Bayesian Inference of Pollster Bias

Nick Ahamed

Introduction

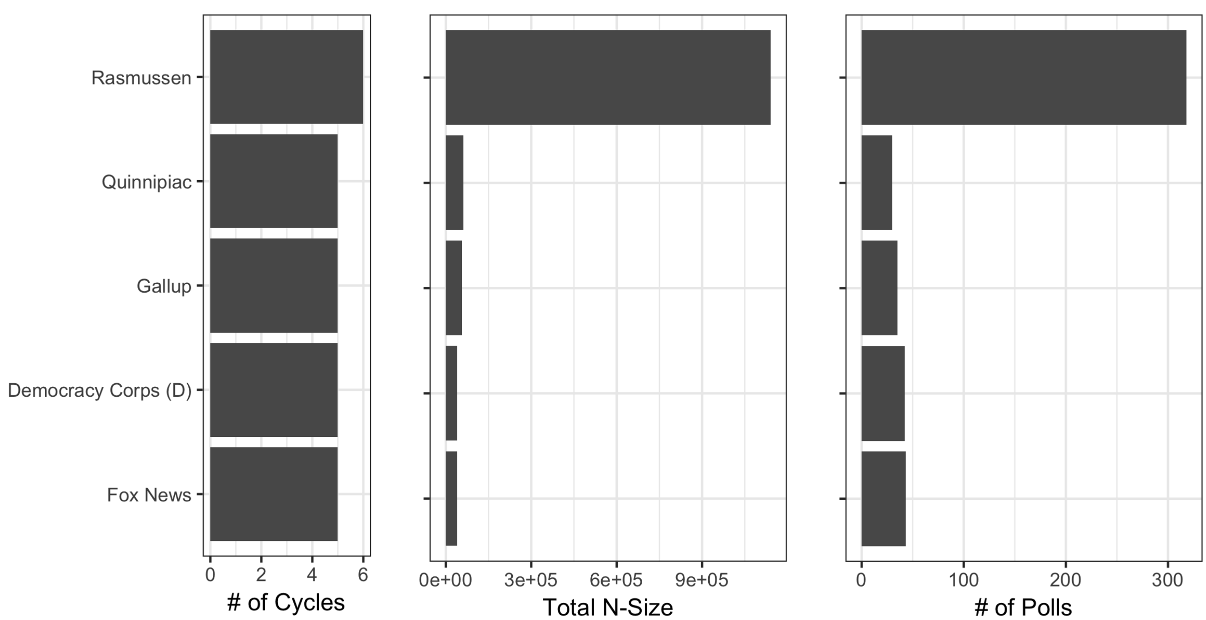
In this analysis, I estimate the bias for each public pollster active in the last 6 congressional elections. My final estimate identifies X as the most conservative pollster and Y as the most liberal. I likewise estimate bias of various sampling universes. Next, I use these biases to estimate the true level of support for Democrats over time in each cycle. Lastly, I regress the final estimate of support in each cycle against the number of seats Democrats won.

The Data

I have two primary sources of data: past polls and election results. The poll response that I use is the 'generic Congressional ballot.' Each pollster has a slightly different wording (and hence why we measure pollster bias), but they are all similar to: 'If the elections for the U.S. House of Representatives were being held today, which party's candidate would you vote for in your congressional district: The Democratic candidate or the Republcian candidate?' The named Congressional ballot question would account for incumbency effects and more closely mirror the choice voters are making in the voting booth. However, since not all candidates are known for 2018 yet, this is the only current question being polled, and so for comparability, I will use the same question for past elections.

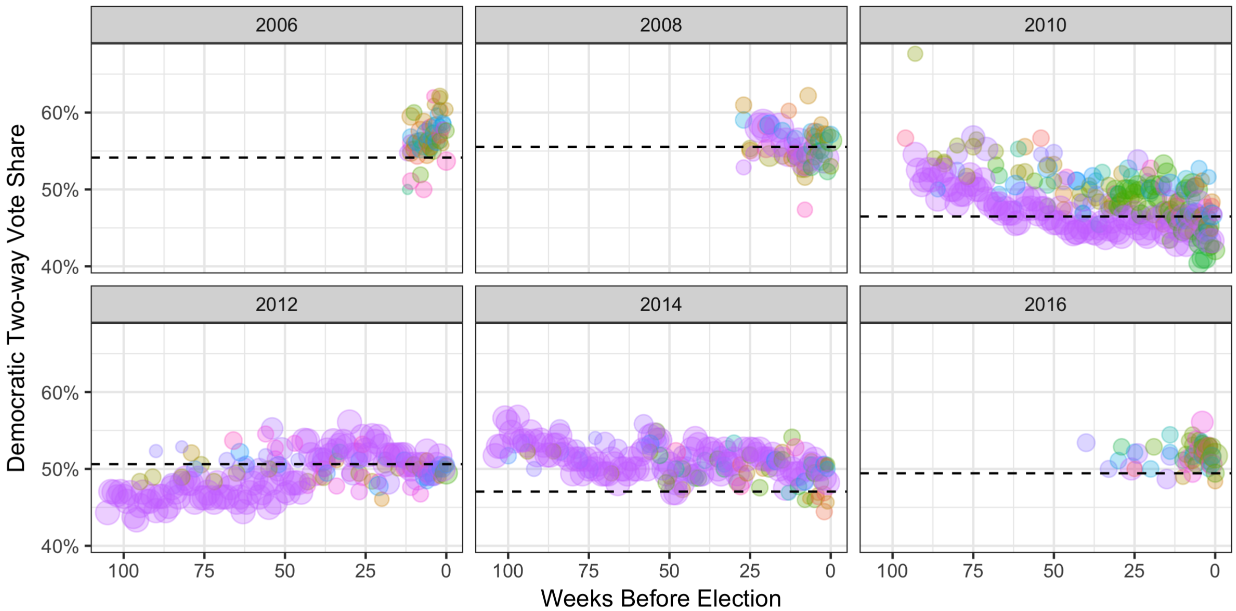
The past polls were taken from Real Clear Politics' database across 6 election cycles: **2006**, **2008**, **2010**, **2012**, **2014** and **2016**. Only polls where the year, date range, pollster, sampling universe and sample size are all known were included. Additionally, the polls' results were transformed to reflect the two-way share for Democrats (Dem/(Dem+Rep)): it is a proportion between 0 and 1. Time is transformed to be the rounded number of weeks between the middle day of the poll and election day. A daily model would be more precise, but would take more data.

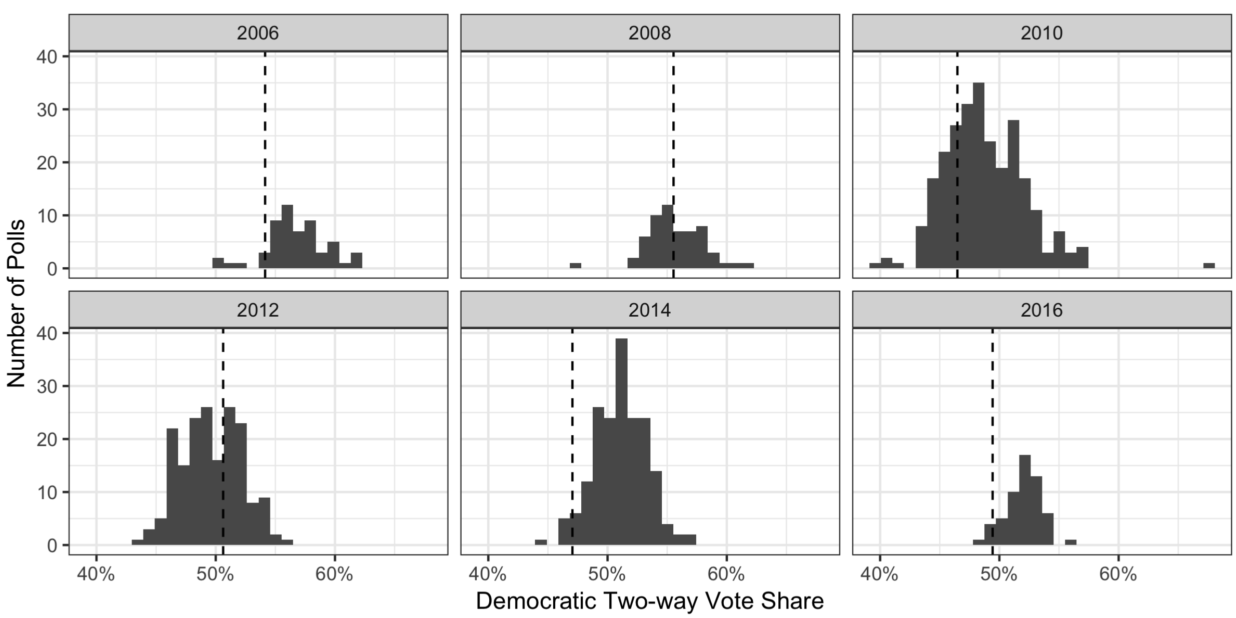
In total, 797 polls from 41 pollsters contacting 1.7m respondents over the 6 election cycles were used. These are the 5 largest pollsters. See Appendix B for full details.



