Bayesian Inference of Pollster Bias

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Introduction

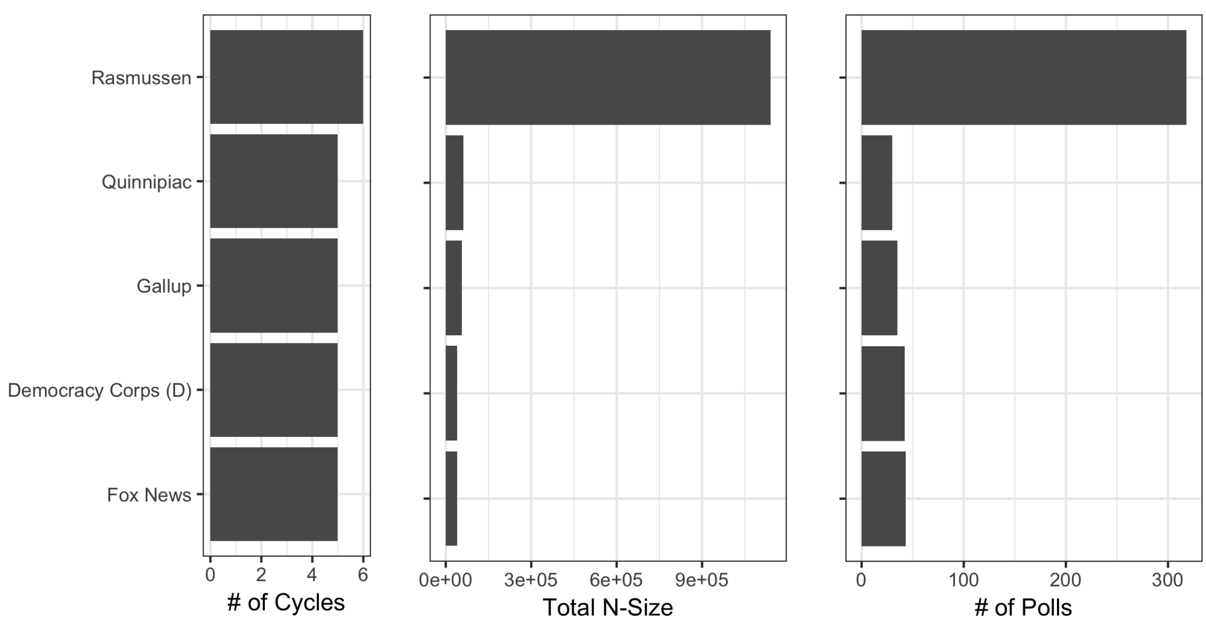
In this analysis, I estimate the bias for each public pollster active in the last 6 congressional elections. My final estimate identifies X as the most conservative pollster and Y as the most liberal. I likewise estimate bias of various sampling universes. Next, I use these biases to estimate the true 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.

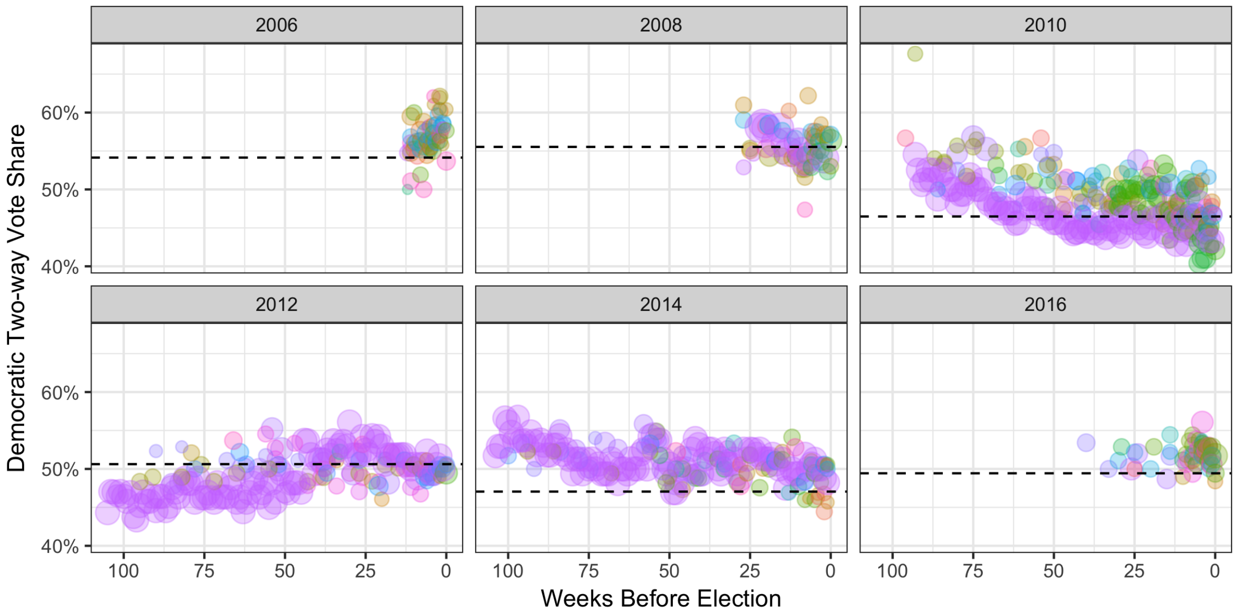
The past polls were taken from Real Clear Politics' database across 6 election cycles: **2006**, **2008**, **2010**, **2012**, **2014** and **2016**. Only polls where the year, date range, pollster, sampling universe and sample size are all known were included. Additionally, the polls' results were transformed 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.

