Does Party Identification influence the Impact of Performance Information? Evidence from a large survey experiment in the field

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Party Identification and the Impact of Performance Information?

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Abstract

When governments publish performance information, they often expect to increase citizen satisfaction with public services. Yet, the impact of publishing performance information is uncertain. The cognitive heuristic of motivated reasoning has been demonstrated to affect judgment from performance information. The motivations for motivated reasoning can be manifold. This paper however focuses on party affiliation. Motivated reasoning predicts that supporters of the ruling coalition more strongly follow the lead provided by performance information. The data are collected from a large survey experiment in the field. We administered a survey on the satisfaction with local public services to all addresses in a Belgian municipality. An information leaflet with performance information was randomly added to half of the surveys. We obtained 3850 survey responses (a response rate of 24%). For the analysis, we estimate a Bayesian linear regression with an interaction effect for party identification. In contrast to previous research, we find no effects of the provision of performance information on citizen satisfaction. Party identification has a very small and uncertain effect on citizen satisfaction. In the discussion, we explore some potential explanations for the absence of the effect.

Introduction

In contemporary governance, the publication of performance information is seen as one of the core mechanisms to hold public organizations accountable (Boswell, 2018; Jakobsen, Baekgaard, Moynihan, & van Loon, 2018; Van Dooren, 2011). Performance information is expected to increase social pressure on organizations through comparison with a social reference group (Hong, 2019). Yet, accountability instruments such as the publication of performance information only work when there are account holders who pass judgments based on the information provided (Bovens, 1998; Grimmelikhuijsen & Meijer, 2014; Willems & Van Dooren, 2011). For public services, the account holders are the citizens who use and/or pay taxes to provide for the services. The many eyes of the citizenry have to keep performance in check. Yet, the vision of the account holder may be blurred. The theory of motivated reasoning explains why new information is not assimilated. Prior beliefs may cloud citizen's judgment of new information. Electoral research has shown that party identification is a strong motivator for biased reasoning. However, with the exception of James and Van Ryzin (2017), research that relates party identification to performance information and satisfaction is scarce.

The effects of performance information on citizens has been one of the prime concerns of behavioral public administration (see Moynihan 2017 and Kroll 2015 for an overview). Research that accounts for the political implications of performance information however is still an emergent topic in the study of performance information use (James 2011). Performance information is not politically neutral. The information always plays out in a political arena. Performance information may provide backing for some political positions while discrediting others. Therefore, this paper asks whether and how party affiliation affects the impact of performance information on citizen satisfaction.

This paper reports on a large survey experiment in the field. We randomly added performance information to a municipal satisfaction survey. Based on previous research, we expect a positive impact of the performance information. Next, we add an interaction effect for the party identification of the respondent. We expect that citizens who intend to vote for the coalition in power will more strongly be affected by the performance treatment than citizens who intend to vote for the opposition.

The article is structured as follows. We first use the literature on the attribution of blame to discuss how performance information becomes political. Next, we explore the empirical evidence on performance information, motivated reasoning and politics. The following section presents the analytical strategy. We use Bayesian regression to estimate probability densities of parameter estimates. Next we present the results. In the discussion, we explore theoretical and methodological explanations for the absence of an effect.

Performance information and the attribution of blame

Publishing performance information is consequential and hence becomes political (James & John, 2006; James & Moseley, 2014; Moynihan, 2009; Van de Walle & Roberts, 2008). Kogan et al. (2016) for instance show a signal of poor school district performance increases the probability of failure to levy taxes through referenda. This effect disproportionally affects less affluent communities. This is particularly problematic because the school district performance ranking does not allow voters to draw valid inferences about quality (Kogan et al., 2016). A study by Holbein (2016) also finds equity effects in publishing school performance data. Signals of poor school performance are more easily picked up by those who are white, affluent, and more likely to vote. A study by Nielsen & Moynihan finds that local councilors use rankings to hold schools accountable for low but not for high performance (2016). Publication of performance information has effect on citizens as well as on accountability and responsibility of public organizations.