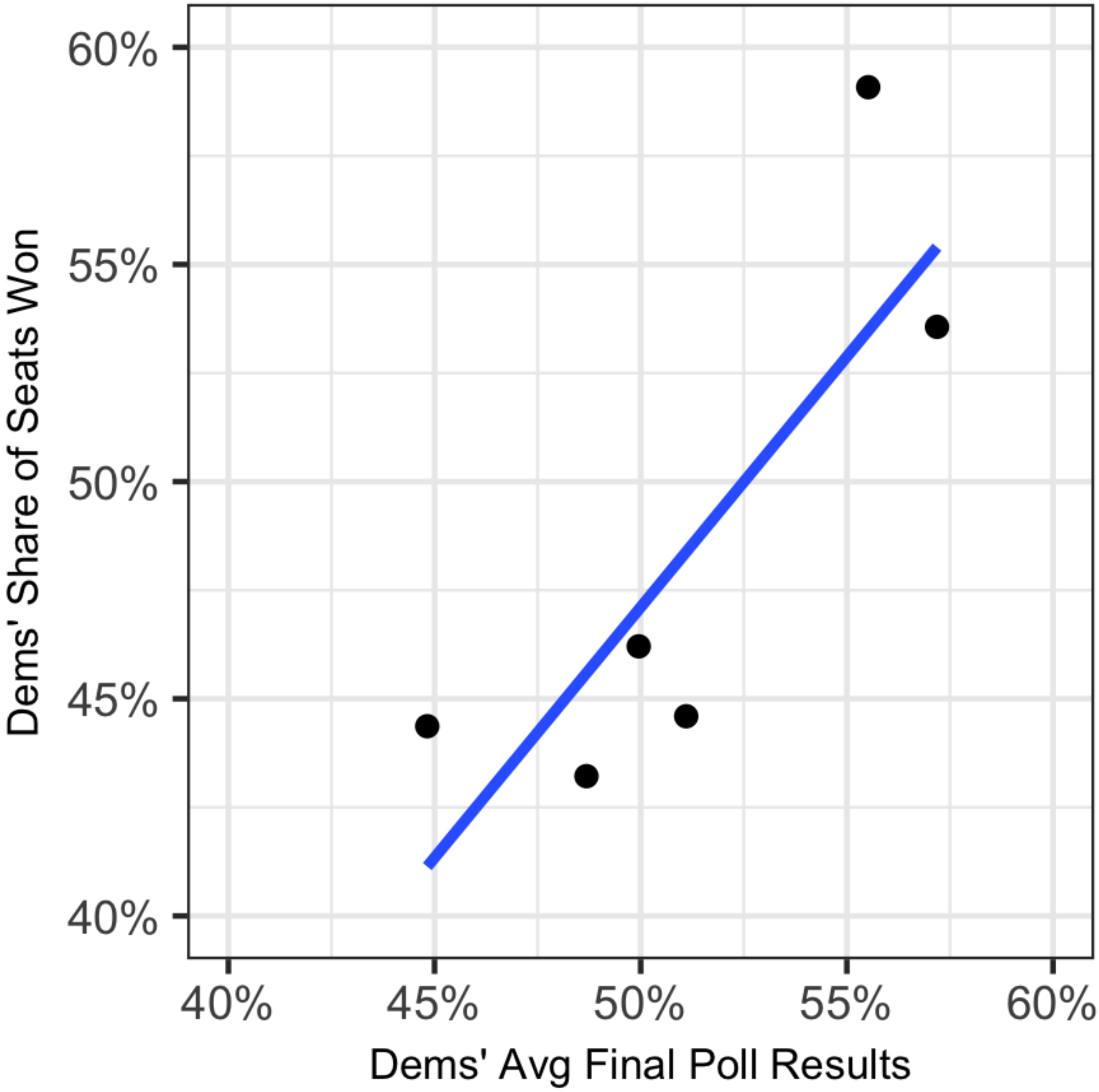
For election results, I use both the popular vote share and the seats won. These were taken from Wikipedia: **2006**, **2008**, **2010**, **2012**, **2014**, and **2016**. Again, I use Democrats' two-way vote share of the popular vote to mimic their two-way support in the polling data, and their percentage share of seats in the Congress.

First, let's explore the trends over time in each cycle. Here, each point is a poll; it's size relfects the sample size and color represents the pollster. The dashed line represents the final two-way popular vote share of Democrats. A couple of observations from this are clear. We see that by election, some pollsters are systematically off. For example, the pink pollster in 2010 was consistently below the final election result, suggesting bias. Last, we see that there are trends in results over time. For example, in 2014 the polls got closer and closer to the true result over time. Further investigation shows that poll results are not normally distributed around the result **across time**, suggesting we will need a time-dependent model.





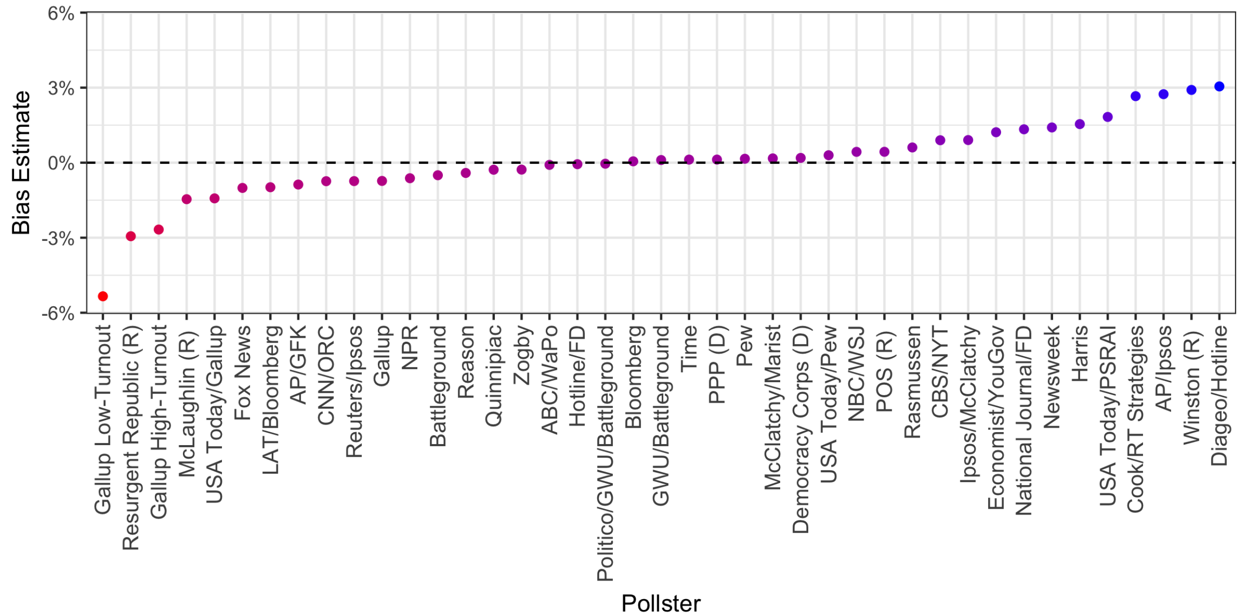
It's also worth exploring the relationship between polls and two-way seats won. While I later improve upon this through modeling, a crude measure is the average poll result within 1 week of election day, weighted by sample size. The correlation between this and two-way seat share is 0.82 suggesting a strong positive relationship.



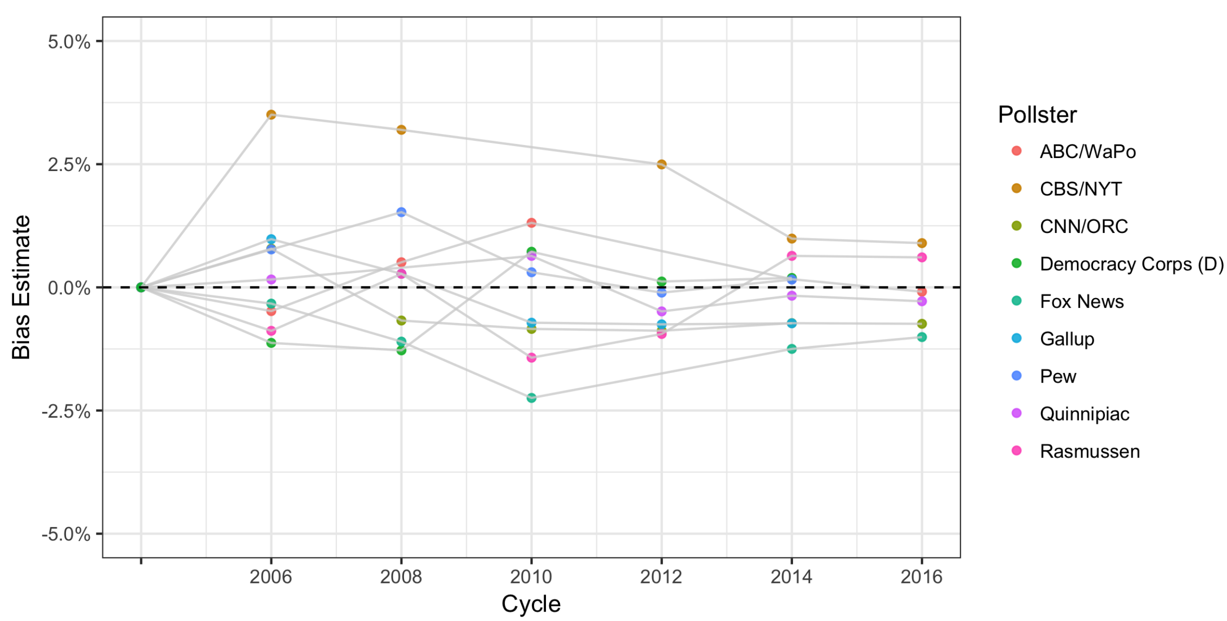
Estimating pollster and universe bias

To estimate bias for each pollster and universe, I use a Bayesian random-walk models anchored to the true final election results. For the first cycle a pollster/universe is used in, its prior is normally distributed around 0pp and assumed to be less than 20pp 95% of the time, in either direction. This prior is updated to be the posterior from the most recent previous cycle the pollster/universe was active in. Full specification of the theoretical model can be found in Appendix A; implementation specifications and key convergance diagnostics can be found in Appendix B.

