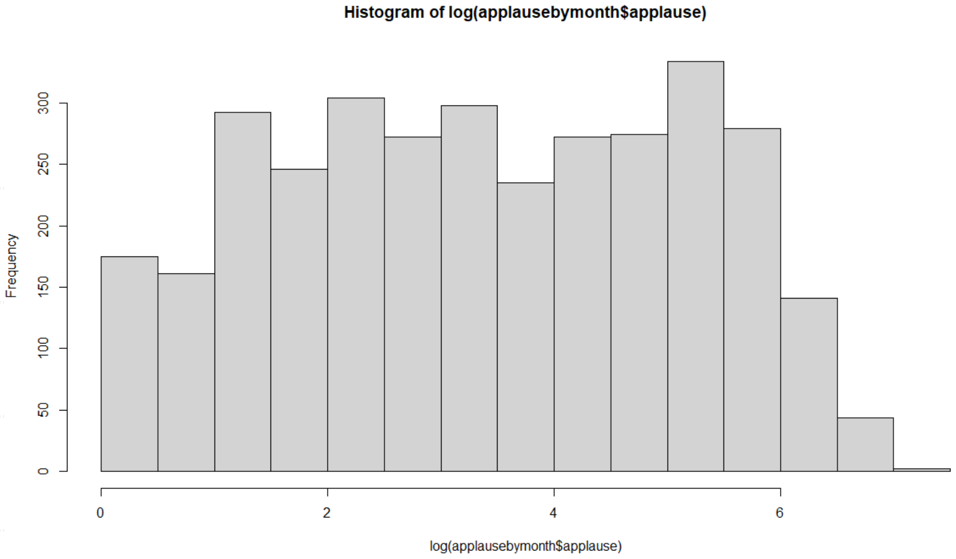


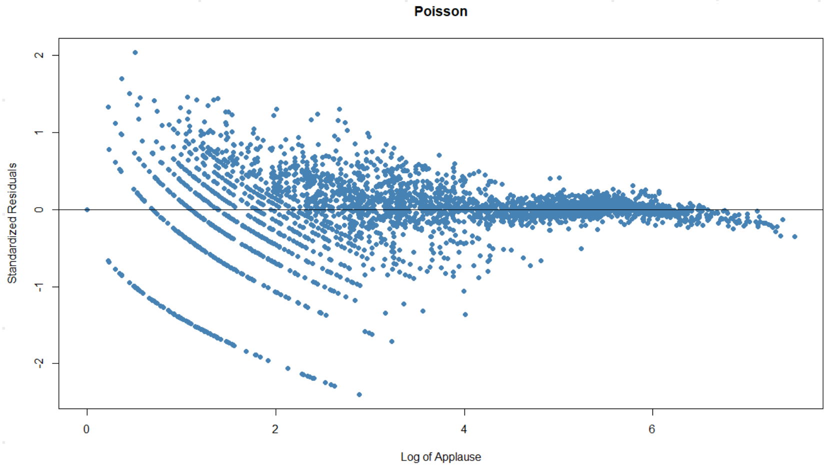
Conclusion: Under-dispersion – variance is now less than the mean. But this is just a result of the transformation.

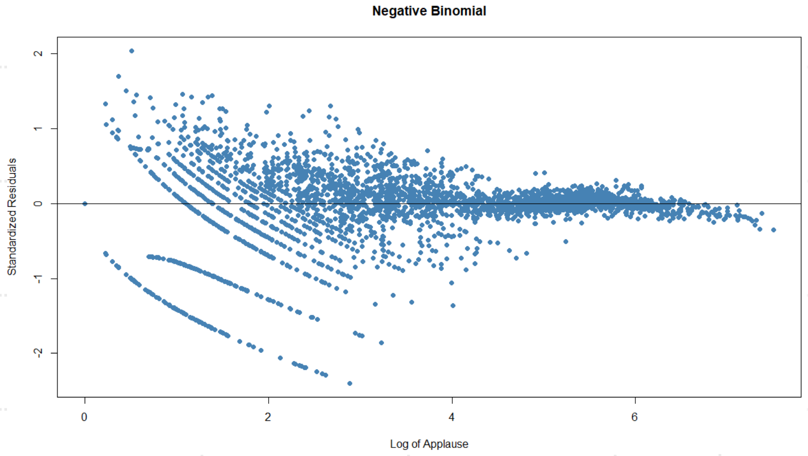
DISCOUNTED EXPLORATION

Log of Applause

```
data:  logp_model
z = -87.088, p-value = 1
alternative hypothesis: true dispersion is greater than 1
sample estimates:
dispersion
 0.1935945
```







Again this merely reflects the transformation.