One of the most prominent ways in which performance information becomes political is through mechanisms of blame attribution (Christopher Hood, 2010). In a study of front-line employees, Petersen et al. (2019) show how good performance leads to credit taking while poor performance triggers blame avoidance by discrediting the performance management regime. Low performers want to avoid being held accountable, while good performers want to take credit. Charbonneau and Bellavance (2012) show that mechanisms of blame avoidance occur even in safe environments with few incentives, no consequences linked to performance, and limited exposure to the citizenry

Opportunities for blame games abound (C. Hood & Dixon, 2010). Olsen (2015) finds that showing a 90 percent satisfaction rate for a public service leads to a more positive evaluation than a logically equivalent of 10 percent dissatisfaction. Presenting the negative logical equivalent of choice may hence lead someone having to digest the blame. Contrarily, the positive equivalent

avoids blame attribution. James and John (2006) find evidence of negativity bias amongst local voters in the UK, with poor performance resulting in punishment but excellent performance not being equally rewarded (see also: Boyne, James, John, & Petrovsky, 2009). Withholding information hence favors underperforming incumbents while publishing performance information puts them in the wind. James and Moseley (2014) find that performance reporting increases accountability when reports are comparative. Olsen (2017) adds that social reference is a stronger cue than historical comparison. In terms of blame avoidance, adding a benchmark may hence attribute or deflect blame; in particular when the comparison makes reference to peer organizations. James et al. (2016) show that providing citizens information of how a failed service is under bureaucratic oversight, reduced blame toward politicians. Yet, providing a vignette that puts the responsibility in the private sector does not reduce the attribution of blame to politicians (for public and private sector cues, see also: Hvidman, 2018). Apparently, it is easier for politicians to push blame down the hierarchy, than to relocate blame outside to private contractors.

Party affiliation and motivated reasoning.

Performance has political consequences for blame attribution and accountability. Yet, strategies of blame avoidance will only have an effect in the political market when the electorate is susceptible to performance information. This is not obvious. The electorate is not a blank slate that neutrally registers the score of the blame game. The electorate holds prior beliefs and will mostly likely resist performance information that is incongruent with prior beliefs (Tilley & Hobolt, 2011). Studies of party affiliation and partisanship suggest that party identification is such a prior belief, having a strong influence shaping citizens' perceptions of, and reactions to, the political world (Bartels, 2002). The mechanisms of motivated reasoning might explain the viscidity of public opinion.

Human reasoning is always motivated (Kunda 1990). By motivation is meant all wishes, desires or preferences that concern the outcome of a reasoning task. Motivations fall under two categories. First, reasoning can be driven by a desire to reach accuracy. In order to come to accurate conclusions, people expend cognitive effort, process information and use complex decision rules. Because of the cognitive effort needed, people will only engage in more thorough decision making when the stakes are high. The second category of reasoning is driven by directional goals. People are motivated to arrive at a particular conclusion and interpret evidence in that light. They attempt to be rational and to construct a justification of their desired conclusion. The objectivity of this justification construction process is illusory because people do

not realize that the process is biased by their goals (Kunda 1990: 483). When the outcome of the process of reasoning has lower stakes, people will be less inclined to expend the cognitive resources for reaching more accurate judgments and hence will be more susceptible to motivated reasoning. In practice, people almost never follow a accuracy-driven, hypothesis-testing framework in judgment (Nickerson, 1998). They update prior beliefs, with a bias towards those beliefs.