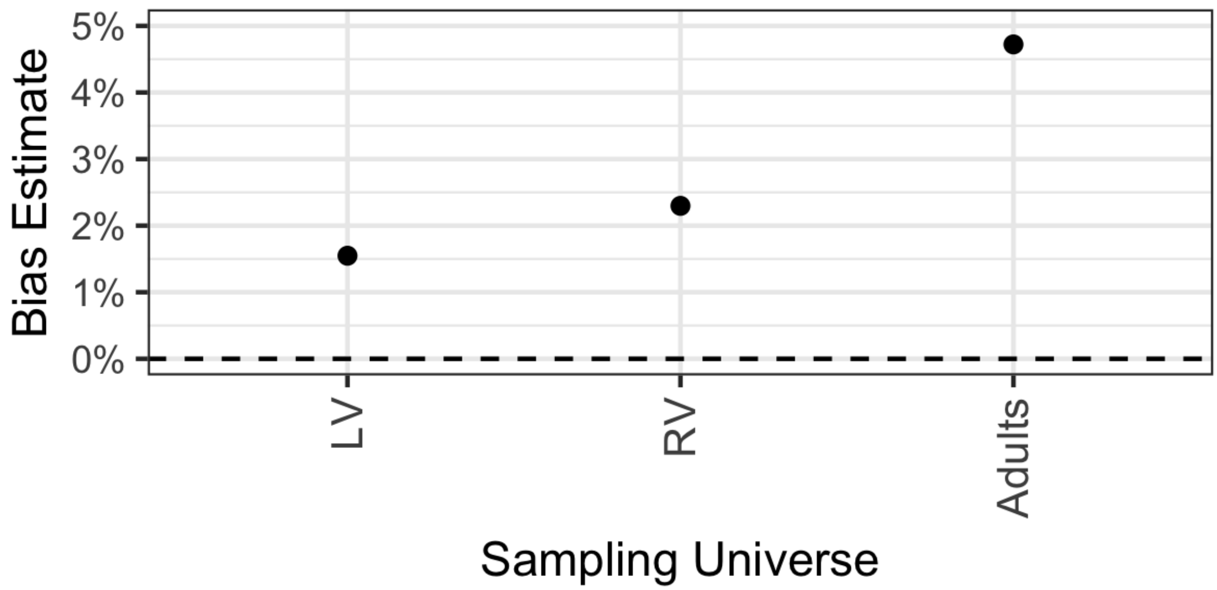
Below I plot the final bias estimate for each pollster. For example, for a pollster who polled in 2014 but not 2016, this will be their 2014 posterior results. Most pollsters are not biased by more than a percentage point in either direction. 'Gallup Low-Turnout' was the mostly conservative estimate (they took 4 polls in 1 election cycle). 'Diageo/Hotline' most consistently overestimted Democratic support (they took 7 polls in 2 election cycles). Bloomberg was the least biased pollseter with an average bias of -0.00008 across their 12 polls in 4 cycles. Full results can be found in Appendix B.



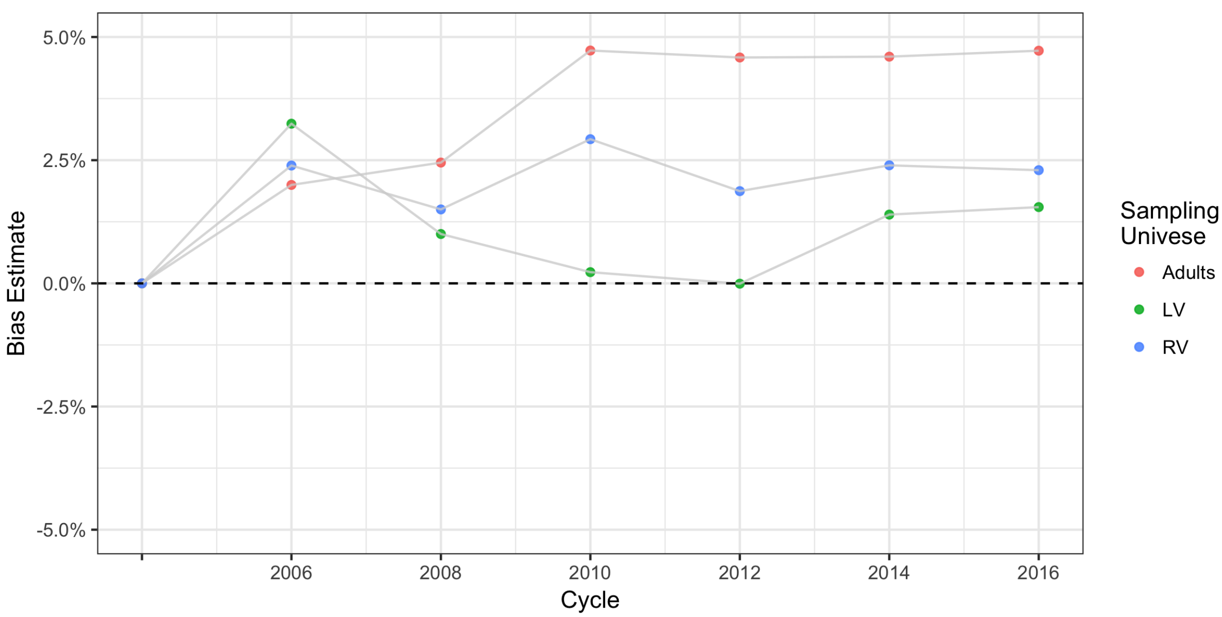
Looking more closely at pollsters that were active in at least 5 of the 6 cycles examine, we some variation in bias across cycles. For example, CBS/NYT strongly oveestimated Democratic support in 2006, but became less and less biased each cycle. Others were too conservative in some cycles and too liberal in others. Fox News underestimated Democratic support in all.



Additionally, we see that most sampling universes also show some overestimation of Democratic support. Our posterior observation from the 2016 cycle shows that likely voter universes across pollsters were biased 1.7pp in favor of Democrats, registered voter universes were biased 2.4pp and samples of just adults were biased nearly 5pp in favor of Democrats. Full results can be found in Appendix B.



These trends were fairly stable over time. The rank order of the universes was the same for all elections except 2006. Both adult and registered voter universes were stable around their final estimate since the 2010 cycle. In 2010 and 2012, there was basically no bias in likely voter universes, but this increased in 2014 and 2016.



Week-by-week estimates of support by cycle

Using the final estimates of bias for pollsters and universes as priors, I now refit the random-walk models, but with no anchor to the true result. This allows us to generate estimates week-by-week for each election, including a final estimate of election outcome, simulating a future prediction. The results are slightly overfit, especially for 2016, since the true results in each election updated the priors which are now inputs to the model. For 2016 specifically, the priors are derived from posterior distribution of the model anchored in the true result, so we should expect the model to be very precise. For full model specification see Appendix A and Appendix B for implementaton, code and full results.

Conclusions

Using the estimate for the true current level of support, about 54%, and the parameter estimates from the regression model previously fit, I predict democrats will win about 52% of the seats, or 225 seats, with a 2.5% lower bound of 177 seats and a 97.5% upper bound of 273 seats. This estimate is similar to other's. For example, one respected **author** finds an 8pp advantage in the generic ballot for Democrats will yield 224 Democratic seats.

Appendix A

To answer question 1 above, I follow **Jackman (2005)** to specify my model to estimate biases, but with an added term for sampling universe. A given poll is assumed to be normally distruted with support as the mean and the standard deviation a function of y_i and sample size. This would be specified as:

$$y_i \sim \mathcal{N}(\mu_i, \sigma_i^2)$$

That poll is centered around mean μ_i, which itself is a function of α_t, the true value of support at the time the poll was taken t, δ_j, the bias of pollster j, and θ_k, the bias of sampling universe k. Fully specified, this is:

$$\mu_i = \alpha_{t_i} + \delta_{j_i} + \theta_{k_i}$$

Due to the trends we see in our initial data exploration, a random walk model is appropriate. In such a model, support at time t is normally distributed around support at time $t-1$.

$$\alpha_t \sim \mathcal{N}(\alpha_{t-1}, \omega^2)$$

By anchoring the model in the final election results, and by using a random walk, I will be able to estimate the consistent bias, δ, of each pollster and the effect, θ, of different sampling universes.

For these given specifications, we have the following priors:

$$\sigma_i^2 = \sqrt{\frac{y_i(1-y_i)}{n_i}}, \quad \delta_j \sim \mathcal{N}(0,1), \quad \theta_k \sim \mathcal{N}(0,1), \quad \alpha_1 \sim \mathcal{U}(0.46, 0.56), \quad \omega^2 \sim IG(1/2, 1/2)$$

σ_i^2 just follows the formula for standard deviation of a sample. For pollster biases (δ), my prior is that there is no bias with a standard deviation large enough to capture 100% bias; my prior for bias from sampling universe (θ) is the same. As a prior for the starting true value of support (α_1), I use a uniform distribution over the minimum and maximum actual vote share of Democrats in the six elections analyzed. Lastly, as a prior for the true standard deviation of support (ω), I use the inverse gamma distribution with an effective sample size of 1 and a prior guess of 1 like the standard deviation for δ and θ.

To answer question 2 above, I will use the pollster and universe biases estimated above, and the same random walk algorithm to generate a final polling average at the time of the election, α_E. I will then use the following model to estimate number of seats:

$$S_{cycle} \sim \mathcal{N}(\phi_{cycle}, \sigma^2)$$

$$\phi_{cycle} = \beta_0 + \beta_1 * \alpha_{E_{cycle}}, \quad cycle = 2006, ..., 2016$$

My priors for this model are:

$$\beta_0 \sim \mathcal{N}(0,1), \quad \beta_1 \sim \mathcal{N}(1,1), \quad \sigma^2 \sim IG(1/2, 1/2)$$

β_0 here has a prior of 0 seats in the House of Representatives with a standard deviation 1. β_1 has a prior that says a 1 unit increase in $\alpha_{E_{cycle}}$ (a 100 perctange point increase in the Democrats' modeled vote share) is associated with a 100 percentage point increase in the share of seats awarded to Democrats, with a standard deviation of the same. Lastly, I use an inverse gamma distribution with a prior guess of 1 and effective sample size of 1 for the standard deviation.