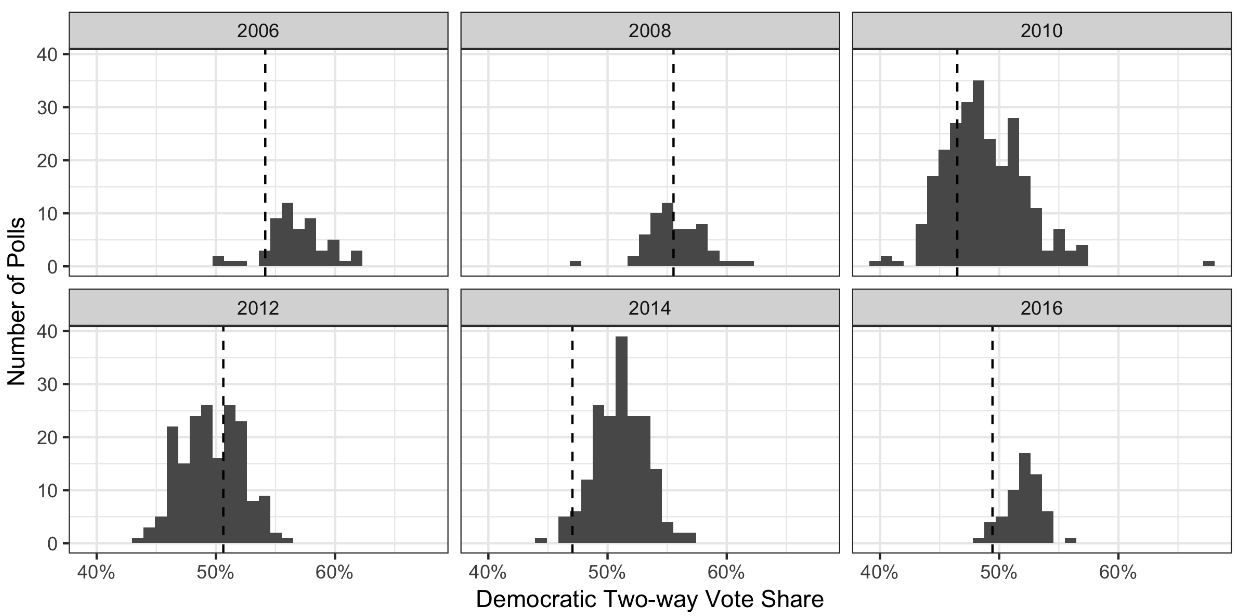
In total, 797 polls from 41 pollsters contacting 1.7m respondents over the 6 election cycles were used. These are the 5 largest pollsters. See Appendix B for full details.



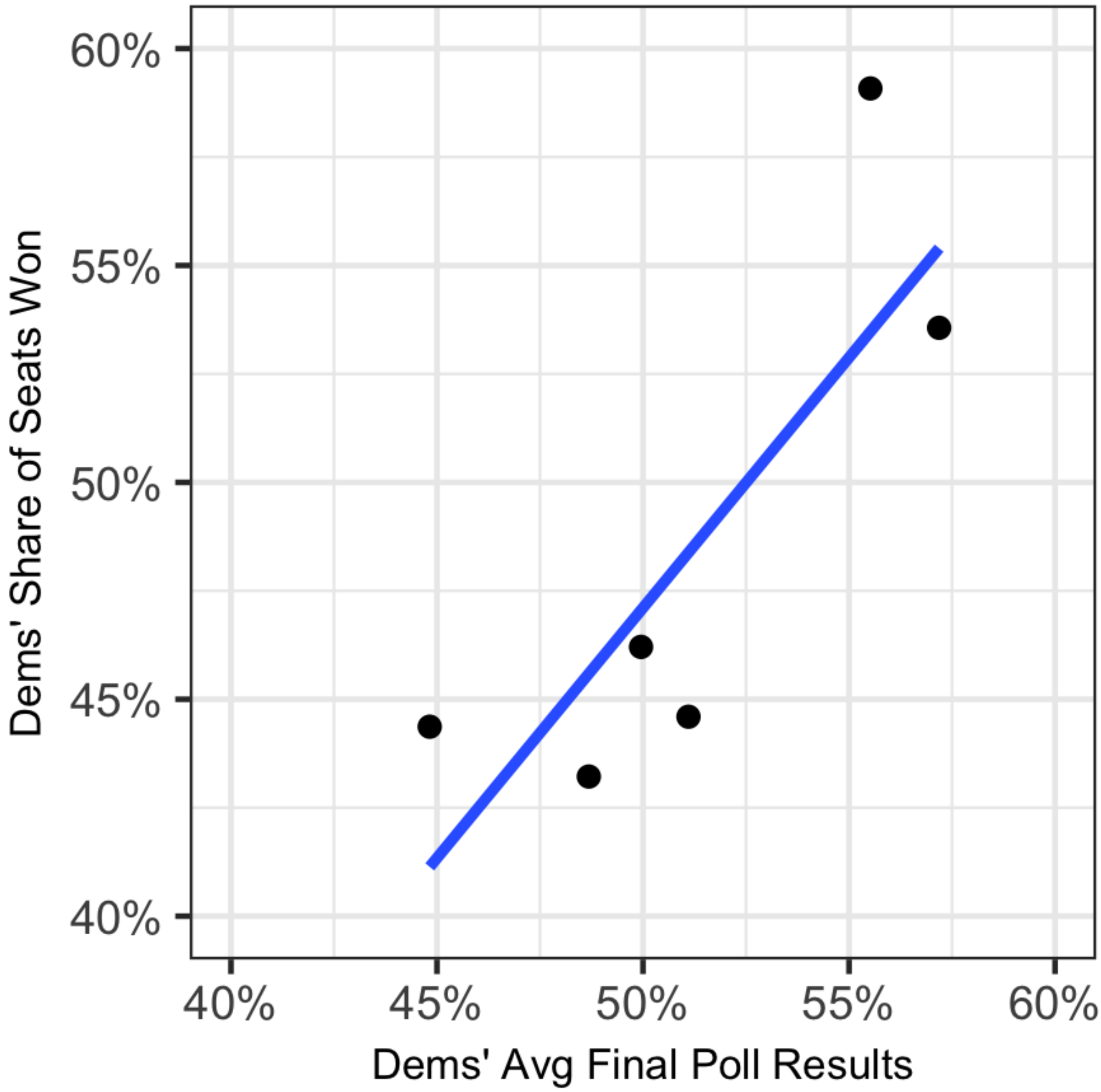
For election results, I use both the popular vote share and the seats won. These were taken from Wikipedia: **2006**, **2008**, **2010**, **2012**, **2014**, and **2016**. Again, I use Democrats' two-way vote share of the popular vote to mimic their two-way support in the polling data, and their percentage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