Evidence of ideologically-driven motivated reasoning is strong (A. S. Gerber & Huber, 2010; Slothuus & de Vreese, 2010). James (2011) In a survey experiment, James & Van Ryzin (2017) primed respondents with a political and a healthcare prime before they had to judge evidence on the Affordable Care act. The political prime widened the gap between Republicans' and Democrats' judgments of the strength of evidence favorable to the Affordable Care Act. Baekgaard and Serritzlew (2016) found that Danish citizens have difficulties in making a correct performance assessment of public and private hospitals and schools. When the mode of provision (public or private) does not align with their preferences for respectively public and private provisions, they make more mistakes in reading a comparative performance table. Nielsen and Moynihan (2016) studied how local councilors attribute blame for low performance to school principals. They found that a critique on the performance ranking by a trade union official canceled out the impact of the ranking, but only for liberal councilors that are ideologically close to the trade union. They conclude that the provision of performance data may encourage polarization among elected officials. In similar vein, Bartels (2002) found that partisanship reinforced sharp differences in opinion between Democrats and Republicans. Taber & Lodge (2006) identify a mechanism of motivated skepticism; when reading arguments for and against a prior belief, citizens argue against arguments that contradict their prior and uncritically accept arguments that support their political prior (Lodge and Taber 2013; Taber and Lodge 2006). In recent study, Christensen et al. (2018) identify another strategy for motivated reasoning. When elected officials are confronted with performance data, they reprioritize their goals.

Not all studies find evidence for partisan motivated reasoning. When confronted with unambiguous information, partisans can make accurate judgments. According to Redlawsk et al. (2010), citizens have an affective tipping point after which motivated reasoning ends. When continuously confronted with information that is incongruent with prior belief, anxiety grows and prior beliefs are updated. Bullock (2009) concludes that '*although most partisans are not Bayesians, their reactions to new information are surprisingly consistent with the ideal of Bayesian rationality*'. Barrows et.

al. (2016) found that the effect of performance information is a combination of priming and learning. Performance information is priming citizen evaluations in the direction of the information cue, but is also leading citizens to update prior beliefs about the quality of public services in a more rational way. Bisgaard (2015), however, nuances the absence of partisan motivated reasoning. While his study agrees that citizens are able to draw correct inferences from undisputable facts, he finds that partisan motivated reasoning gets back in by the backdoor when citizens attribute blame.

In our study, we study how the provision of performance information may lead to divergent judgments of performance in the electorate. We expect a positive impact of performance information on citizen satisfaction (James, 2011). In addition, based on theories of motivated reasoning, we also expect performance information to have a different effect for citizens that support the majority compared to citizens that support opposition parties.

Research Design and Analytical Strategy

The research design is a large survey experiment in the field. We added an experimental treatment to a satisfaction survey of a municipality. This strategy has been used in other research designs. Corbacho et al. (2016) analyze governmental corruption by embedding an experiment in a large-scale household survey. Brancati (2014) also conducted a field experiment with a post experimental face-to-face survey as dependent variable. The treatment was an information leaflet with performance information. The performance information consisted of four main categories presented in the following order: information on youth initiatives, performance results on streets and facilities for vulnerable road users, information on sports facilities in the municipality, and performance data on communication efforts.

The town of Schoten, our case study, is a wealthy municipality in the Antwerp suburbs with a total of 33,766 inhabitants (2017). The municipality has autonomous competences in fields of public education and childcare, social welfare, library services, local youth and elderly care, sport infrastructures, nature conservation, and municipal roads and public places. The services included in the performance information treatment are largely provided by the municipality. The political parties in power during the study were the Flemish nationalist NV.A (14/31 seats), the Christian democrats (8/31) and the liberal party Open VLD (1/31). Opposition parties were the extreme right Vlaams Belang (4/31), the greens Groen (2/31), and the social democratic party SP.A

(2/31). Hence, the majority was centre-right with a left wing opposition. The extreme-right is, as anywhere in Flanders, also in the opposition.