To answer question 3, I will use the same random walk algorithm already mentioned, along with the pollster and universe biases to generate a polling average for today. I will then use this α with the coefficients estimated in the second model to predict the number of seats Democrats will win in 2018.

Appendix B

Functions and setup

```r
library(ggplot2)
library(tidyverse)
library(rjags)
library(cowplot)
set.seed(102)
scipen=999

data_prep <- function(data, res, year, anchor = T) {
  data <- data %>%
    filter(cycle == year) %>%
    mutate(pollster_num = as.numeric(as.factor(as.character(pollster))),
           univ_num = as.numeric(univ),
           prec = 1 / (sqrt((twoway * (1 - twoway)) / n_size)),
           week_adj = -1 * (week - max(week)) + 1) %>%
    select(-pollster_raw)

  data_jags = as.list(data)


  if(anchor) {
    xi <- rep(NA, max(length(unique(data$week_adj)), max(data$week_adj))+1)
    xi[max(data$week_adj+1)] <- res$twoway_vote[res$cycle == year]
  }  else {
    xi <- rep(NA, max(length(unique(data$week_adj)), max(data$week_adj)))
    }

  data_jags$xi <- xi
  return(data_jags)
}

bias_priors <- function(data_jags, deltas, thetas) {
  thetas <- thetas %>%
    filter(theta_univ %in% unique(data_jags$univ)) %>%
    mutate(theta_univ_num = as.numeric(theta_univ)) %>%
    arrange(theta_univ_num)

  deltas <- deltas %>%
    filter(delta_pollster %in% unique(data_jags$pollster)) %>%
    mutate(delta_pollster_num = as.numeric(as.factor(as.character(delta_pollster)))) %>%
    arrange(delta_pollster_num)
```

```
  data_jags <- append(data_jags, as.list(thetas))
  data_jags <- append(data_jags, as.list(deltas))
  return(data_jags)
}

run_model <- function(data_jags,
                      anchor = T,
                      chains = 4,
                      thining = 10,
                      burnin = 10000,
                      iter = 1000000,
                      params = c("xi", "delta", "theta")) {
  mod_string_1 <- " model {
  xi[1] ~ dunif(0.46, 0.56) #The lower and upper limit of Dem two-way vote share in the 6 elections exa

  for(i in 1:length(twoway)){
    mu[i] <- xi[week_adj[i]] + delta[pollster_num[i]] + theta[univ_num[i]]
    twoway[i] ~ dnorm(mu[i],prec[i])
  }

  for(t in 2:length(xi)){
    xi[t] ~ dnorm(xi[t-1],tau)
  }

  ## prior for standard deviations
  #omega2 ~ dgamma(1.0/2.0,1.0/2.0) I(0.001, 0.999)
  omega ~ dunif(0, .1)
  tau <- 1/pow(omega,2) "

  if(anchor) {
    mod_string_2 <- "
      ## priors for house effects
      for (i in 1:max(pollster_num)) {
        delta[i] ~ dnorm(delta_mu[i], 1.0/delta_sigma2[i])
      }

       for (i in 1:max(univ_num)) {
        theta[i] ~ dnorm(theta_mu[i], 1.0/theta_sigma2[i])
      }
      } "
  } else {
    mod_string_2 <- "
      ## priors for house effects
      for (i in 1:max(pollster_num)) {
        delta[i] = delta_mu[i]
      }

       for (i in 1:max(univ_num)) {
        theta[i] = theta_mu[i]
      }
      } "
  }
```

```r
  mod_string <- paste(mod_string_1, mod_string_2)

  mod <- jags.model(textConnection(mod_string), data = data_jags, n.chains = chains)
  update(mod, burnin) # burn-in
  mod_sim <- coda.samples(model = mod, variable.names = params, n.iter= iter, thin = thining)
  return(mod_sim)
}

calculate_priors <- function(mod_res, year, data_jags) {
  mod_csim <- as.mcmc(do.call(rbind, mod_res))
  param_ests <- data.frame(iter_mean = colMeans(mod_csim),
                           iter_sigma2 = (apply(mod_csim, 2, FUN ="sd"))^2)

  delta_est <- param_ests %>%
    filter(substr(row.names(param_ests),1,1) == 'd') %>%
    mutate(delta_pollster_num = data_jags$delta_pollster_num,
           pollster = data_jags$delta_pollster) %>%
    full_join(data.frame(pollster = levels(data_jags$pollster)), by = "pollster") %>%
    mutate(delta_cycle = year,
           delta_mu = iter_mean,
           delta_sigma2 = iter_sigma2,
           delta_pollster = pollster) %>%
    select(delta_cycle, delta_pollster, delta_mu, delta_sigma2)

  theta_est <- param_ests %>%
    filter(substr(row.names(param_ests),1,1) == 't') %>%
    mutate(theta_univ_num = data_jags$theta_univ_num,
           univ = data_jags$theta_univ) %>%
    full_join(data.frame(univ = levels(data_jags$univ)), by = "univ") %>%
    mutate(theta_cycle = year,
           theta_mu = iter_mean,
           theta_sigma2 = iter_sigma2,
           theta_univ = univ) %>%
    select(theta_cycle, theta_univ, theta_mu, theta_sigma2)

  return(list(deltas_est = delta_est, thetas_est = theta_est))
}

update_priors <- function(deltas_all, thetas_all, deltas_new, thetas_new) {
  x <- rbind(deltas_all, deltas_new)
  y <- rbind(thetas_all, thetas_new)

  w <- x %>%
    filter(!is.na(delta_mu)) %>%
    group_by(delta_pollster) %>%
    filter(delta_cycle == max(delta_cycle)) %>%
    ungroup()

  z <- y %>%
    filter(!is.na(theta_mu)) %>%
    group_by(theta_univ) %>%
    filter(theta_cycle == max(theta_cycle)) %>%
    ungroup()
```

```
  return(list(deltas = w, deltas_all = x, thetas = z, thetas_all = y))
}

convergence_diagnostics <- function(chains = 4,
                                    thining = 10,
                                    burnin = 10000,
                                    iter = 1000000,
                                    data_jags) {
  xi <- paste0("xi[", sample(seq(1,length(data_jags$xi)), 1), "]")
  delta <- paste0("delta[", sample(seq(1,length(data_jags$delta_pollster)), 1), "]")
  theta <- paste0("theta[", sample(seq(1,length(data_jags$theta_univ)), 1), "]")
  params <- c(xi, delta, theta)

  mod_res <- run_model(chains = chains,
                       thining = thining,
                       burnin = burnin,
                       iter = iter,
                       params = params,
                       data_jags = data_jags)

  return(list(gelman = gelman.diag(mod_res), autocorr = autocorr.diag(mod_res)))
}

extract_time_est <- function(mod_res, year, data_jags) {
  mod_csim <- as.mcmc(do.call(rbind, mod_res))
  param_ests <- data.frame(iter_mean = colMeans(mod_csim),
                           iter_sigma2 = (apply(mod_csim, 2, FUN ="sd"))^2)

  time_est <- param_ests %>%
    filter(substr(row.names(param_ests),1,1) == 'x') %>%
    mutate(time_before_elec = seq((length(data_jags$xi) - 1), 0, -1),
           upper_bound = iter_mean + 1.96*sqrt(iter_sigma2),
           lower_bound = iter_mean - 1.96*sqrt(iter_sigma2),
           cycle = year)

  return(time_est)
}
```

Load, prep and explore data

```
pollster_lkup <- read.csv("pollsters.csv")

res <- read.csv("election_results.csv") %>%
  mutate(twoway_vote = dem_vote/(dem_vote+rep_vote),
         twoway_seat = dem_seats/(dem_seats+rep_seats)) %>%
  arrange(cycle)

polls <- read.csv("training_dat.csv") %>%
  mutate(twoway = dem/(dem+rep)) %>%
  inner_join(res[,c("cycle","date")], by="cycle") %>%
  mutate(week = round(as.numeric((as.Date(as.character(date),  format="%m/%d/%y") -
           as.Date(as.character(end_date),  format="%m/%d/%y")) +
```

```r
           (as.Date(as.character(end_date),  format="%m/%d/%y") -
           as.Date(as.character(start_date),  format="%m/%d/%y"))/2)/7),
         n_size = as.numeric(as.character(n_size)))
```

```
## Warning in strptime(x, format, tz = "GMT"): unknown timezone 'zone/tz/
## 2017c.1.0/zoneinfo/Europe/London'
```

```r
polling_summary <- polls %>%
  group_by(pollster) %>%
  summarise(`Total N-Size` = sum(n_size),
            `# of Polls` = n(),
            `# of Cycles` = length(unique(cycle))) %>%
  arrange(desc(`Total N-Size`)) %>%
  inner_join(pollster_lkup, by = "pollster") %>%
    mutate(pollster_raw = factor(pollster_raw, levels = pollster_raw[order(`Total N-Size`)]))

print(polling_summary) #Flextable
```

```
## # A tibble: 41 x 5
##         pollster `Total N-Size` `# of Polls` `# of Cycles`
##           <fctr>          <dbl>        <int>         <int>
##  1     rasmussen        1140483          318             6
##  2    quinnipiac          61471           30             5
##  3        gallup          56170           35             5
##  4     dem_corps          40457           42             5
##  5      fox_news          40139           43             5
##  6           pew          29423           20             5
##  7 reuters_ipsos          28448           26             3
##  8           ppp          28410           32             4
##  9       cnn_orc          26294           33             6
## 10       nbc_wsj          21483           23             4
## # ... with 31 more rows, and 1 more variables: pollster_raw <fctr>
```