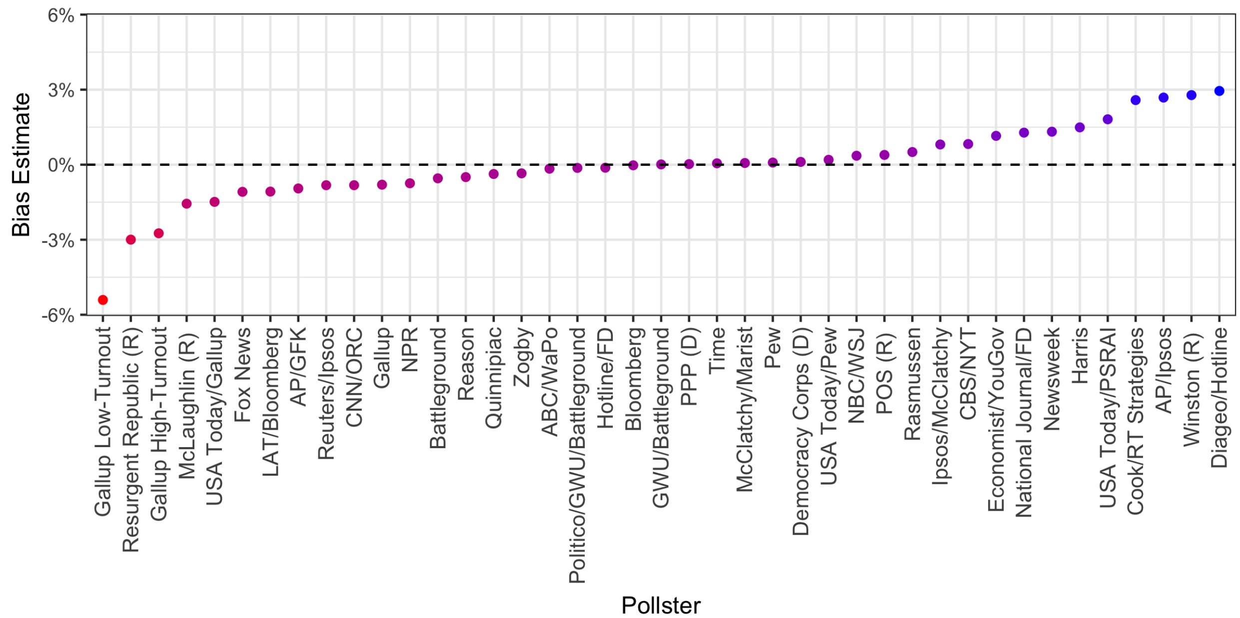
It's also worth exploring the relationship between polls and two-way seats won. While I later improve upon this through modeling, a crude measure is the average poll result within 1 week of election day, weighted by sample size. The correlation between this and two-way seat share is 0.82 suggesting a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



