Table 1: Simulated data

rule_id	coalition_id	coalitions	coalition_unopposed	coalition_success	coalition_size	coalition_business	comment_length	comments	cong_support
1046	1822	2	1	0.5	11	1	12.9	94673	0
1012	131	2	1	0.5	2	1	12.9	42138	0
184	873	1	0	0.0	5	0	8.2	43581	4
707	1781	1	0	0.5	8	1	7.1	1	2
1284	1313	2	1	-0.5	5	1	15.3	51026	0
1335	306	2	1	0.5	7	1	9.4	68987	0
1455	1110	2	1	0.0	1	1	14.1	69308	0
1086	755	2	1	0.5	9	1	8.2	110494	0
551	1975	1	0	0.5	8	0	12.9	18034	0
1291	893	2	1	0.5	3	1	17.6	80354	2

1 Pre-analysis

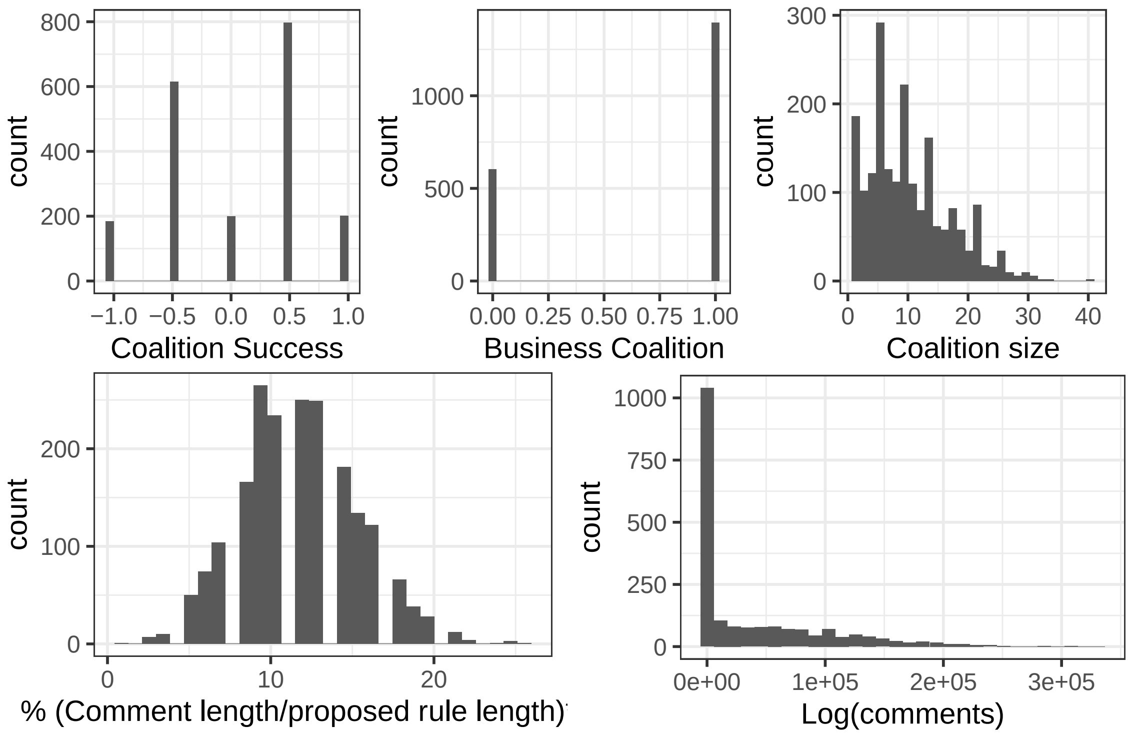
1.1 Simulated Data

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.

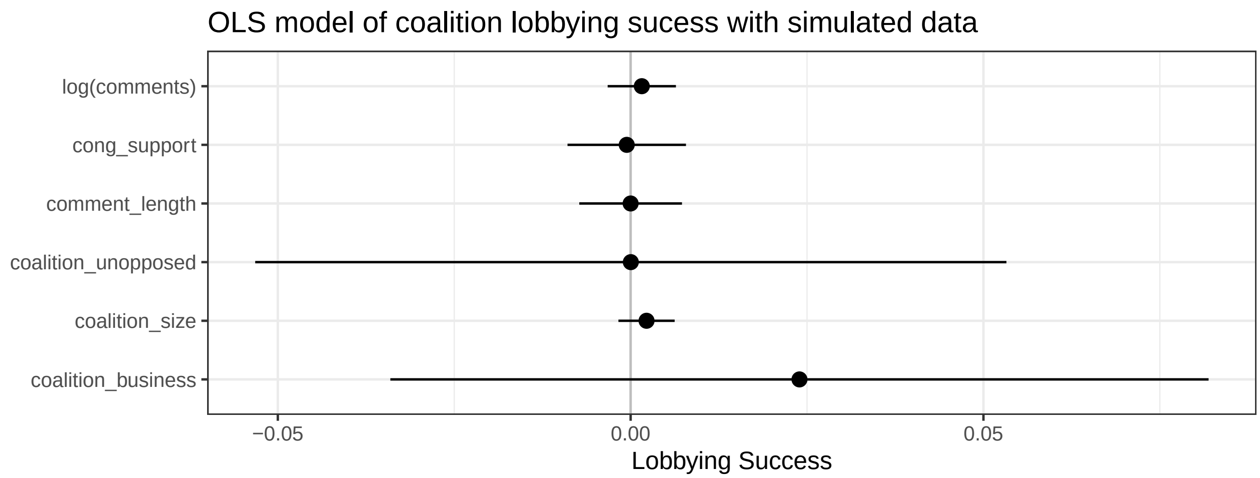
```
coalition_success <- sample(x = c(-1, -.5, 0, .5, 1), 1000, prob = c(0.1, 0.3, .1, 0.4,

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 +
          cong_support,
        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           -9.63e-06    -1.99e-04         0.00    0.86
## ADE             1.52e-03    -3.09e-03         0.01    0.55
## Total Effect    1.51e-03    -3.18e-03         0.01    0.56
## Prop. Mediated -1.93e-03    -2.65e-01         0.41    0.89
##
## Sample Size Used: 2000
##
##
## Simulations: 1000
```