The outcome variable is based on five satisfaction items based on the American Customer Satisfaction Index (ACSI) (Anderson & Fornell, 2000). Van Ryzin (2004) and Van Ryzin et al. (2005) already applied this scale to the public, local level. The items in the ACSI model measure overall citizens' attitude towards government (see appendix). The satisfaction index is the factor score of a principal component analysis (PCA) on the five items of the ASCI. The first dimension of the PCA analysis explains 53% of the variance with four items. The factor scores of the first dimension are therefore used as the independent variable (see annex for the full PCA analysis).

The survey was organized in three steps. Participants received the following bits of information: (1) a short introduction to the study, (2) the treatment, being performance information on service delivery in the local municipality (both numerical, such as investments made, as the description of realizations in the municipality), and (3) a survey with questions on citizen attitude, intentional behavior and socio-demographics (including voting intentions). The control group received an identical survey, but without the performance information. Each household in the municipality received a survey version by post with a free return envelope. Respondents who filled in the printed versions could use the free return envelopes or could drop the surveys at several delivery points, such as public hall or the public library. Additionally, an online link to an online version of the survey was provided to maximize response rate. The participants were residents of the municipality of Schoten. The addressed population consisted of 16.000 households. We recorded 3805 usable responses.

We estimate a Bayesian regression with an interaction effect for the support for the ruling majority. One of the advantages of Bayesian inference is that interpretation of the estimated parameters is more intuitive (Gill & Witko, 2013; McElreath, 2015). Bayesian estimates provide the probability densities of a parameter value (e.g. an effect size) given the observed data. Inferential statistics do exactly the opposite. They provide the probability of the data, given an assumed parameter value (e.g. a null hypothesis). Typically, we are more interested in the probability of the parameter than in the probability of the data (see Gill & Witko 2013 for a discussion). An added benefit of Bayesian estimation is that we do not have to rely on the significance levels for inference, but can directly interpret the probability distribution of the

parameters[1]. We use the rethinking package in R that accompanies the handbook by Richard McElreath (2016). The full analysis and annotated code is provided in appendix.

Results

We first study whether citizen satisfaction is influenced by the provision of performance information. The linear model uses a normally distributed likelihood; assuming that the probability of the mean satisfaction level at different values of the predictor is normally distributed. The prior for the effect size is broad and positive, in line with the assumption that the publishing performance information has a positive effect on satisfaction. The intercept and the standard deviation of the likelihood have uninformative priors.

$Y \sim Normal(\mu, \sigma)$ [likelihood]

$\mu_i = \alpha + \beta x_i$ [linear model]

$\alpha \sim Normal(50,100)$ [α prior]

$\beta \sim Normal(0,1)$ [β prior]

$\sigma \sim Unif(0,10)$ [σ prior]

The results point in the direction of an absence of an effect (Table 1). The effect of the treatment is negligible (-0.04) and in the midst of the credible interval, which tells us that 95% of the effect sizes, given de model and the data, lie between -0,31 and 0,23. With 95% certainty, we can assert that the effect of the treatment did shift satisfaction somewhere between -0,34 and 0,23 points on a 0 to 35 scale.

	Mean	StDev	2,5%	97,5%
α [intercept]	0,00	0.04	-0.08	0.09
β [effect]	-0.01	0.06	-0.13	0.12
σ [SE likelihood]	1,63	0.02	1,59	1,68

Table 1: Posterior mean (maximum a posteriori) and credible interval of the parameter estimates of the linear model with only the treatment and the outcome variables (n=2593).

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[1] Bayesian estimation updates a prior probability distribution of parameter values in the light of new data, making use of a likelihood function. A prior distribution hence needs to be defined. We use uninformative prior probability distributions; a practice that is generally not advised. In our study, the prior is not very important. With a sample of 2593 observations, the data overwhelms the prior. Different priors lead to very similar results.

