1 Pre-analysis

1.1 Simulated Data

To illustrate my planned analysis, I simulate data for each variable described above.

Dependent variable: *Coalition success* is drawn from a descrete distribution {-1, -.5, 0, .5, 1}.

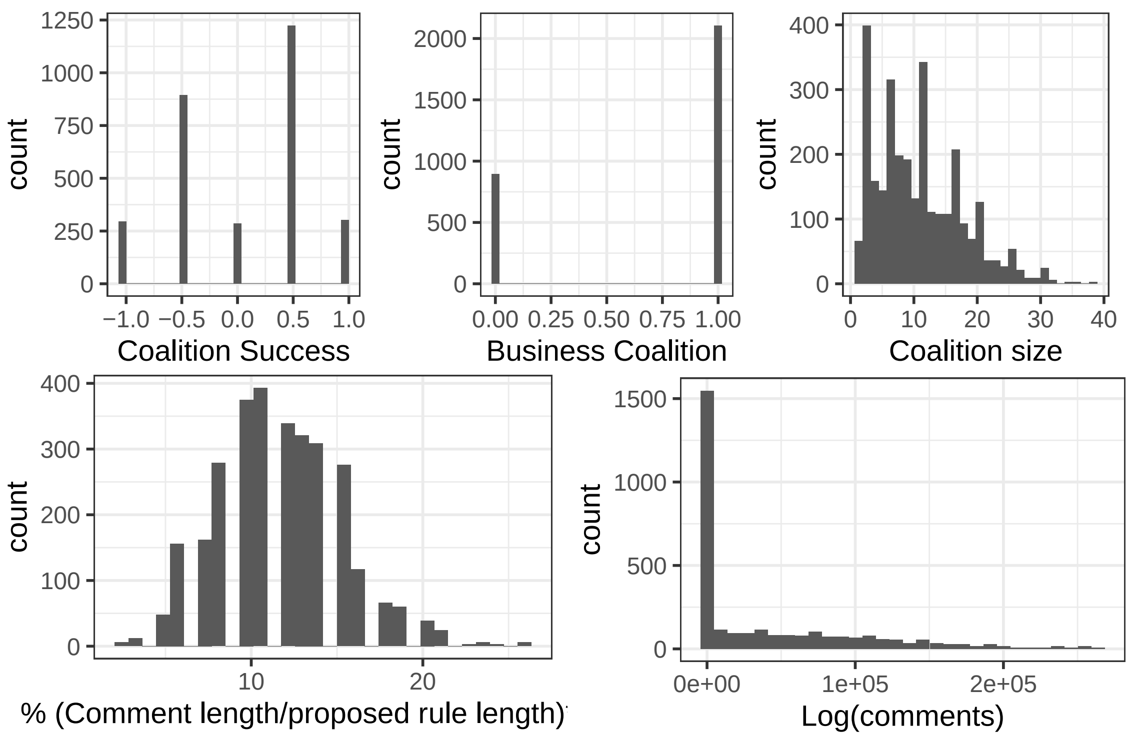
Explanatory variables: *Coalition size* (a count) is drawn from a Poisson distribution. *Business colation* is binomial. In reality, business coalitions are more common than non-business coalitions, but here I estimate a balanced sample. I set rule pages constant at 85 and draw *comment lengths* from a Poisson distribution. While in reality, less than one percent of coalitions lobbying in rulemaking opt for a mass-comment campaign, I aim to gather a balanced sample, so half of the simulated data are assumed to have no mass comment campaign ($comments = 1$, $log(comments) = 0$) and the other half have a number of *comments* drawn from a Zero-Truncated Poisson distribution, which is then transformed to a log scale.

```
coalition_success <- sample(x = c(-1, -.5, 0, .5, 1), 1000, replace = T, prob = c(0.1, 0

coalition_size <- rtnorm(1000, mean = 5, sd= 10, lower = 1) %>% round()

coalition_business <- sample(x = c(0,1), 1000, replace = T, prob = c(0.3, .7))

comment_length <- round(rpois(1000, 10)/85 *100, 1)

comments <- c(rtnorm(500, mean = 10000, sd = 100000, lower = 100),
              rep(1, 500)) %>%
  sample() %>% round()

cong_support <- c(rtnorm(500, mean = 1, sd = 5, lower = 0),
                  rep(0, 500)) %>%
  sample() %>% round()

d = tibble(coalition_success,
           coalition_size,
           coalition_business,
           comment_length,
           comments,
           cong_support)

# if there is one coalition, it must be unnopposed
d1 <- d %>% mutate(rule_id = sample(1:1000),
                   coalition_id = sample(1:1000),
                   coalitions  = 1,
```