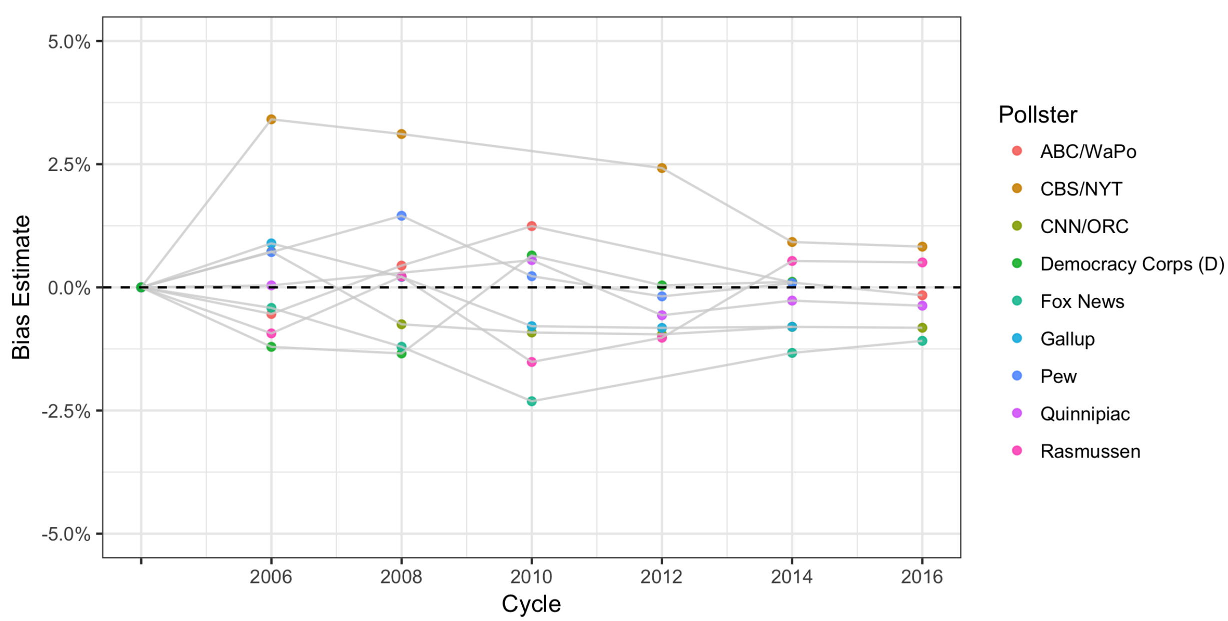
Estimating pollster and universe bias

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.

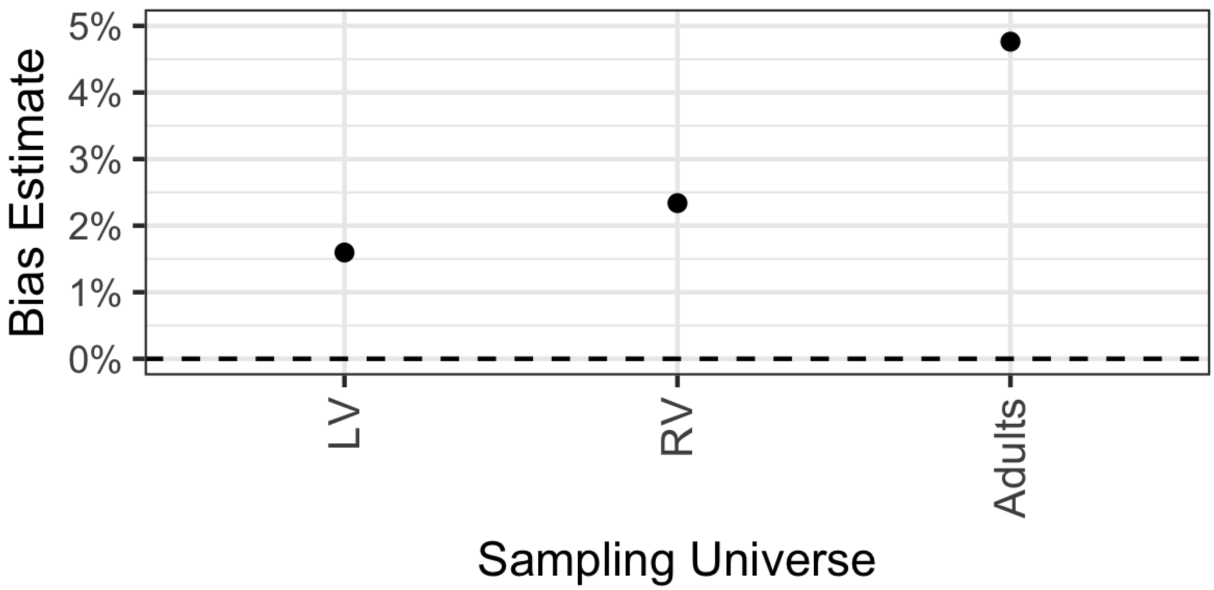
Below I plot the final bias estimate for each pollster. For example, for a pollster who polled in 2014 but not 2016, this will be their 2014 posterior results. Most pollsters are not biased by more than a percentage point in either direction. 'Gallup Low-Turnout' was the mostly conservative estimate (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.