In the second model, we add an interaction term that reflects whether respondents support the coalition in power. We expect that performance information will strengthen satisfaction of those who already are supportive of the majority in power. The linear model is extended to include both the Treatment variable (T) and the Party variable (P). The slope of T is again a linear model. The prior of the strength of the interaction effect (β_{PT}) is broad and positive, because we expected that support for the coalition would increase the effect of treatment.

$$Y \sim Normal(\mu, \sigma) \qquad \text{[likelihood]}$$
$$\mu_i = \alpha + \gamma_i T_i + \beta_P P_i \qquad \text{[linear model]}$$
$$\gamma_i = \beta_T + \beta_{PT} P_i \qquad \text{[linear model of the slope]}$$
$$\alpha \sim Normal(50,100) \qquad \text{[α prior]}$$
$$\beta T \sim Normal(0,1) \qquad \text{[βT prior]}$$
$$\beta P \sim Normal(0,1) \qquad \text{[βP prior]}$$
$$\beta PT \sim Normal(0,1) \qquad \text{[βPT prior]}$$
$$\sigma \sim Unif(0,10) \qquad \text{[σ prior]}$$

Evidence for the hypothesized interaction effect is negligible (Table 2). The credible interval includes zero, which means that 95% of the probability mass of the posterior distribution of the βPT lies between -0,21 and +0,79. The chances of having a positive interaction effect of supporting the majority are higher of having a negative effect. A comparison of the effects (γ) of citizen who intend to vote for the coalition and others learns that the most plausible value (the maximum a posteriori value) for the supporters of the coalition is 0.13, while the effect for opposition voters is -0,16. The sign of the slopes changes, but the effect is again so small that it seems safe to say that the treatment did not play out differently in the two groups.

	Mean	StDev	2,5%	97,5%
α [intercept]	- 0.51	0,07	-0.64	-0.38
βT [effect of treatment]	-0,08	0,10	-0,27	0,11
βP [effect of majority support]	0.86	0,09	0.69	1,03
βPT [interaction effect]	0,12	0,12	-0,12	0,36
σ [SE likelihood]	1.57	0,02	1.53	1.61

Table 2: Posterior mean (maximum a posteriori) and credible interval of the parameter estimates of the linear model with the treatment and an interaction effect for coalition support on the outcome variables (n= 2593)
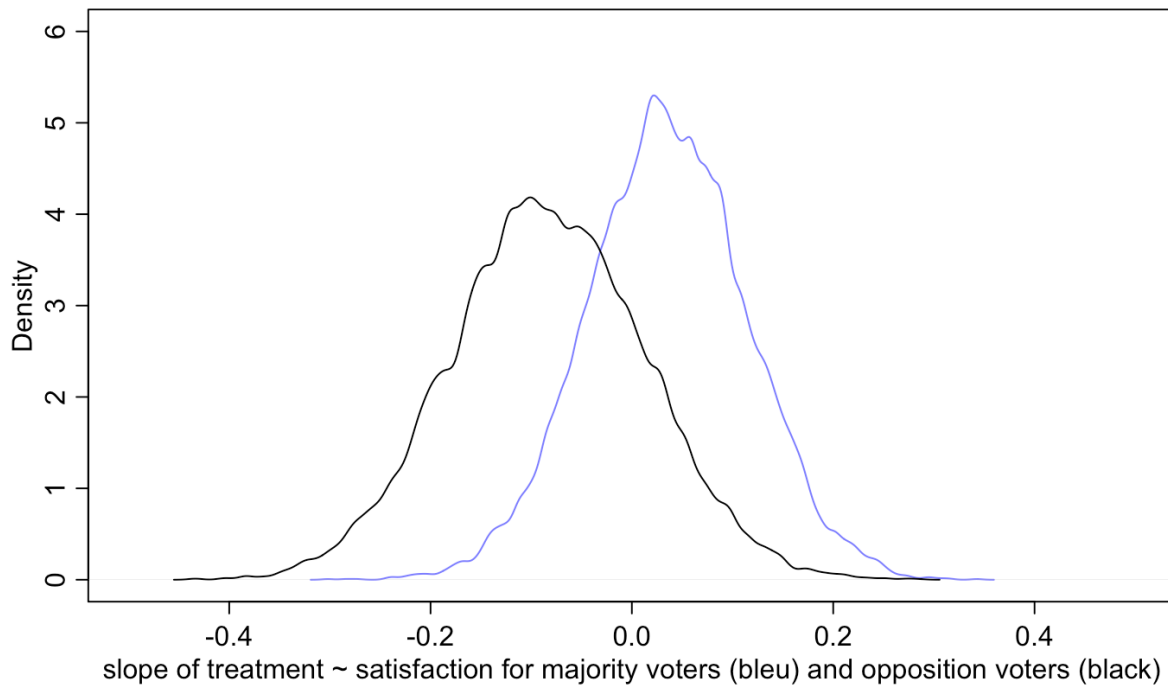
Figure 1: probability density function of the treatment effect on satisfaction amongst supporters of the coalition (bleu) and opposition (black).

