# Applied Statistical Analysis II: Replication Study

Media Coverage of Campaign Promises Throughout the Electoral Cycle

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# Original Paper Overview

A lot of studies confirm that governments fulfil a large share of their promises.

However, there is a disconnect, most voters do not believe governments try to keep their promises.

This phenomenon has been referred to as “The Pledge Puzzle”.

# The “Pledge Puzzle”

**Idea posited by Elin Naurin.**

Naurin, E. (2011) ‘The Pledge Puzzle’, in E. Naurin (ed.) *Election Promises, Party Behaviour and Voter Perceptions*. London: Palgrave Macmillan UK, pp. 3–12. Available at: https://doi.org/10.1057/9780230319301_1.

**"The Pledge Puzzle" refers to the notable discrepancy between scholarly findings and public perceptions regarding the fulfillment of election promises by political representatives. Research has shown that political parties act on a significant portion of their election promises, demonstrating a higher level of commitment and follow-through than commonly assumed by the general public.**

**Müller’s research paper builds on this idea, focusing on the aspect that this discrepancy is fuelled by media bias in the reporting of government pledges.**

# Hypothesises

- Three hypothesises are made in connection with the idea of media bias in pledge reporting:
  - H1 (Electoral Cycle Hypothesis) Media coverage about promises increases until approximately the end of the first quarter and peaks toward the end of an electoral cycle.
  - H2 (Unfulfilled Promises Hypothesis) News outlets report more extensively about unfulfilled promises than about fulfilled promises.
  - H3 (Increasing Negativity Hypothesis) The focus on broken relative to fulfilled promises has increased over time.
- My twist will focus on the models testing the first hypothesis.

# Data in the Original Study

The paper uses text analysis of over 430,000 statements on political commitment made in 22 newspapers, across 33 electoral cycles in Australia, Canada, Ireland, and the United Kingdom, from 1979 to 2017.

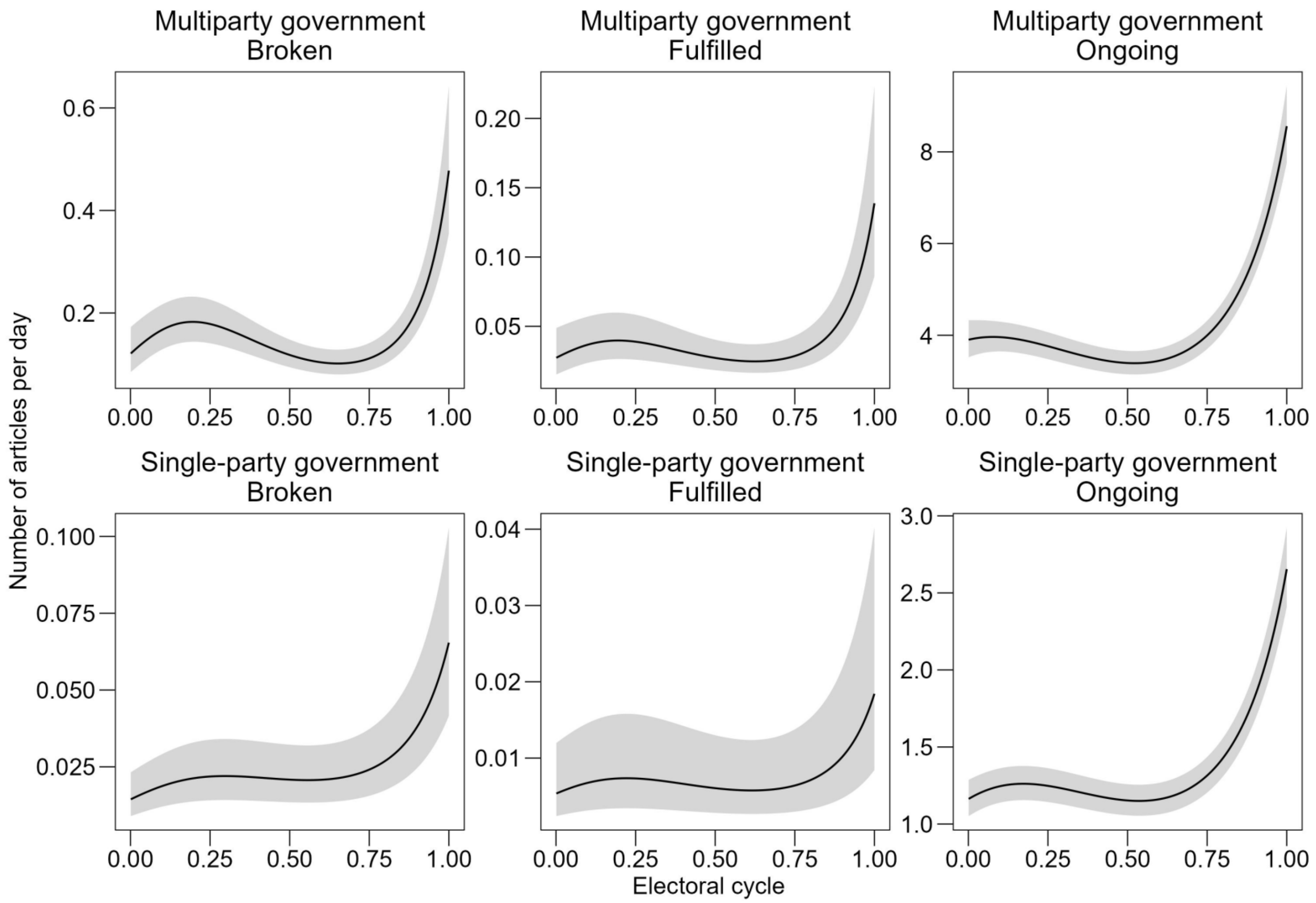
The corpus was separated into three categories: Ongoing, Broken, and Fulfilled Promises.