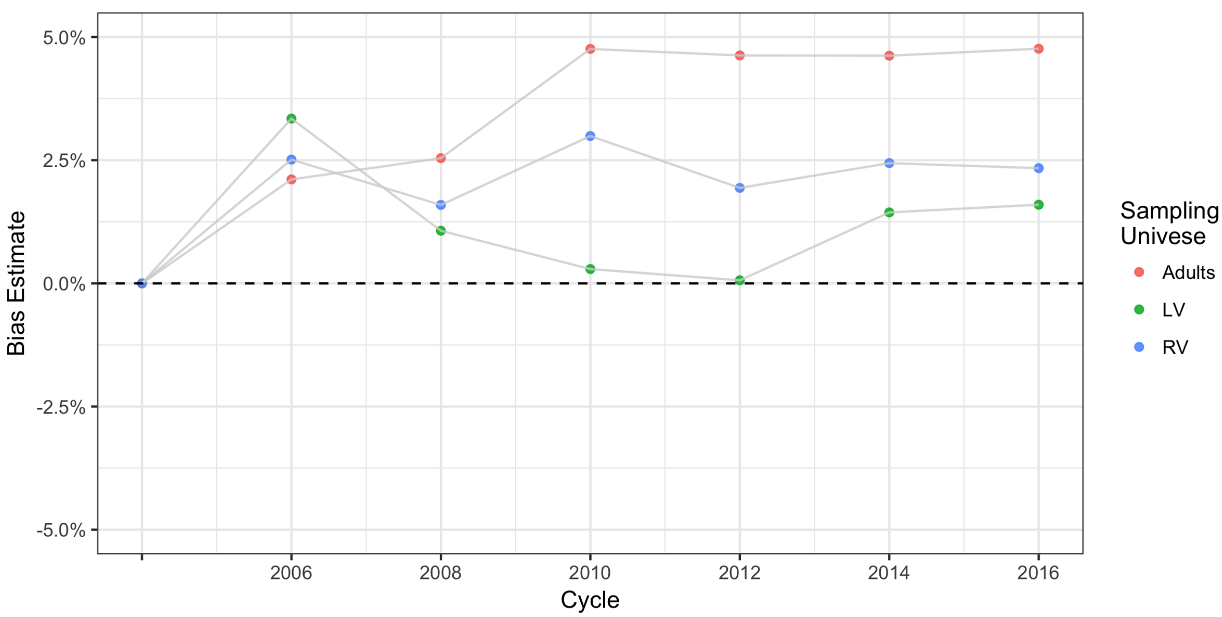
Looking more closely at pollsters that were active in at least 5 of the 6 cycles examine, we some variation in bias across cycles. For example, CBS/NYT strongly oveestimated Democratic support in 2006, but became less and less biased each cycle. Others were too conservative in some cycles and too liberal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