Figure 1 reflects the uncertainty around the slope (γ). The probability densities of both groups overlap strongly, which means that there is a lot of uncertainty around the estimates. Yet, the distribution hints at an interaction effect. The parameter value with the highest probability is slightly positive for the supporters of the majority, while the parameter value with highest probability is slightly negative for the supporters of the opposition parties. Given the uncertainty around the estimates, we have to use extreme caution when interpreting this result.

Discussion

We tested in a large survey experiment in the field (n=2593) whether adding positive performance information to a satisfaction survey increases satisfaction levels. We also tested whether supporters of the coalition in power are more susceptible to the performance cues compared to those citizens supporting opposition parties. Theories of motivated reasoning would expect this to be the case. Support for a coalition, may lead supporters to seek confirmation in performance data. Contrary to previous studies, we did not find an effect of the provision of performance information. We also did not find evidence for the interaction effect of political orientation. Only a very modest hint of an interaction effect could be observed. This is surprising, given that the large sample size would allow for identifying small effects.

Why is there no effect? Several ex-post explanations can be provided; explanations that may inform future research. First, the dependent variable is general satisfaction and not a concrete judgmental task related to the treatment. An advantage of the use of a general satisfaction measure is that respondents will not make a link between the performance information provided and the dependent variable. The study therefore does not suffer from experimenter demand effects. A disadvantage is that the outcome variable is less responsive. Implicit attitudes toward government and the public sector have a profound effect on perceptions about public sector performance (Marvel, 2016). These implicit attitudes may overwhelm the effect of showing some performance data.

Secondly, there are several measures of how of citizens evaluate government; most notably satisfaction, trust and subjective performance assessments. In line of research of Kampen et al., REF, we assumed that measures of satisfaction, trust and general performance show strong correlations; reflecting an underlying attitude towards government. Yet, maybe this assumption is not tenable. For instance, research suggests that the mere provision of a logo may have a positive impact on evaluations of trust, not satisfaction or performance evaluations (Alon-Barkat & Gilad, 2017).