Crowd sourced coding of a random sample of the ongoing promises corpus was used to validate the data, 80% of the random sample was determined to be accurately categorized.

# Example of findings:

First, second and third order polynomials of electoral cycle are included to more accurately reflect the non-linear complexity of the effect of electoral cycle on the number of daily articles.

The trend stated in hypothesis 1 is clearly demonstrated in these plots.



# Twist: Testing and comparing Alternative Models

- Running Poisson models showed overdispersion, a model which accounts for this is indeed needed.

```
data:  poisson_single_broken
z = 7.2924, p-value = 1.523e-13
alternative hypothesis: true dispersion is greater than 1
sample estimates:
dispersion
  2.669636
```

```
data:  poisson_single_fulfilled
z = 6.1213, p-value = 4.64e-10
alternative hypothesis: true dispersion is greater than 1
sample estimates:
dispersion
  1.724353
```

```
data:  poisson_single_ongoing
z = 31.223, p-value < 2.2e-16
alternative hypothesis: true dispersion is greater than 1
sample estimates:
dispersion
  7.583723
```

```
data:  poisson_multi_fulfilled
z = 5.265, p-value = 7.008e-08
alternative hypothesis: true dispersion is greater than 1
sample estimates:
dispersion
  1.595708
```

```
data:  poisson_multi_ongoing
z = 26.825, p-value < 2.2e-16
alternative hypothesis: true dispersion is greater than 1
sample estimates:
dispersion
  5.729869
```

```
data:  poisson_multi_broken
z = 8.3596, p-value < 2.2e-16
alternative hypothesis: true dispersion is greater than 1
sample estimates:
dispersion
  2.222692
```