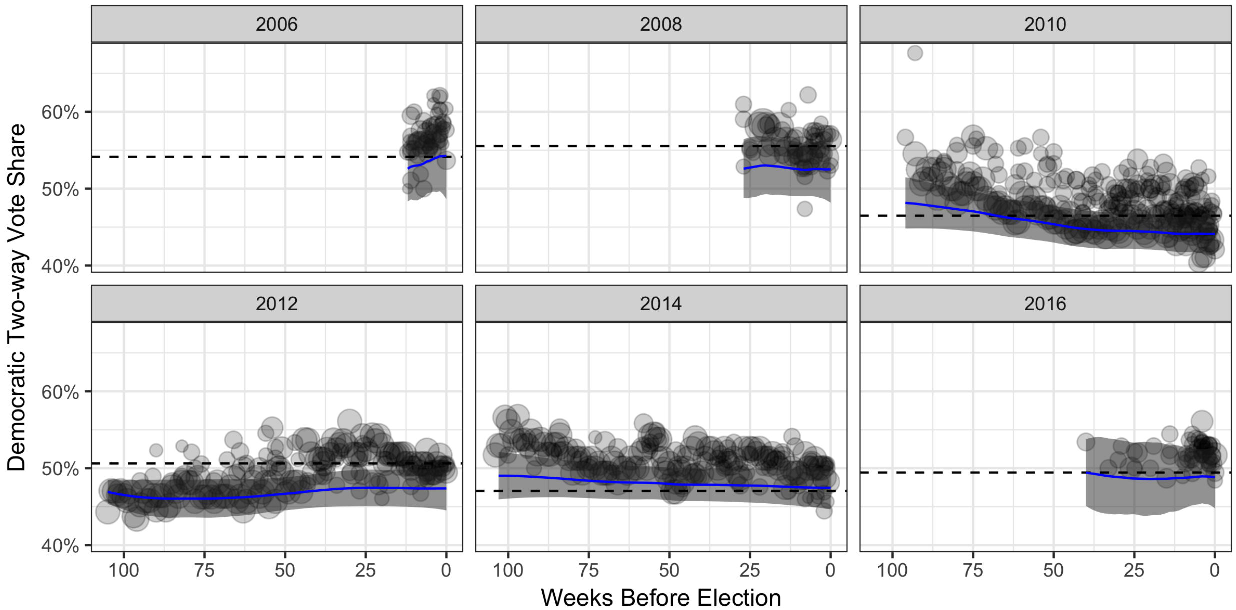


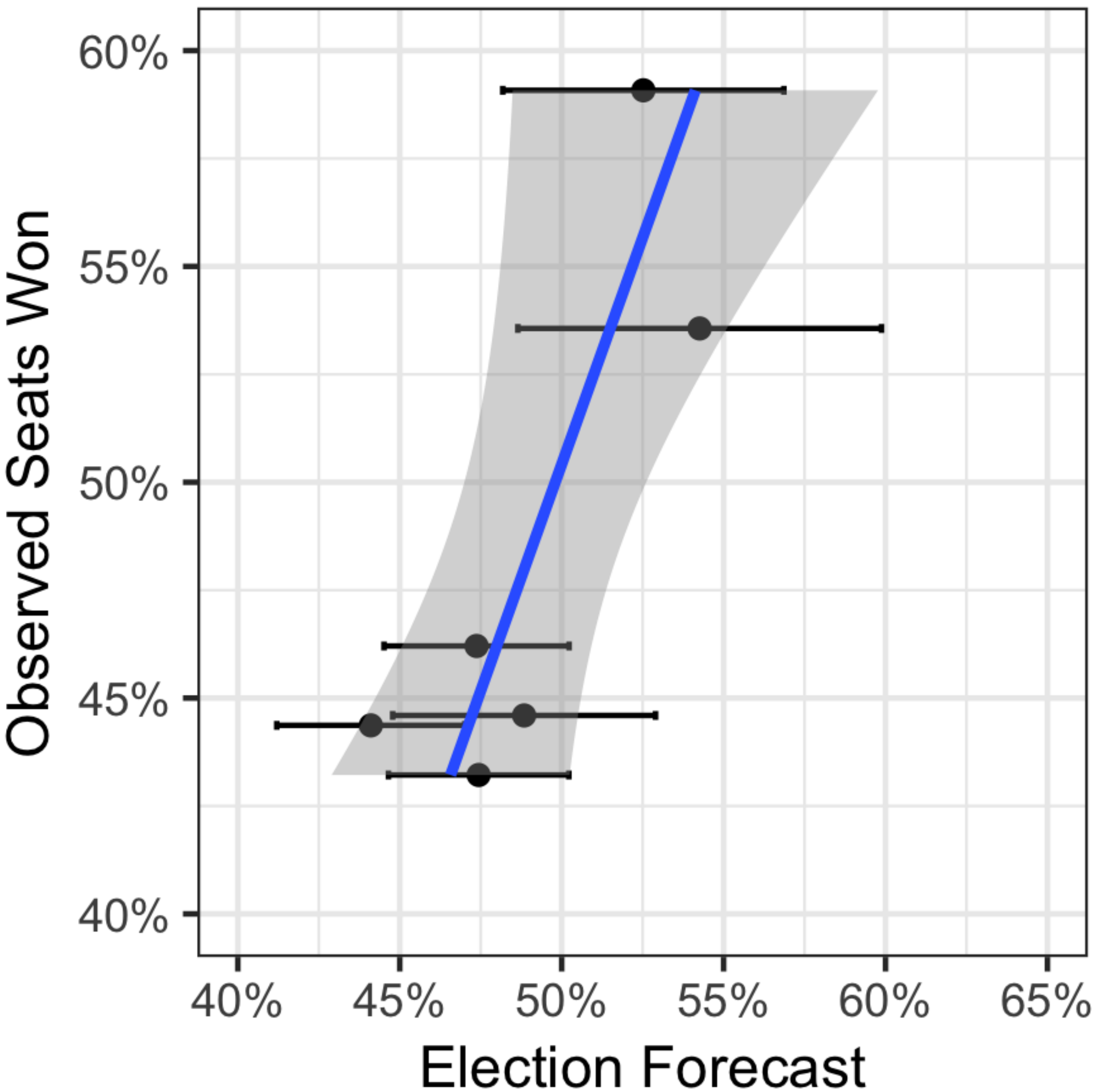
These trends were fairly stable over time. The rank order of the universes was the same for all elections except 2006. Both adult and registered voter universes were stable around their final estimate since the 2010 cycle. In 2010 and 2012, there was basically no bias in likely voter universes, but this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

  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]
      }
      } "
  }

  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)
```

```r
  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")) +
           (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'
```

```
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`)) %>%
```

```r
  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)
  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
}
```

```r
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   1.0000000000 1.000000000  1.0000000000
## Lag 10  0.2445259265 0.569077062  0.4630583553
## Lag 50  0.0627509373 0.157272682  0.0879823359
## Lag 100 0.0122757308 0.028920535  0.0211248974
## Lag 500 0.0008124322 0.001746556 -0.0007014931
```

```
## 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    1.0000000000 1.000000000 1.00000000
## Lag 10   0.0569999100 0.302573395 0.69595473
## Lag 50   0.0009719112 0.032511979 0.41597106
## Lag 100  0.0018236070 0.019730419 0.25180491
## Lag 500 -0.0014534723 0.002196649 0.03101867
```

```
## 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   1.000000000 1.00000000 1.00000000
## Lag 10  0.053331836 0.25897587 0.30702748
## Lag 50  0.004296288 0.13330088 0.14372717
## Lag 100 0.001192921 0.12604516 0.10560381
## Lag 500 0.002873576 0.07626071 0.04679898
```

```
## 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  0.018601569 0.05958484 0.8977321
## Lag 50  0.015362948 0.05666102 0.7840805
## Lag 100 0.013454749 0.05099776 0.7094229
## Lag 500 0.005899275 0.03552638 0.4602087
```

```
## 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  0.008939093 0.2069485 0.8570945
## Lag 50  0.005381014 0.2001767 0.6993678
## Lag 100 0.006466919 0.1900636 0.6004499
## Lag 500 0.001111191 0.1458464 0.3427827
```

```
## 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 1.000000e+00 1.000000000
## Lag 10  0.025349452 1.403155e-02 0.302718486
## Lag 50  0.012241025 9.025631e-03 0.096738011
## Lag 100 0.009137053 5.700552e-03 0.052714166
## Lag 500 0.002130057 9.788608e-06 0.008417222