Thirdly, and related to the previous point, the treatment may not have be strong enough. The performance information leaflet could easily be skipped when filling out the survey. In order to explore this point, we ran our analysis on the subset of 902 online surveys. For these surveys, we know how long people take to fill out the entire survey. If people take longer, the chances are higher that the exposure to the treatment has been substantial. When we rerun the analysis on a subset of 358 respondents that took at least 10 minutes to fill out the online survey and, the interaction effect is becoming stronger. The effects are still not strong, but may hint to some motivated reasoning after all. The effect of the treatment without the political interaction effect remains close to zero, which is not unsurprising given that the slopes of the interaction effects work in opposite directions.
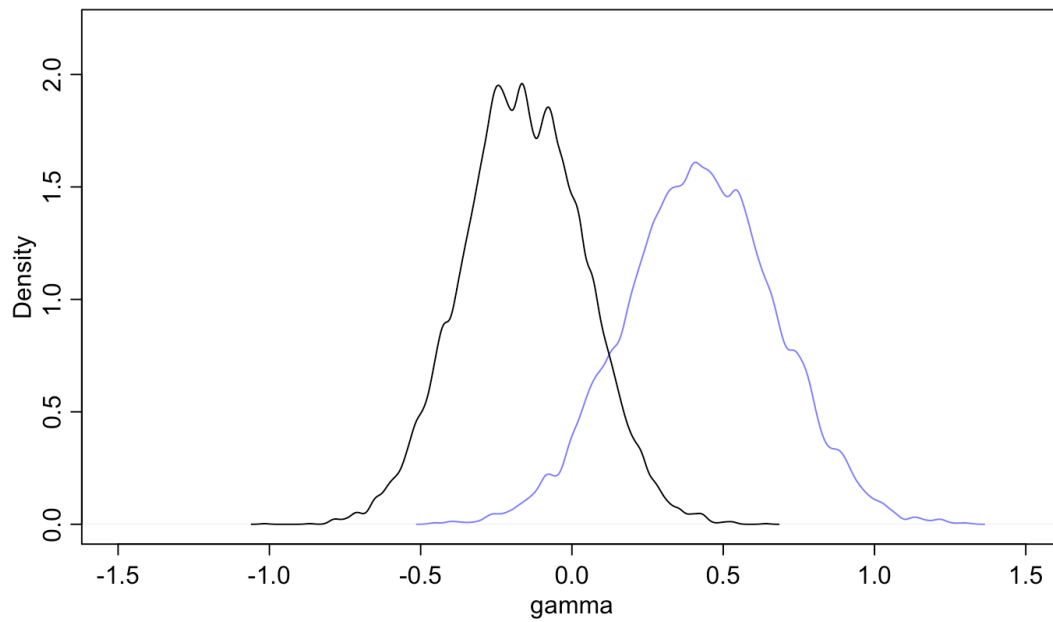
Figure 2: Explorative analysis of the interaction effect for online surveys with longer exposure to the treatment (> 10 min to fill out the survey) (n= 358). The interaction effect becomes stronger. Probability density functions of for the treatment effect in the opposition group (black) and the majority group (bleu) diverge.

Fourthly, the performance indicators were mostly positively framed. Previous research on negativity bias in processing performance information however suggests that bad performance attracts more attention than good performance (James & Van Ryzin, 2017; Holm 2018). Polictical science research has found that people only update prior beliefs when stakes are high and information is novel, credible, strong (Bullock, 2009; A. Gerber & Green, 1999). Holm (2018) also finds evidence of a focus on low goals with performance.

Fifthly, some countervailing heuristics may have been at work. An alternative theory that might inform the interaction effect between performance information and citizen satisfaction is the Expectation-Disconfirmation Model (Andersen & Hjortskov, 2016). The expectation-disconfirmation would suggest that performance is more influential when performance information is surprising (James, 2011). For opposition voters, good performance data may come as a bigger surprise and hence may attract more attention compared to majority voters. For majority voters, good performance information may have confirmed their expectations and therefore the data may have attracted less attention.

Sixthly, the measure of support for the majority is based on voting intentions? A measure of voting intentions however may be noisy. We did specify in the question on voting intentions that we probed for elections for the local council. Yet, regional and federal political debates may influence voting intentions in local elections.

This study provides strong evidence for the absence of an effect of performance information on satisfaction. This result does not confirm a substantial empirical literature suggesting that performance information does have an impact. We also find no string evidence for motivated reasoning, although some very exploratory analysis might suggest that a political bias may be at play. While mostly a null finding, we hope that our work still has a contribution to make to the evidence base of behavioral public administration and the effects of publishing performance information.