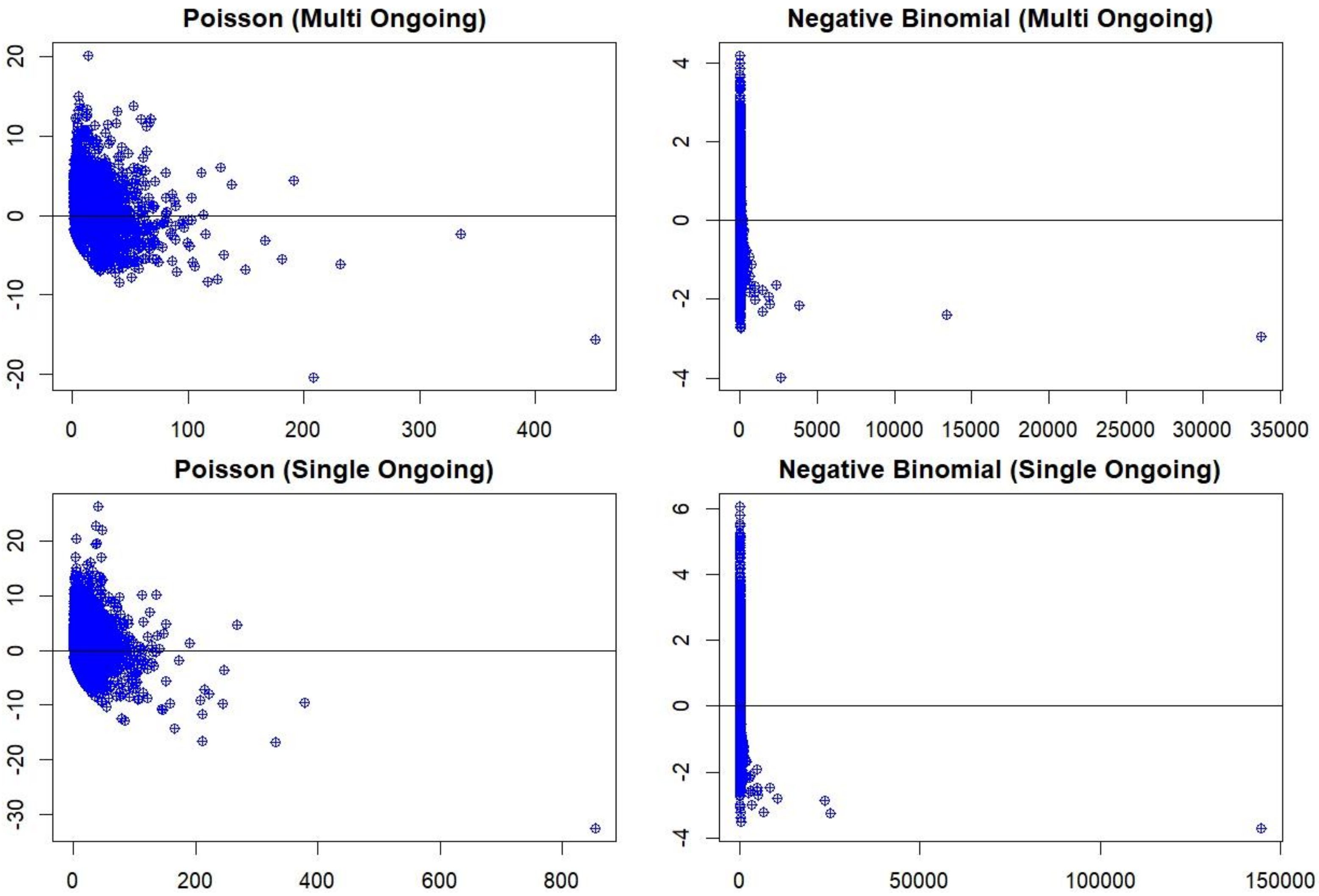
# Comparison of residuals, Both Government Types
# Ongoing Promises

```r
# Plot 1: Poisson (Multi Ongoing)
poisson_resid_mo <- resid(poisson_multi_ongoing)
plot(fitted(poisson_multi_ongoing),
     poisson_resid_mo, col = "blue", pch = 10,
     xlab = "Number of articles", ylab = "Residuals",
     main = "Poisson (Multi Ongoing)")
abline(0, 0)

# Plot 2: Negative Binomial (Multi Ongoing)
nb_resid_mo <- resid(nb_multi_ongoing)
plot(fitted(nb_multi_ongoing),
     nb_resid_mo, col = "blue", pch = 10,
     xlab = "Number of articles", ylab = "Residuals",
     main = "Negative Binomial (Multi Ongoing)")
abline(0, 0)

poisson_resid_so <- resid(poisson_single_ongoing)
plot(fitted(poisson_single_ongoing),
     poisson_resid_so, col = "blue", pch = 10,
     xlab = "Number of articles", ylab = "Residuals",
     main = "Poisson (Single Ongoing)")
abline(0, 0)

# Plot 4: Negative Binomial (Single Ongoing)
nb_resid_so <- resid(nb_single_ongoing)
plot(fitted(nb_single_ongoing),
     nb_resid_so, col = "blue", pch = 10,
     xlab = "Number of articles", ylab = "Residuals",
     main = "Negative Binomial (Single Ongoing)")
abline(0, 0)
```




**Plots show negative binomial is a better fit in both cases for ongoing promises data, the residuals are smaller.**

# More Complexity?: Zero Inflated Negative Poisson to further compensate for dispersion

- I fit zero inflated negative polynomial (ZINB) models for all the data.

```
zinb_single_ongoing <- zeroinfl(
                      n_articles_day ~
                       n_articles_day_lag +
                      poly(electoral_cycle, 3)+
                      log_gdp_change_lag +
                      poll_change_to_election +
                      country_cycle | 1,
                      data = filter(dat_timeseries_day_single,
                                    class_inductive == "Ongoing"),
                      dist = "negbin")
```

- Comparison of Bayesian Information Criterion (BIC):
  BIC was lower in some ZINB models, suggesting a better fit but given the lack of a theoretical reason for the zeros to be inflated there is no justification to use this more complex model.

```
> BIC(nb_single_ongoing)
[1] 152525.8
> BIC(zinb_single_ongoing)
[1] 152321
```