Estimate bias for pollsters and universes

```r
deltas <- data.frame(delta_cycle = 0,
                     delta_pollster = unique(polls$pollster),
                     delta_mu = rep(0, length(unique(polls$pollster))),
                     delta_sigma2 = rep(0.2, length(unique(polls$pollster))))
deltas_all <- deltas

thetas <- data.frame(theta_cycle = 0,
                     theta_univ = unique(polls$univ),
                     theta_mu = rep(0, length(unique(polls$univ))),
                     theta_sigma2 = rep(0.2, length(unique(polls$univ))))
thetas_all <- thetas

convergence <- list()

#Estimation
for(cycle in res$cycle) {
  data_jags <- data_prep(data = polls, res = res, year = cycle)
  data_jags <- bias_priors(data_jags = data_jags, deltas = deltas, thetas = thetas)
```

```r
  convergence[[paste(cycle)]] <- convergence_diagnostics(data_jags = data_jags)
  mod_res <- run_model(data_jags = data_jags)

  prior_ests <- calculate_priors(mod_res = mod_res, year = cycle, data_jags = data_jags)
  new_priors <- update_priors(deltas_all = deltas_all, thetas_all = thetas_all,
                              deltas_new = prior_ests$deltas_est, thetas_new = prior_ests$thetas_est)
  deltas <- new_priors$deltas
  deltas_all <- new_priors$deltas_all

  thetas <- new_priors$thetas
  thetas_all <- new_priors$thetas_all
}

deltas <- deltas %>%
    arrange(delta_mu) %>%
    inner_join(pollster_lkup, by = c("delta_pollster" = "pollster")) %>%
    mutate(pollster_raw = factor(pollster_raw, levels = pollster_raw[order(delta_mu)]))

deltas_all <- deltas_all %>%
    inner_join(pollster_lkup, by = c("delta_pollster" = "pollster"))

thetas <- thetas %>%
    arrange(theta_mu) %>%
    mutate(theta_univ = factor(theta_univ, levels = theta_univ[order(theta_mu)]))
```

```
## Sample convergance diagnostics for 2006 parameters:
```

```
## Potential scale reduction factors:
##
##            Point est. Upper C.I.
## delta[10]          1          1
## theta[3]           1          1
## xi[9]              1          1
##
## Multivariate psrf
##
## 1
##            delta[10]    theta[3]       xi[9]
## Lag 0   1.000000000 1.0000000000 1.000000000
## Lag 10  0.240796591 0.5663816543 0.458121271
## Lag 50  0.063888175 0.1533917642 0.086093913
## Lag 100 0.009692925 0.0338364521 0.020910600
## Lag 500 0.001400416 0.0006983637 0.004820756
```

```
## Sample convergance diagnostics for 2008 parameters:
```

```
## Potential scale reduction factors:
##
##           Point est. Upper C.I.
## delta[2]          1          1
## theta[2]          1          1
## xi[16]            1          1
##
## Multivariate psrf
##
```

```
## 1
##              delta[2]    theta[2]     xi[16]
## Lag 0    1.000000000 1.000000000 1.00000000
## Lag 10   0.057483356 0.303031532 0.70424055
## Lag 50   0.001570726 0.030869752 0.42359319
## Lag 100 -0.001210117 0.018549717 0.25709346
## Lag 500 -0.001744395 0.002933962 0.03522796
```

```
## Sample convergance diagnostics for 2010 parameters:
```

```
## Potential scale reduction factors:
##
##           Point est. Upper C.I.
## delta[10]          1          1
## theta[3]           1          1
## xi[96]             1          1
##
## Multivariate psrf
##
## 1
##             delta[10]   theta[3]     xi[96]
## Lag 0   1.0000000000 1.00000000 1.00000000
## Lag 10  0.0562636268 0.26355181 0.31143342
## Lag 50  0.0029033272 0.13780554 0.14674419
## Lag 100 0.0025165401 0.13051922 0.11522795
## Lag 500 0.0007039515 0.08298719 0.05240482
```

```
## Sample convergance diagnostics for 2012 parameters:
```

```
## Potential scale reduction factors:
##
##           Point est. Upper C.I.
## delta[15]       1.00       1.00
## theta[3]        1.00       1.00
## xi[45]          1.01       1.02
##
## Multivariate psrf
##
## 1.01
##           delta[15]   theta[3]    xi[45]
## Lag 0   1.000000000 1.00000000 1.0000000
## Lag 10  0.017102128 0.05916292 0.9029967
## Lag 50  0.011817432 0.05677337 0.7929310
## Lag 100 0.011678633 0.05436774 0.7230420
## Lag 500 0.005593665 0.03637165 0.4753711
```

```
## Sample convergance diagnostics for 2014 parameters:
```

```
## Potential scale reduction factors:
##
##          Point est. Upper C.I.
## delta[9]          1       1.00
## theta[2]          1       1.00
## xi[86]            1       1.01
##
## Multivariate psrf
##
```

```
## 1
##           delta[9]  theta[2]    xi[86]
## Lag 0   1.000000000 1.0000000 1.0000000
## Lag 10  0.006918732 0.2067330 0.8566693
## Lag 50  0.004367867 0.1987667 0.6974419
## Lag 100 0.002495346 0.1904950 0.5961670
## Lag 500 0.001883886 0.1449025 0.3342843
```

```
## Sample convergance diagnostics for 2016 parameters:
```

```
## Potential scale reduction factors:
##
##           Point est. Upper C.I.
## delta[10]          1          1
## theta[2]           1          1
## xi[39]             1          1
##
## Multivariate psrf
##
## 1
##           delta[10]    theta[2]      xi[39]
## Lag 0   1.000000000 1.000000000 1.000000000
## Lag 10  0.023539728 0.015864520 0.297228871
## Lag 50  0.014259529 0.004038198 0.096855448
## Lag 100 0.009419446 0.003323641 0.057298645
## Lag 500 0.003019756 0.002181784 0.008249728
```

```
## Final estimates of pollster bias:
```

```
## # A tibble: 41 x 5
##    delta_cycle    delta_pollster     delta_mu delta_sigma2
##          <dbl>            <fctr>        <dbl>        <dbl>
##  1        2010         gallup_lt -0.053417849 0.0033138141
##  2        2012 resurgen_republic -0.029400591 0.0053575982
##  3        2010         gallup_ht -0.026732934 0.0033321047
##  4        2010        mclaughlin -0.014596049 0.0082441697
##  5        2012  usa_today_gallup -0.014266470 0.0014053283
##  6        2016          fox_news -0.010092141 0.0005365954
##  7        2008     lat_bloomberg -0.009816405 0.0071002604
##  8        2016            ap_gfk -0.008744687 0.0029312914
##  9        2016           cnn_orc -0.007400197 0.0007632130
## 10        2016     reuters_ipsos -0.007361886 0.0007307248
## # ... with 31 more rows, and 1 more variables: pollster_raw <fctr>
```

```
## Estimate for each pollster and cycle:
```

```
##     delta_cycle           delta_pollster     delta_mu delta_sigma2
## 1             0                rasmussen  0.0000000000 0.2000000000
## 2             0                  cnn_orc  0.0000000000 0.2000000000
## 3             0                  hotline  0.0000000000 0.2000000000
## 4             0         usa_today_gallup  0.0000000000 0.2000000000
## 5             0                  cbs_nyt  0.0000000000 0.2000000000
## 6             0               quinnipiac  0.0000000000 0.2000000000
## 7             0                     time  0.0000000000 0.2000000000
## 8             0                 newsweek  0.0000000000 0.2000000000
## 9             0                     cook  0.0000000000 0.2000000000
## 10            0                 fox_news  0.0000000000 0.2000000000
```

```
## 11             0                    abc_wapo  0.0000000000 0.2000000000
## 12             0                      gallup  0.0000000000 0.2000000000
## 13             0                         pew  0.0000000000 0.2000000000
## 14             0                     nbc_wsj  0.0000000000 0.2000000000
## 15             0                    ap_ipsos  0.0000000000 0.2000000000
## 16             0               lat_bloomberg  0.0000000000 0.2000000000
## 17             0                       zogby  0.0000000000 0.2000000000
## 18             0                 battleground  0.0000000000 0.2000000000
## 19             0                   dem_corps  0.0000000000 0.2000000000
## 20             0                      harris  0.0000000000 0.2000000000
## 21             0                      ap_gfk  0.0000000000 0.2000000000
## 22             0            gwu_battleground  0.0000000000 0.2000000000
## 23             0                      diageo  0.0000000000 0.2000000000
## 24             0                         ppp  0.0000000000 0.2000000000
## 25             0                  mclaughlin  0.0000000000 0.2000000000
## 26             0                         npr  0.0000000000 0.2000000000
## 27             0                         pos  0.0000000000 0.2000000000
## 28             0              ipsos_mcclatchy  0.0000000000 0.2000000000
## 29             0                 nat_journal  0.0000000000 0.2000000000
## 30             0                   bloomberg  0.0000000000 0.2000000000
## 31             0               reuters_ipsos  0.0000000000 0.2000000000
## 32             0 politico_gwu_battleground  0.0000000000 0.2000000000
## 33             0             mcclatchy_marist  0.0000000000 0.2000000000
## 34             0                   gallup_ht  0.0000000000 0.2000000000
## 35             0                   gallup_lt  0.0000000000 0.2000000000
## 36             0            resurgen_republic  0.0000000000 0.2000000000
## 37             0                      reason  0.0000000000 0.2000000000
## 38             0               usa_today_pew  0.0000000000 0.2000000000
## 39             0             usa_today_psrai  0.0000000000 0.2000000000
## 40             0            economist_yougov  0.0000000000 0.2000000000
## 41             0                     winston  0.0000000000 0.2000000000
## 42          2006                    abc_wapo -0.0048178823 0.0238623307
## 43          2006                    ap_ipsos  0.0165096620 0.0140021152
## 44          2006                 battleground -0.0191780204 0.0233789126
## 45          2006                     cbs_nyt  0.0350481598 0.0143071875
## 46          2006                     cnn_orc  0.0078477622 0.0118825142
## 47          2006                        cook  0.0265993798 0.0132173811
## 48          2006                   dem_corps -0.0112714939 0.0232142908
## 49          2006                    fox_news -0.0032982467 0.0118928217
## 50          2006                      gallup  0.0097803726 0.0249303876
## 51          2006                      harris  0.0154293472 0.0240633342
## 52          2006                     hotline -0.0006045764 0.0164715905
## 53          2006               lat_bloomberg  0.0020836100 0.0228974449
## 54          2006                     nbc_wsj  0.0087657684 0.0150611487
## 55          2006                    newsweek  0.0147098606 0.0127498247
## 56          2006                         pew  0.0076967773 0.0131831240
## 57          2006                  quinnipiac  0.0015986859 0.0242165285
## 58          2006                   rasmussen -0.0088256260 0.0238441945
## 59          2006                        time  0.0159187920 0.0146993156
## 60          2006             usa_today_gallup -0.0182867117 0.0124046874
## 61          2006                       zogby -0.0027744550 0.0166112494
## 62          2006                      ap_gfk            NA           NA
## 63          2006                   bloomberg            NA           NA
## 64          2006                      diageo            NA           NA
```

```