Table 1: Simulated data

rule_id	coalition_id	coalition_success	coalition_size	coalition_business	comment_length	comments	cong_support	coalitions	coalition_unopposed
1224	2767	0.5	25	0	9.4	1	0	2	0
1700	2085	-0.5	7	0	8.2	1	0	2	0
1055	2597	-0.5	5	1	10.6	1	16	2	0
1282	1073	-0.5	18	1	5.9	1	0	2	0
11	726	-0.5	18	1	14.1	69041	2	1	1
1758	1848	1.0	27	1	17.6	72903	0	2	0
143	337	0.0	5	1	15.3	27625	7	1	1
638	695	1.0	11	1	8.2	230656	0	1	1
165	878	-0.5	16	0	16.5	1	10	1	1
1368	2877	0.5	14	0	14.1	1	0	2	0

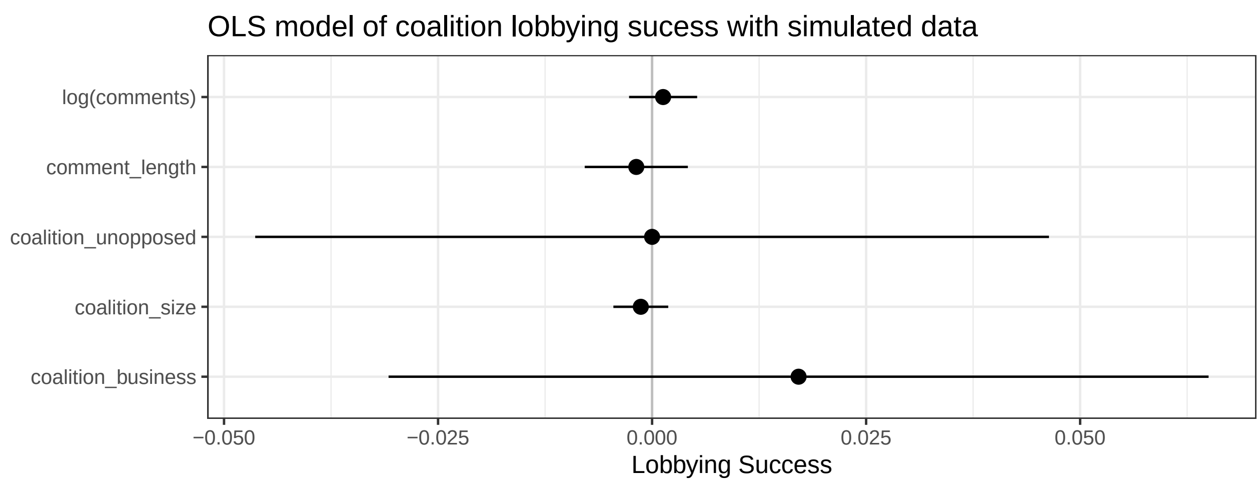
```
                    coalition_unopposed = 1)
# if there are two coalitions, I assume they are opposing (for simulation only)
d2 <- d %>% mutate(rule_id = sample(1001:2000),
                    coalition_id = 1001:2000,
                    coalitions  = 2,
                    coalition_unopposed = 0)
d3 <- d %>% mutate(rule_id = sample(1001:2000),
                    coalition_id = 2001:3000,
                    coalitions  = 2,
                    coalition_unopposed = 0)

d <- full_join(d1,d2) %>% full_join(d3)

d %>% sample_n(10) %>% dplyr::select(rule_id, coalition_id, everything()) %>% knitr::kab
```



1.2 Simulated Results

Unsurprisingly this model yields no significant results. With lobbying success as the dependent variable, the coefficient on the main variable of interest would be interpreted as a one-unit increase in the logged number of comments corresponds to a $\beta_{logmasscomments}$ increase in the five-point influence scale.

```
m <- lm(coalition_success ~ log(comments) +
          comment_length +
          coalition_business +
          coalition_size +
          coalition_unopposed,
        data = d)
```



To assess congressional support as a mediator in the influence of public pressure campaigns on rulemaking, I estimate the average conditional marginal effect (ACME, conditional on the number of comments from Members of Congress) and average direct effect (ADE) of mass comments using causal mediation analysis.

```
library(mediation)

# model predicting mediator
model.m <- lm(cong_support ~  log(comments) + comment_length + coalition_business+  coal

# model predicting DV
model.y <- lm(coalition_success ~ log(comments) + cong_support + comment_length + coalit

med.cont <- mediate(model.m, model.y, sims=1000, treat = "log(comments)",
mediator = "cong_support")

summary(med.cont)
```

```
##
```

```
## Causal Mediation Analysis
##
## Quasi-Bayesian Confidence Intervals
##
##                 Estimate 95% CI Lower 95% CI Upper p-value
## ACME            1.31e-04    -6.12e-05         0.00    0.20
## ADE             1.18e-03    -2.49e-03         0.00    0.58
## Total Effect    1.31e-03    -2.33e-03         0.01    0.52
## Prop. Mediated  3.72e-02    -1.09e+00         1.19    0.61
##
## Sample Size Used: 3000
##
##
## Simulations: 1000
```