## 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 -0.054082492 0.0033069401
##  2        2012 resurgen_republic -0.029966231 0.0053551393
##  3        2010         gallup_ht -0.027434046 0.0033364616
##  4        2010        mclaughlin -0.015596968 0.0082250323
##  5        2012  usa_today_gallup -0.014865011 0.0014064116
##  6        2016          fox_news -0.010851414 0.0005337405
##  7        2008      lat_bloomberg -0.010752850 0.0071090674
##  8        2016            ap_gfk -0.009505441 0.0029422690
##  9        2016      reuters_ipsos -0.008207589 0.0007298973
## 10        2016           cnn_orc -0.008200193 0.0007600370
## # ... 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 -0.0053994410 0.0239024667
## 43       2006                  ap_ipsos  0.0157478299 0.0139653485
## 44       2006              battleground -0.0195792257 0.0232985900
## 45       2006                   cbs_nyt  0.0341061905 0.0142404046
## 46       2006                   cnn_orc  0.0072736423 0.0118917629
## 47       2006                      cook  0.0258310256 0.0132160408
## 48       2006                 dem_corps -0.0120761702 0.0231696393
## 49       2006                  fox_news -0.0041738126 0.0118916536
## 50       2006                    gallup  0.0089264045 0.0250058697
## 51       2006                    harris  0.0149196423 0.0240908692
## 52       2006                   hotline -0.0012145421 0.0164731363
## 53       2006             lat_bloomberg  0.0014248029 0.0228454260
## 54       2006                   nbc_wsj  0.0081717774 0.0150138488
## 55       2006                  newsweek  0.0140308274 0.0127210159
## 56       2006                       pew  0.0071535934 0.0131662398
## 57       2006                quinnipiac  0.0003994740 0.0240879221
## 58       2006                 rasmussen -0.0093437028 0.0237809039
## 59       2006                      time  0.0151492203 0.0146195819
## 60       2006          usa_today_gallup -0.0189353254 0.0123708358
## 61       2006                     zogby -0.0034666847 0.0166064144
## 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  0.0044130048 0.0124559503
## 84          2008                     ap_gfk -0.0051361319 0.0102422239
## 85          2008                   ap_ipsos  0.0268302166 0.0081598450
## 86          2008                battleground -0.0114143198 0.0056199378
## 87          2008                    cbs_nyt  0.0311224816 0.0035408441
## 88          2008                    cnn_orc -0.0074962937 0.0054931039
## 89          2008                  dem_corps -0.0134178122 0.0035980148
## 90          2008                     diageo -0.0311831700 0.0171374775
## 91          2008                   fox_news -0.0120599291 0.0056922980
## 92          2008                     gallup  0.0021103650 0.0081507823
## 93          2008           gwu_battleground -0.0184640311 0.0050743773
## 94          2008              lat_bloomberg -0.0107528499 0.0071090674
## 95          2008                    nbc_wsj  0.0109198885 0.0033383056
## 96          2008                   newsweek -0.0002788923 0.0074246086
## 97          2008                        pew  0.0145290079 0.0070658221
## 98          2008                  rasmussen  0.0021947209 0.0023777081
## 99          2008                       time  0.0083117719 0.0078619910
## 100         2008           usa_today_gallup -0.0263898294 0.0047360558
## 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  0.0124346838 0.0043016165
## 125         2010                     ap_gfk -0.0085618200 0.0047541877
## 126         2010                battleground -0.0054568977 0.0042072726
## 127         2010                  bloomberg  0.0109500905 0.0038707806
## 128         2010                    cnn_orc -0.0091622237 0.0013938321
## 129         2010                  dem_corps  0.0064721475 0.0011147585
## 130         2010                     diageo  0.0294797325 0.0031037311
## 131         2010                   fox_news -0.0231178084 0.0013130816
```