## 65          2006          economist_yougov            NA           NA
## 66          2006                 gallup_ht            NA           NA
## 67          2006                 gallup_lt            NA           NA
## 68          2006          gwu_battleground            NA           NA
## 69          2006           ipsos_mcclatchy            NA           NA
## 70          2006          mcclatchy_marist            NA           NA
## 71          2006                mclaughlin            NA           NA
## 72          2006               nat_journal            NA           NA
## 73          2006                       npr            NA           NA
## 74          2006 politico_gwu_battleground            NA           NA
## 75          2006                       pos            NA           NA
## 76          2006                       ppp            NA           NA
## 77          2006                    reason            NA           NA
## 78          2006         resurgen_republic            NA           NA
## 79          2006             reuters_ipsos            NA           NA
## 80          2006             usa_today_pew            NA           NA
## 81          2006           usa_today_psrai            NA           NA
## 82          2006                   winston            NA           NA
## 83          2008                  abc_wapo  0.0050967341 0.0125800030
## 84          2008                    ap_gfk -0.0042838773 0.0101894717
## 85          2008                  ap_ipsos  0.0273907518 0.0081381440
## 86          2008              battleground -0.0110180729 0.0056328506
## 87          2008                   cbs_nyt  0.0319736158 0.0035539382
## 88          2008                   cnn_orc -0.0067322116 0.0054936139
## 89          2008                 dem_corps -0.0127852356 0.0036099269
## 90          2008                    diageo -0.0308766760 0.0171783055
## 91          2008                  fox_news -0.0110114000 0.0056784360
## 92          2008                    gallup  0.0027546003 0.0081876429
## 93          2008          gwu_battleground -0.0176709893 0.0050737167
## 94          2008             lat_bloomberg -0.0098164047 0.0071002604
## 95          2008                   nbc_wsj  0.0116534190 0.0033423184
## 96          2008                  newsweek  0.0007828673 0.0074581601
## 97          2008                       pew  0.0152647384 0.0070808735
## 98          2008                 rasmussen  0.0027519301 0.0023752584
## 99          2008                      time  0.0089840029 0.0078657222
## 100         2008          usa_today_gallup -0.0258327535 0.0047330148
## 101         2008                 bloomberg            NA           NA
## 102         2008                      cook            NA           NA
## 103         2008          economist_yougov            NA           NA
## 104         2008                 gallup_ht            NA           NA
## 105         2008                 gallup_lt            NA           NA
## 106         2008                    harris            NA           NA
## 107         2008                   hotline            NA           NA
## 108         2008           ipsos_mcclatchy            NA           NA
## 109         2008          mcclatchy_marist            NA           NA
## 110         2008                mclaughlin            NA           NA
## 111         2008               nat_journal            NA           NA
## 112         2008                       npr            NA           NA
## 113         2008 politico_gwu_battleground            NA           NA
## 114         2008                       pos            NA           NA
## 115         2008                       ppp            NA           NA
## 116         2008                quinnipiac            NA           NA
## 117         2008                    reason            NA           NA
## 118         2008         resurgen_republic            NA           NA
```

```
## 119        2008              reuters_ipsos            NA           NA
## 120        2008              usa_today_pew            NA           NA
## 121        2008            usa_today_psrai            NA           NA
## 122        2008                    winston            NA           NA
## 123        2008                      zogby            NA           NA
## 124        2010                   abc_wapo  0.0130975209 0.0043228003
## 125        2010                     ap_gfk -0.0076300026 0.0047464046
## 126        2010               battleground -0.0050174800 0.0042095820
## 127        2010                  bloomberg  0.0117568597 0.0038708873
## 128        2010                    cnn_orc -0.0084339370 0.0013923406
## 129        2010                  dem_corps  0.0072318660 0.0011140393
## 130        2010                     diageo  0.0304992241 0.0031014561
## 131        2010                   fox_news -0.0224429451 0.0013102481
## 132        2010                     gallup -0.0071731874 0.0009320629
## 133        2010                  gallup_ht -0.0267329338 0.0033321047
## 134        2010                  gallup_lt -0.0534178488 0.0033138141
## 135        2010           gwu_battleground -0.0024032333 0.0031958077
## 136        2010            ipsos_mcclatchy  0.0090453821 0.0033146503
## 137        2010           mcclatchy_marist -0.0028809352 0.0104457298
## 138        2010                 mclaughlin -0.0145960489 0.0082441697
## 139        2010                nat_journal  0.0133506127 0.0080033191
## 140        2010                   newsweek  0.0153610801 0.0029029799
## 141        2010                        npr -0.0051463356 0.0063374946
## 142        2010                        pew  0.0030635648 0.0013817401
## 143        2010 politico_gwu_battleground  0.0135490565 0.0056638092
## 144        2010                        pos  0.0043510776 0.0060110466
## 145        2010                        ppp -0.0033086412 0.0020700473
## 146        2010                 quinnipiac  0.0063866901 0.0019716426
## 147        2010                  rasmussen -0.0142725488 0.0006496973
## 148        2010              reuters_ipsos  0.0033080215 0.0038315114
## 149        2010                       time  0.0012318585 0.0042873096
## 150        2010           usa_today_gallup -0.0137982912 0.0023606548
## 151        2010                    winston  0.0290883100 0.0154542514
## 152        2010                   ap_ipsos            NA           NA
## 153        2010                    cbs_nyt            NA           NA
## 154        2010                       cook            NA           NA
## 155        2010           economist_yougov            NA           NA
## 156        2010                     harris            NA           NA
## 157        2010                    hotline            NA           NA
## 158        2010              lat_bloomberg            NA           NA
## 159        2010                    nbc_wsj            NA           NA
## 160        2010                     reason            NA           NA
## 161        2010          resurgen_republic            NA           NA
## 162        2010              usa_today_pew            NA           NA
## 163        2010            usa_today_psrai            NA           NA
## 164        2010                      zogby            NA           NA
## 165        2012                  bloomberg  0.0024010796 0.0024030420
## 166        2012                    cbs_nyt  0.0249520939 0.0030422809
## 167        2012                    cnn_orc -0.0088026677 0.0011283906
## 168        2012                  dem_corps  0.0011845028 0.0006209766
## 169        2012                     gallup -0.0075094078 0.0008545348
## 170        2012           mcclatchy_marist -0.0026485232 0.0065781057
## 171        2012                   newsweek  0.0140845610 0.0025524283
## 172        2012                        npr -0.0089575864 0.0036430837
```

```
## 173         2012                      pew -0.0010713630 0.0011584703
## 174         2012 politico_gwu_battleground -0.0006771160 0.0011154435
## 175         2012                      ppp -0.0013302817 0.0013218024
## 176         2012               quinnipiac -0.0048801478 0.0009273536
## 177         2012                rasmussen -0.0094654998 0.0002868763
## 178         2012        resurgen_republic -0.0294005906 0.0053575982
## 179         2012            reuters_ipsos -0.0156010118 0.0012406528
## 180         2012         usa_today_gallup -0.0142664701 0.0014053283
## 181         2012                 abc_wapo            NA           NA
## 182         2012                   ap_gfk            NA           NA
## 183         2012                 ap_ipsos            NA           NA
## 184         2012             battleground            NA           NA
## 185         2012                     cook            NA           NA
## 186         2012                   diageo            NA           NA
## 187         2012         economist_yougov            NA           NA
## 188         2012                 fox_news            NA           NA
## 189         2012                gallup_ht            NA           NA
## 190         2012                gallup_lt            NA           NA
## 191         2012         gwu_battleground            NA           NA
## 192         2012                   harris            NA           NA
## 193         2012                  hotline            NA           NA
## 194         2012           ipsos_mcclatchy            NA           NA
## 195         2012             lat_bloomberg            NA           NA
## 196         2012               mclaughlin            NA           NA
## 197         2012              nat_journal            NA           NA
## 198         2012                  nbc_wsj            NA           NA
## 199         2012                      pos            NA           NA
## 200         2012                   reason            NA           NA
## 201         2012                     time            NA           NA
## 202         2012            usa_today_pew            NA           NA
## 203         2012          usa_today_psrai            NA           NA
## 204         2012                  winston            NA           NA
## 205         2012                    zogby            NA           NA
## 206         2014                 abc_wapo  0.0016621936 0.0025385127
## 207         2014                   ap_gfk -0.0153972062 0.0036588692
## 208         2014                bloomberg  0.0026647599 0.0021292506
## 209         2014                  cbs_nyt  0.0098973752 0.0021350157
## 210         2014                  cnn_orc -0.0072649843 0.0008339515
## 211         2014                dem_corps  0.0019078307 0.0005486548
## 212         2014                 fox_news -0.0124936355 0.0006443277
## 213         2014                   gallup -0.0072968425 0.0008041845
## 214         2014         gwu_battleground -0.0023001836 0.0018013339
## 215         2014         mcclatchy_marist -0.0018367327 0.0023023119
## 216         2014                  nbc_wsj  0.0115721306 0.0024574879
## 217         2014                      npr -0.0062140549 0.0030223189
## 218         2014                      pew  0.0015712518 0.0008821090
## 219         2014 politico_gwu_battleground -0.0004151990 0.0010456560
## 220         2014                      ppp  0.0015692503 0.0007726413
## 221         2014               quinnipiac -0.0016963990 0.0005554543
## 222         2014                rasmussen  0.0063914957 0.0001786631
## 223         2014                   reason -0.0041082606 0.0170269105
## 224         2014            usa_today_pew  0.0029797987 0.0047765566
## 225         2014          usa_today_psrai  0.0182924163 0.0174517374
## 226         2014                 ap_ipsos            NA           NA
```

```
## 227          2014                  battleground            NA           NA
## 228          2014                          cook            NA           NA
## 229          2014                        diageo            NA           NA
## 230          2014              economist_yougov            NA           NA
## 231          2014                     gallup_ht            NA           NA
## 232          2014                     gallup_lt            NA           NA
## 233          2014                        harris            NA           NA
## 234          2014                       hotline            NA           NA
## 235          2014                ipsos_mcclatchy            NA           NA
## 236          2014                 lat_bloomberg            NA           NA
## 237          2014                    mclaughlin            NA           NA
## 238          2014                   nat_journal            NA           NA
## 239          2014                      newsweek            NA           NA
## 240          2014                           pos            NA           NA
## 241          2014             resurgen_republic            NA           NA
## 242          2014                 reuters_ipsos            NA           NA
## 243          2014                          time            NA           NA
## 244          2014              usa_today_gallup            NA           NA
## 245          2014                       winston            NA           NA
## 246          2014                         zogby            NA           NA
## 247          2016                      abc_wapo -0.0008806849 0.0017961463
## 248          2016                        ap_gfk -0.0087446870 0.0029312914
## 249          2016                     bloomberg  0.0005448998 0.0015442525
## 250          2016                       cbs_nyt  0.0089772952 0.0016426974
## 251          2016                       cnn_orc -0.0074001970 0.0007632130
## 252          2016              economist_yougov  0.0121779353 0.0016186858
## 253          2016                      fox_news -0.0100921411 0.0005365954
## 254          2016              gwu_battleground  0.0010600255 0.0013644009
## 255          2016              mcclatchy_marist  0.0017177770 0.0016494065
## 256          2016                       nbc_wsj  0.0043295149 0.0010687251
## 257          2016                           ppp  0.0012412857 0.0006729502
## 258          2016                    quinnipiac -0.0028213302 0.0005104373
## 259          2016                     rasmussen  0.0060849901 0.0001755610
## 260          2016                 reuters_ipsos -0.0073618860 0.0007307248
## 261          2016                      ap_ipsos            NA           NA
## 262          2016                  battleground            NA           NA
## 263          2016                          cook            NA           NA
## 264          2016                     dem_corps            NA           NA
## 265          2016                        diageo            NA           NA
## 266          2016                        gallup            NA           NA
## 267          2016                     gallup_ht            NA           NA
## 268          2016                     gallup_lt            NA           NA
## 269          2016                        harris            NA           NA
## 270          2016                       hotline            NA           NA
## 271          2016               ipsos_mcclatchy            NA           NA
## 272          2016                 lat_bloomberg            NA           NA
## 273          2016                    mclaughlin            NA           NA
## 274          2016                   nat_journal            NA           NA
## 275          2016                      newsweek            NA           NA
## 276          2016                           npr            NA           NA
## 277          2016                           pew            NA           NA
## 278          2016 politico_gwu_battleground            NA           NA
## 279          2016                           pos            NA           NA
## 280          2016                        reason            NA           NA
```

