Table 1: Simulated data

rule_id	coalition_id	coalitions	coalition_unopposed	coalition_success	coalition_size	coalition_business	comment_length	comments	cong_support
527	561	1	0	0.5	17	0	20.0	60885	0
554	1378	1	0	0.5	3	1	16.5	59688	9
1187	1287	2	1	-0.5	24	0	10.6	111855	0
1328	1066	2	1	-0.5	9	1	15.3	1	0
1289	750	2	1	0.5	14	1	16.5	189593	4
170	635	1	0	0.5	15	1	9.4	24996	7
107	786	1	0	0.5	24	1	14.1	25592	3
88	1376	1	0	-0.5	9	1	9.4	93001	5
740	329	1	0	0.5	8	0	15.3	1	2
743	1119	1	0	0.0	17	0	12.9	1	2

1 Pre-analysis

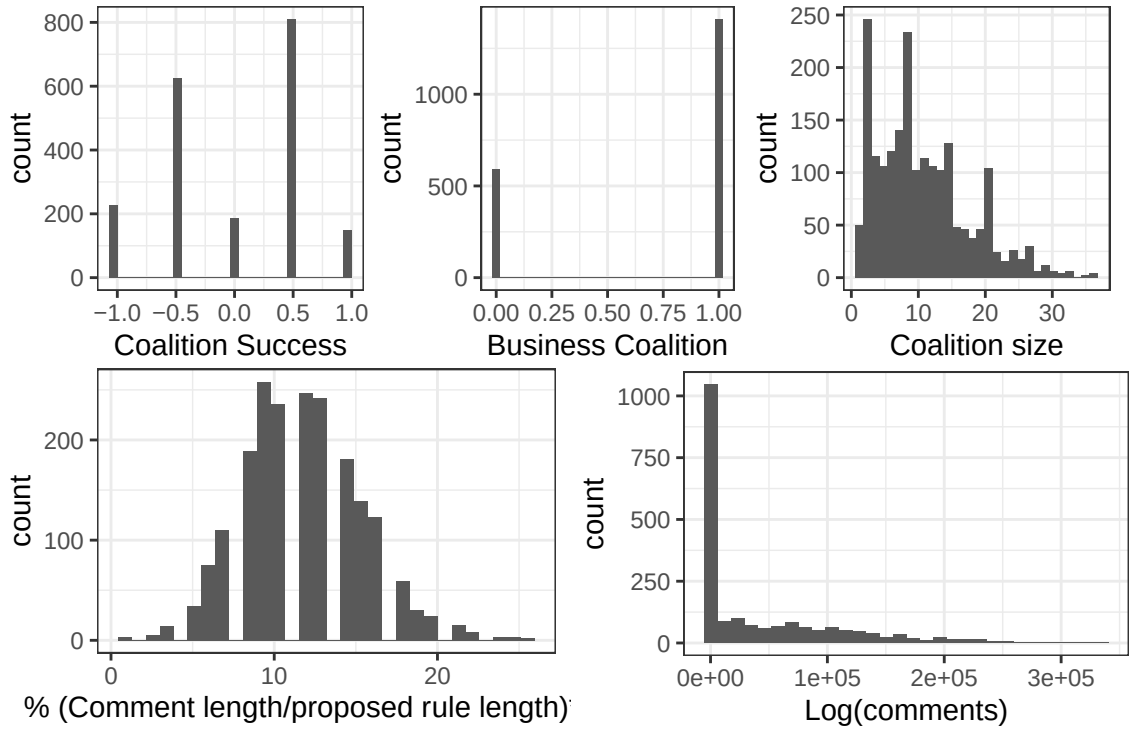
1.1 Simulated Data

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.

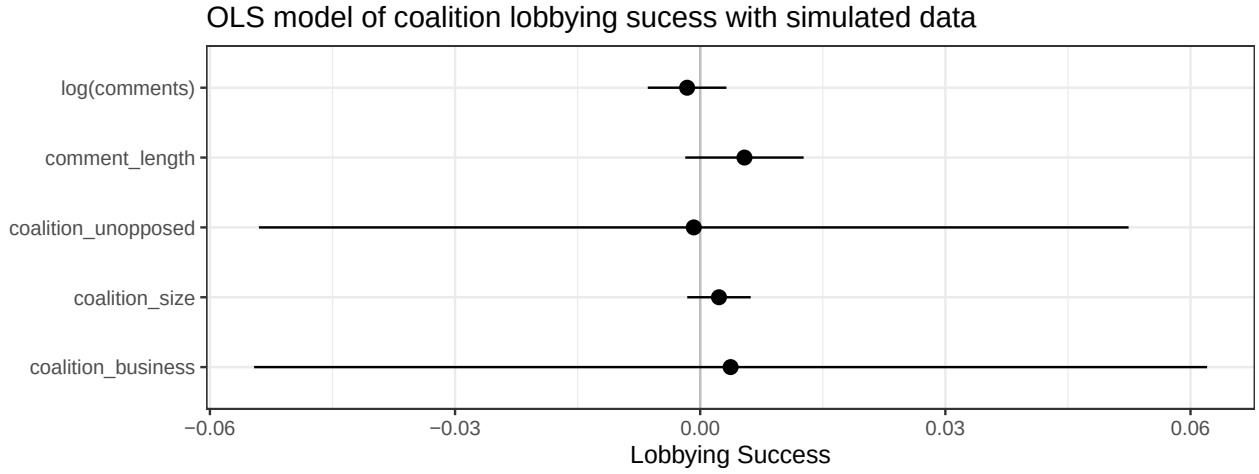
```
coalition_success <- sample(x = c(-1, -.5, 0, .5, 1), 1000, prob = c(0.1, 0.3, .1, 0.4,

d = tibble(rule_id = c(1:1000, rep(1001:1500, 2)),
           coalition_id = sample(1:2000),
           coalitions  = c(rep(1, 1000), rep(2, 1000)),
           coalition_unopposed = c(rep(0, 1000), rep(1, 1000)),
           coalition_success = c(coalition_success, sort(coalition_success)),
           coalition_size = rtnorm(1000, mean = 5, sd= 10, lower = 1) %>% rep(2) %>% rou
           coalition_business = sample(x = c(0,1), 2000, replace = T, prob = c(0.3, .7))
           comment_length = round(rpois(2000, 10)/85 *100, 1),
           comments= c(rtnorm(1000, mean = 10000, sd = 100000, lower = 100), rep(1, 1000
           cong_support = c(rtnorm(1000, mean = 1, sd = 5, lower = 0), rep(0, 1000)) %>%

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            4.54e-06    -1.10e-04         0.00    0.91
## ADE            -1.71e-03    -6.28e-03         0.00    0.50
## Total Effect   -1.71e-03    -6.28e-03         0.00    0.50
## Prop. Mediated -4.02e-04    -1.86e-01         0.16    0.94
##
## Sample Size Used: 2000
##
##
## Simulations: 1000
```