```
## 132         2010                   gallup -0.0078837727 0.0009305075
## 133         2010                gallup_ht -0.0274340455 0.0033364616
## 134         2010                gallup_lt -0.0540824916 0.0033069401
## 135         2010        gwu_battleground -0.0032803839 0.0031958126
## 136         2010          ipsos_mcclatchy  0.0080732292 0.0033219658
## 137         2010        mcclatchy_marist -0.0035492308 0.0104151779
## 138         2010               mclaughlin -0.0155969684 0.0082250323
## 139         2010              nat_journal  0.0128119828 0.0080327680
## 140         2010                 newsweek  0.0144427624 0.0029023532
## 141         2010                      npr -0.0065881705 0.0063093903
## 142         2010                      pew  0.0022630465 0.0013736440
## 143         2010 politico_gwu_battleground  0.0128032840 0.0056631215
## 144         2010                      pos  0.0039021324 0.0060137553
## 145         2010                      ppp -0.0042676595 0.0020841491
## 146         2010               quinnipiac  0.0055335189 0.0019791175
## 147         2010                rasmussen -0.0151444796 0.0006491263
## 148         2010             reuters_ipsos  0.0025436536 0.0038342971
## 149         2010                     time  0.0005469444 0.0043049413
## 150         2010         usa_today_gallup -0.0144989275 0.0023623476
## 151         2010                  winston  0.0278174054 0.0154498295
## 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  0.0016464683 0.0023985781
## 166         2012                  cbs_nyt  0.0242119386 0.0030318131
## 167         2012                  cnn_orc -0.0095416208 0.0011300741
## 168         2012                dem_corps  0.0003992991 0.0006230319
## 169         2012                   gallup -0.0082331361 0.0008544447
## 170         2012        mcclatchy_marist -0.0036622698 0.0065453589
## 171         2012                 newsweek  0.0131862053 0.0025506902
## 172         2012                      npr -0.0100907762 0.0036390975
## 173         2012                      pew -0.0018327673 0.0011508790
## 174         2012 politico_gwu_battleground -0.0015086156 0.0011175978
## 175         2012                      ppp -0.0021782571 0.0013300846
## 176         2012               quinnipiac -0.0056641712 0.0009330094
## 177         2012                rasmussen -0.0102182180 0.0002875544
## 178         2012        resurgen_republic -0.0299662309 0.0053551393
## 179         2012             reuters_ipsos -0.0164479243 0.0012379731
## 180         2012         usa_today_gallup -0.0148650114 0.0014064116
## 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  0.0009864316 0.0025420721
## 207         2014                      ap_gfk -0.0163212617 0.0036690904
## 208         2014                   bloomberg  0.0018122605 0.0021179765
## 209         2014                     cbs_nyt  0.0092036278 0.0021380167
## 210         2014                     cnn_orc -0.0080201703 0.0008285321
## 211         2014                   dem_corps  0.0011214884 0.0005498969
## 212         2014                    fox_news -0.0133030756 0.0006416544
## 213         2014                      gallup -0.0079988321 0.0008106144
## 214         2014            gwu_battleground -0.0033372760 0.0018069458
## 215         2014             mcclatchy_marist -0.0029053013 0.0023037868
## 216         2014                     nbc_wsj  0.0107482927 0.0024659445
## 217         2014                         npr -0.0074355441 0.0030282995
## 218         2014                         pew  0.0008513936 0.0008763586
## 219         2014 politico_gwu_battleground -0.0012883977 0.0010435364
## 220         2014                         ppp  0.0004561586 0.0007762575
## 221         2014                  quinnipiac -0.0026901852 0.0005579591
## 222         2014                   rasmussen  0.0053570520 0.0001794830
## 223         2014                      reason -0.0049608450 0.0170263799
## 224         2014                usa_today_pew  0.0019524637 0.0047931919
## 225         2014              usa_today_psrai  0.0181515030 0.0174810583
## 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 -0.0016096123 0.0017909152
## 248        2016                   ap_gfk -0.0095054409 0.0029422690
## 249        2016                bloomberg -0.0002446860 0.0015497203
## 250        2016                  cbs_nyt  0.0082604509 0.0016469999
## 251        2016                  cnn_orc -0.0082001931 0.0007600370
## 252        2016         economist_yougov  0.0115274430 0.0016133524
## 253        2016                 fox_news -0.0108514135 0.0005337405
## 254        2016         gwu_battleground  0.0001052708 0.0013565419
## 255        2016          mcclatchy_marist  0.0006751487 0.0016442953
## 256        2016                  nbc_wsj  0.0035759539 0.0010757658
## 257        2016                      ppp  0.0002363241 0.0006755544
## 258        2016               quinnipiac -0.0037205807 0.0005153677
## 259        2016                rasmussen  0.0050592227 0.0001765328
## 260        2016            reuters_ipsos -0.0082075893 0.0007298973
## 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 0.01596482 0.0001329264
## 2        2016         RV 0.02338311 0.0002178063
## 3        2016     Adults 0.04763284 0.0018096272
```

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

```
##    theta_cycle theta_univ     theta_mu theta_sigma2
## 1            0         LV 0.0000000000 0.2000000000
## 2            0     Adults 0.0000000000 0.2000000000
## 3            0         RV 0.0000000000 0.2000000000
## 4         2006     Adults 0.0210996520 0.0110815541
## 5         2006         LV 0.0334382849 0.0101673765
## 6         2006         RV 0.0251190100 0.0118993805
## 7         2008     Adults 0.0254188895 0.0086206882
## 8         2008         LV 0.0106802193 0.0020426944
## 9         2008         RV 0.0159184790 0.0024556905
## 10        2010     Adults 0.0475875842 0.0030126012
## 11        2010         LV 0.0029033028 0.0005617518
## 12        2010         RV 0.0299013340 0.0007108394
## 13        2012     Adults 0.0462627603 0.0025626236
## 14        2012         LV 0.0006183682 0.0002668847
## 15        2012         RV 0.0193759507 0.0004051631
## 16        2014     Adults 0.0462067290 0.0025242212
## 17        2014         LV 0.0144001889 0.0001655448
## 18        2014         RV 0.0244048312 0.0002675046
## 19        2016     Adults 0.0476328388 0.0018096272
## 20        2016         LV 0.0159648153 0.0001329264
## 21        2016         RV 0.0233831102 0.0002178063
```

```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) {
```

```r
  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, params = c("xi"), anchor = F)
  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
summary(glm(twoway_seat ~ iter_mean, data = all_cycle_est %>%
  filter(time_before_elec == 0) %>%
  inner_join(avgs, by = "cycle")))
```

```
##
## Call:
## glm(formula = twoway_seat ~ iter_mean, data = all_cycle_est %>%
##     filter(time_before_elec == 0) %>% inner_join(avgs, by = "cycle"))
##
## Deviance Residuals:
##         1          2          3          4          5          6
## -0.021818   0.057698   0.028376   0.001066  -0.029729  -0.035593
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -0.2022     0.2434  -0.831   0.4529
## iter_mean     1.4000     0.4946   2.830   0.0473 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.001690536)
##
##     Null deviance: 0.0203039  on 5  degrees of freedom
## Residual deviance: 0.0067621  on 4  degrees of freedom
## AIC: -17.702
##
## Number of Fisher Scoring iterations: 2
```