```
## 281        2016        resurgen_republic            NA            NA
## 282        2016                     time            NA            NA
## 283        2016         usa_today_gallup            NA            NA
## 284        2016            usa_today_pew            NA            NA
## 285        2016          usa_today_psrai            NA            NA
## 286        2016                  winston            NA            NA
## 287        2016                    zogby            NA            NA
##                 pollster_raw
## 1                  Rasmussen
## 2                    CNN/ORC
## 3                 Hotline/FD
## 4            USA Today/Gallup
## 5                    CBS/NYT
## 6                 Quinnipiac
## 7                       Time
## 8                   Newsweek
## 9          Cook/RT Strategies
## 10                  Fox News
## 11                  ABC/WaPo
## 12                    Gallup
## 13                       Pew
## 14                   NBC/WSJ
## 15                  AP/Ipsos
## 16             LAT/Bloomberg
## 17                     Zogby
## 18               Battleground
## 19       Democracy Corps (D)
## 20                    Harris
## 21                    AP/GFK
## 22           GWU/Battleground
## 23             Diageo/Hotline
## 24                   PPP (D)
## 25            McLaughlin (R)
## 26                       NPR
## 27                   POS (R)
## 28            Ipsos/McClatchy
## 29       National Journal/FD
## 30                 Bloomberg
## 31             Reuters/Ipsos
## 32  Politico/GWU/Battleground
## 33           McClatchy/Marist
## 34       Gallup High-Turnout
## 35        Gallup Low-Turnout
## 36     Resurgent Republic (R)
## 37                    Reason
## 38             USA Today/Pew
## 39           USA Today/PSRAI
## 40           Economist/YouGov
## 41               Winston (R)
## 42                  ABC/WaPo
## 43                  AP/Ipsos
## 44               Battleground
## 45                   CBS/NYT
## 46                   CNN/ORC
```

```
## 47         Cook/RT Strategies
## 48        Democracy Corps (D)
## 49                   Fox News
## 50                     Gallup
## 51                     Harris
## 52                 Hotline/FD
## 53              LAT/Bloomberg
## 54                    NBC/WSJ
## 55                   Newsweek
## 56                        Pew
## 57                 Quinnipiac
## 58                  Rasmussen
## 59                       Time
## 60           USA Today/Gallup
## 61                      Zogby
## 62                     AP/GFK
## 63                  Bloomberg
## 64             Diageo/Hotline
## 65           Economist/YouGov
## 66        Gallup High-Turnout
## 67         Gallup Low-Turnout
## 68           GWU/Battleground
## 69            Ipsos/McClatchy
## 70           McClatchy/Marist
## 71            McLaughlin (R) 
## 72        National Journal/FD
## 73                        NPR
## 74  Politico/GWU/Battleground
## 75                   POS (R) 
## 76                    PPP (D)
## 77                     Reason
## 78     Resurgent Republic (R)
## 79              Reuters/Ipsos
## 80              USA Today/Pew
## 81            USA Today/PSRAI
## 82               Winston (R) 
## 83                   ABC/WaPo
## 84                     AP/GFK
## 85                   AP/Ipsos
## 86                Battleground
## 87                    CBS/NYT
## 88                    CNN/ORC
## 89        Democracy Corps (D)
## 90             Diageo/Hotline
## 91                   Fox News
## 92                     Gallup
## 93           GWU/Battleground
## 94              LAT/Bloomberg
## 95                    NBC/WSJ
## 96                   Newsweek
## 97                        Pew
## 98                  Rasmussen
## 99                       Time
## 100          USA Today/Gallup
```

```
## 101                  Bloomberg
## 102        Cook/RT Strategies
## 103          Economist/YouGov
## 104       Gallup High-Turnout
## 105        Gallup Low-Turnout
## 106                     Harris
## 107                Hotline/FD
## 108           Ipsos/McClatchy
## 109          McClatchy/Marist
## 110            McLaughlin (R)
## 111       National Journal/FD
## 112                        NPR
## 113 Politico/GWU/Battleground
## 114                   POS (R)
## 115                    PPP (D)
## 116                 Quinnipiac
## 117                     Reason
## 118    Resurgent Republic (R)
## 119             Reuters/Ipsos
## 120              USA Today/Pew
## 121           USA Today/PSRAI
## 122               Winston (R)
## 123                      Zogby
## 124                   ABC/WaPo
## 125                     AP/GFK
## 126               Battleground
## 127                  Bloomberg
## 128                    CNN/ORC
## 129       Democracy Corps (D)
## 130            Diageo/Hotline
## 131                   Fox News
## 132                     Gallup
## 133       Gallup High-Turnout
## 134        Gallup Low-Turnout
## 135          GWU/Battleground
## 136           Ipsos/McClatchy
## 137          McClatchy/Marist
## 138            McLaughlin (R)
## 139       National Journal/FD
## 140                   Newsweek
## 141                        NPR
## 142                        Pew
## 143 Politico/GWU/Battleground
## 144                   POS (R)
## 145                    PPP (D)
## 146                 Quinnipiac
## 147                  Rasmussen
## 148             Reuters/Ipsos
## 149                       Time
## 150          USA Today/Gallup
## 151               Winston (R)
## 152                   AP/Ipsos
## 153                    CBS/NYT
## 154        Cook/RT Strategies
```

```
## 155          Economist/YouGov
## 156                    Harris
## 157               Hotline/FD
## 158             LAT/Bloomberg
## 159                   NBC/WSJ
## 160                    Reason
## 161    Resurgent Republic (R)
## 162             USA Today/Pew
## 163           USA Today/PSRAI
## 164                     Zogby
## 165                 Bloomberg
## 166                   CBS/NYT
## 167                   CNN/ORC
## 168       Democracy Corps (D)
## 169                    Gallup
## 170          McClatchy/Marist
## 171                  Newsweek
## 172                       NPR
## 173                       Pew
## 174 Politico/GWU/Battleground
## 175                   PPP (D)
## 176                Quinnipiac
## 177                 Rasmussen
## 178    Resurgent Republic (R)
## 179             Reuters/Ipsos
## 180          USA Today/Gallup
## 181                   ABC/WaPo
## 182                    AP/GFK
## 183                  AP/Ipsos
## 184              Battleground
## 185        Cook/RT Strategies
## 186           Diageo/Hotline
## 187          Economist/YouGov
## 188                  Fox News
## 189       Gallup High-Turnout
## 190        Gallup Low-Turnout
## 191          GWU/Battleground
## 192                    Harris
## 193               Hotline/FD
## 194           Ipsos/McClatchy
## 195             LAT/Bloomberg
## 196           McLaughlin (R) 
## 197       National Journal/FD
## 198                   NBC/WSJ
## 199                  POS (R) 
## 200                    Reason
## 201                      Time
## 202             USA Today/Pew
## 203           USA Today/PSRAI
## 204              Winston (R) 
## 205                     Zogby
## 206                  ABC/WaPo
## 207                    AP/GFK
## 208                 Bloomberg
```

```
## 209                    CBS/NYT
## 210                    CNN/ORC
## 211       Democracy Corps (D)
## 212                   Fox News
## 213                     Gallup
## 214           GWU/Battleground
## 215           McClatchy/Marist
## 216                    NBC/WSJ
## 217                        NPR
## 218                        Pew
## 219 Politico/GWU/Battleground
## 220                    PPP (D)
## 221                 Quinnipiac
## 222                  Rasmussen
## 223                     Reason
## 224              USA Today/Pew
## 225            USA Today/PSRAI
## 226                   AP/Ipsos
## 227               Battleground
## 228        Cook/RT Strategies
## 229            Diageo/Hotline
## 230           Economist/YouGov
## 231      Gallup High-Turnout
## 232       Gallup Low-Turnout
## 233                     Harris
## 234                 Hotline/FD
## 235            Ipsos/McClatchy
## 236              LAT/Bloomberg
## 237            McLaughlin (R)
## 238       National Journal/FD
## 239                   Newsweek
## 240                   POS (R)
## 241    Resurgent Republic (R)
## 242              Reuters/Ipsos
## 243                       Time
## 244           USA Today/Gallup
## 245               Winston (R)
## 246                      Zogby
## 247                    ABC/WaPo
## 248                     AP/GFK
## 249                  Bloomberg
## 250                    CBS/NYT
## 251                    CNN/ORC
## 252           Economist/YouGov
## 253                   Fox News
## 254           GWU/Battleground
## 255           McClatchy/Marist
## 256                    NBC/WSJ
## 257                    PPP (D)
## 258                 Quinnipiac
## 259                  Rasmussen
## 260              Reuters/Ipsos
## 261                   AP/Ipsos
## 262               Battleground
```

```
## 263        Cook/RT Strategies
## 264       Democracy Corps (D)
## 265            Diageo/Hotline
## 266                    Gallup
## 267       Gallup High-Turnout
## 268        Gallup Low-Turnout
## 269                    Harris
## 270                Hotline/FD
## 271            Ipsos/McClatchy
## 272              LAT/Bloomberg
## 273            McLaughlin (R) 
## 274       National Journal/FD
## 275                  Newsweek
## 276                       NPR
## 277                       Pew
## 278 Politico/GWU/Battleground
## 279                  POS (R) 
## 280                    Reason
## 281    Resurgent Republic (R)
## 282                      Time
## 283          USA Today/Gallup
## 284             USA Today/Pew
## 285            USA Today/PSRAI
## 286              Winston (R) 
## 287                     Zogby
```

```
## Final estimates of sampling universe bias:
```

```
## # A tibble: 3 x 4
##   theta_cycle theta_univ   theta_mu theta_sigma2
##         <dbl>     <fctr>      <dbl>        <dbl>
## 1        2016         LV 0.01548088 0.0001331457
## 2        2016         RV 0.02297230 0.0002155282
## 3        2016     Adults 0.04722174 0.0018186331
```

```
## Estimate for each universe and cycle:
```

```
##    theta_cycle theta_univ      theta_mu theta_sigma2
## 1            0         LV  0.000000e+00 0.2000000000
## 2            0     Adults  0.000000e+00 0.2000000000
## 3            0         RV  0.000000e+00 0.2000000000
## 4         2006     Adults  1.997749e-02 0.0111421777
## 5         2006         LV  3.240671e-02 0.0101860988
## 6         2006         RV  2.391658e-02 0.0119590140
## 7         2008     Adults  2.451485e-02 0.0086760155
## 8         2008         LV  1.001667e-02 0.0020377711
## 9         2008         RV  1.500799e-02 0.0024618561
## 10        2010     Adults  4.725948e-02 0.0030226466
## 11        2010         LV  2.275264e-03 0.0005640732
## 12        2010         RV  2.926435e-02 0.0007129032
## 13        2012     Adults  4.584378e-02 0.0025667145
## 14        2012         LV -6.812085e-05 0.0002661694
## 15        2012         RV  1.871878e-02 0.0004046690
## 16        2014     Adults  4.601271e-02 0.0025414460
## 17        2014         LV  1.395613e-02 0.0001657483
## 18        2014         RV  2.396129e-02 0.0002657623
```