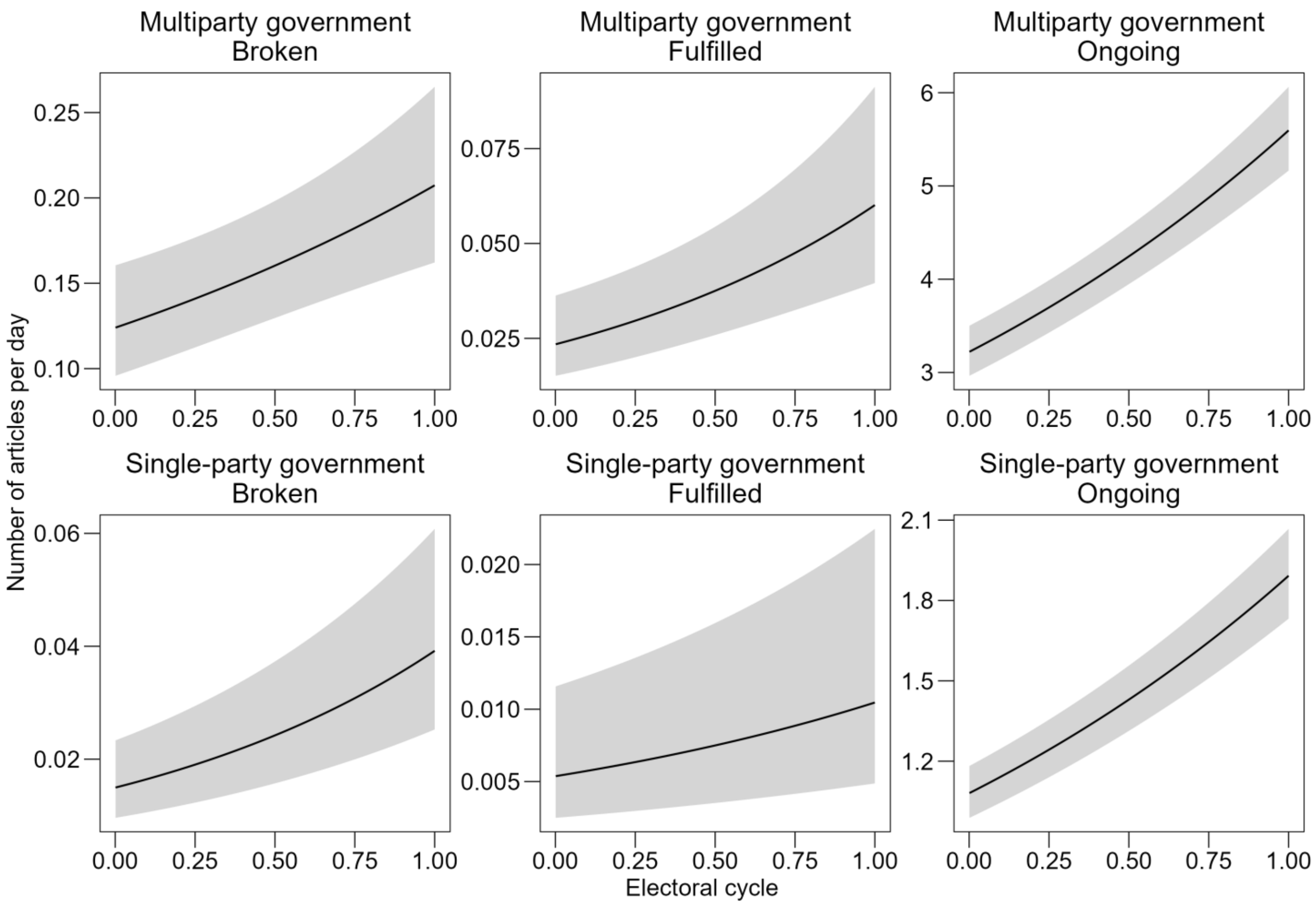
- The results were less severe in other models, with BIC being almost equal in some, giving more support to the fact that the ZINB model is unjustified.
- After testing alternative models, it can be concluded that the negative binomial model is the preferred model.

# Are the polynomials justified?

"I add the second- and third-order polynomials of Electoral cycle to allow for curvilinear effects over time"

Plots without the orthogonal polynomial form of dependent variable election cycle:

In this model hypothesis 1 not proven.



# Log Likelihood Test, Polynomial vs. Non-Polynomial

Using the lrtest function from lmtest package.

```
lmtest::lrtest(nb_single_ongoing_np, nb_single_ongoing)
```

Higher log likelihood -76115 > -76364 suggests better fit of polynomial model, and the low p-value indicates statistical significance.

```
Likelihood ratio test

Model 1: n_articles_day ~ n_articles_day_lag + electoral_cycle + log_gdp_change_lag +
    poll_change_to_election + country_cycle
Model 2: n_articles_day ~ n_articles_day_lag + poly(electoral_cycle, 3) +
    log_gdp_change_lag + poll_change_to_election + country_cycle
  #Df LogLik Df  Chisq Pr(>Chisq)
1  27 -76364
2  29 -76115  2 499.23  < 2.2e-16 ***
---
Signif. codes:
0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

**The result were the same for all six models tested, confirming the justification of the polynomial model and reaffirming hypothesis 1.**