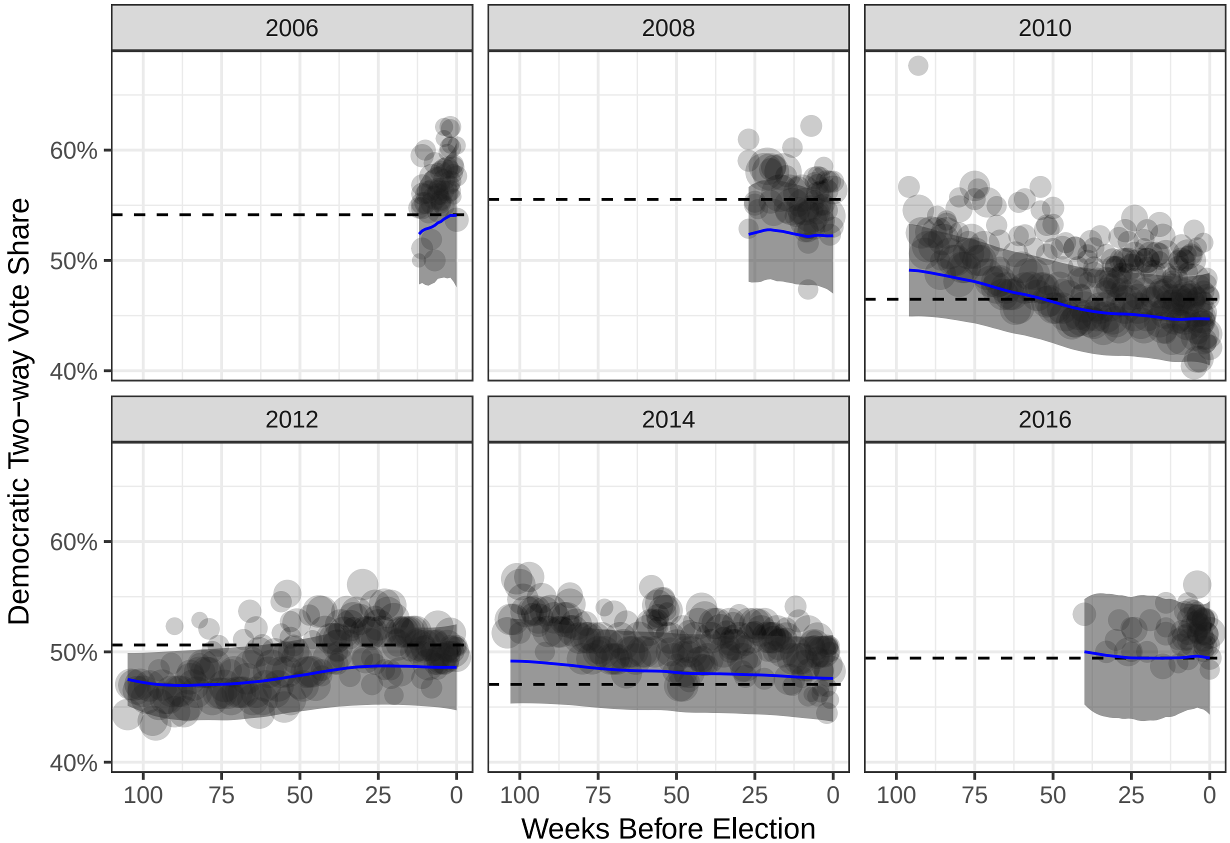
```
## 19        2016     Adults  4.722174e-02 0.0018186331
## 20        2016         LV  1.548088e-02 0.0001331457
## 21        2016         RV  2.297230e-02 0.0002155282
```

```r
#Estimate week-by-week movement using past pollster and universe bias
all_cycle_est <- data.frame(iter_mean = numeric(0),
                            iter_sigma2 = numeric(0),
                            time_before_elec = numeric(0),
                            upper_bound = numeric(0),
                            lower_bound = numeric(0),
                            cycle = numeric(0))

for(cycle in res$cycle) {
  data_jags <- data_prep(data = polls, res = res, year = cycle, anchor = F)
  data_jags <- bias_priors(data_jags = data_jags, deltas = deltas, thetas = thetas)

  mod_res <- run_model(data_jags = data_jags)
  cycle_time_est <- extract_time_est(mod_res = mod_res, year = cycle, data_jags = data_jags)
  all_cycle_est <- rbind(all_cycle_est, cycle_time_est)
}
```

```r
ggplot(data=all_cycle_est, aes(x=time_before_elec, y=iter_mean)) +
  geom_point(data=polls, aes(x=week, y=twoway, size=sqrt(n_size)), alpha=0.2) +
  geom_ribbon(aes(ymin=lower_bound,ymax=upper_bound), alpha = 0.5) +
  geom_hline(data=res, aes(yintercept = twoway_vote), linetype="dashed") +
  geom_line(color = "blue") +
  theme_bw() +
  facet_wrap(~cycle) +
  scale_x_reverse(name = "Weeks Before Election") +
  scale_y_continuous(name = "Democratic Two-way Vote Share", labels=scales::percent) +
  guides(size=F, color = F)
```




```
timeseries <-

ggsave(filename = "figures/time_series.png", plot = timeseries, width = 8, height = 4, units = "in")
```