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ANNEX: Does Party Identification influence the Impact of Performance Information?

paper for the PMRC 2019

Packages

- *Haven* for importing SPSS file

- *Tidyverse* for data wrangling (dplyr) and visualisation (ggplot2)

- *baseR* for linear modelling

- *Rethinking* for Bayesian estimation - McElreath, R. (2016) Statistical Rethinking: A Bayesian course with examples in R and Stan. Taylor and Francis: London.
- *FactoMiner* for PCA

```r
library(haven)
library(tidyverse)
library(rethinking)
library(rstan)
library(FactoMineR)
```

Data

Original file is an SPSS file

```r
data <- read_spss("READ ONLY Tevredenheidsonderzoek Schoten.sav")
```

Data Wrangling and Variables

Dependent variable is the summation of five likert variables (1-7) that measure citizen satisfaction based on the American Consumer Satisfaction survey

- "I have high expectations of the municipality to meet my needs and those of my household." (expectations)
- "I consider municipal service delivery of high quality."" (quality)
- "In general, I am satisfied with the municipality." (satisfaction)
- "I belief the municipality can fulfill my expectations about service delivery." (expectations)
- "I have confidence in the people running the municipality." (confidence)

Independent variable is the treatment (1)/control (0) Interaction effect with political affiliation

```r
modeldata <- data.frame(version=numeric(3850), party=character(3850))
modeldata <- bind_cols(modeldata, data[,c(6,58:62)])
modeldata <- select(data,c(15,6,110,58:62))
modeldata <- mutate(modeldata, rulingparty = ifelse(Partij == "NA", "NA",
                                        ifelse(Partij %in% c(1,3,5),1,
                                            ifelse(Partij %in% c(-2,-1,0),NA,0))))

modeldata[4:8] <- sapply(modeldata[4:8],as.numeric) #coerce to numeric
```

```r
modeldata <- filter(modeldata, Versie %in% c(0,1))

modeldata <- modeldata %>%
  filter(!is.na(Partij))%>%
  filter (!is.na(ACSI_verwacht))%>%
  filter (!is.na(ACSI_kwaliteit))%>%
  filter (!is.na(ACSI_dienstenverbeterd))%>%
  filter (!is.na(ACSI_algemenetevredenheid))%>%
  filter (!is.na(ACSI_vertrouwen))%>%
  filter (!is.na(rulingparty))

modeldata <- as.data.frame(modeldata)
```

## descriptives

```r
summary(modeldata)
```

```
##      Versie       Duration__in_seconds_    Partij       ACSI_verwacht
## Min.   :0.0000   Min.   :    147.0     Min.   :1.000   Min.   :1.000
## 1st Qu.:0.0000   1st Qu.:    436.0     1st Qu.:1.000   1st Qu.:4.000
## Median :0.0000   Median :    555.0     Median :2.000   Median :5.000
## Mean   :0.4817   Mean   :   1160.9     Mean   :3.347   Mean   :5.058
## 3rd Qu.:1.0000   3rd Qu.:    773.8     3rd Qu.:6.000   3rd Qu.:6.000
## Max.   :1.0000   Max.   :260253.0      Max.   :9.000   Max.   :7.000
##                  NA's   :1689
## ACSI_kwaliteit  ACSI_dienstenverbeterd ACSI_algemenetevredenheid
## Min.   :1.000   Min.   :1.00           Min.   :1.000
## 1st Qu.:5.000   1st Qu.:4.00           1st Qu.:6.000
## Median :5.000   Median :5.00           Median :7.000
## Mean   :5.304   Mean   :4.86           Mean   :6.343
## 3rd Qu.:6.000   3rd Qu.:6.00           3rd Qu.:7.000
## Max.   :7.000   Max.   :7.00           Max.   :7.000
##
## ACSI_vertrouwen  rulingparty
## Min.   :1.000   Min.   :0.0000
## 1st Qu.:5.000   1st Qu.:0.0000
## Median :6.000   Median :1.0000
## Mean   :5.705   Mean   :0.6008
## 3rd Qu.:7.000   3rd Qu.:1.0000
## Max.   :7.000   Max.   :1.0000
##
```
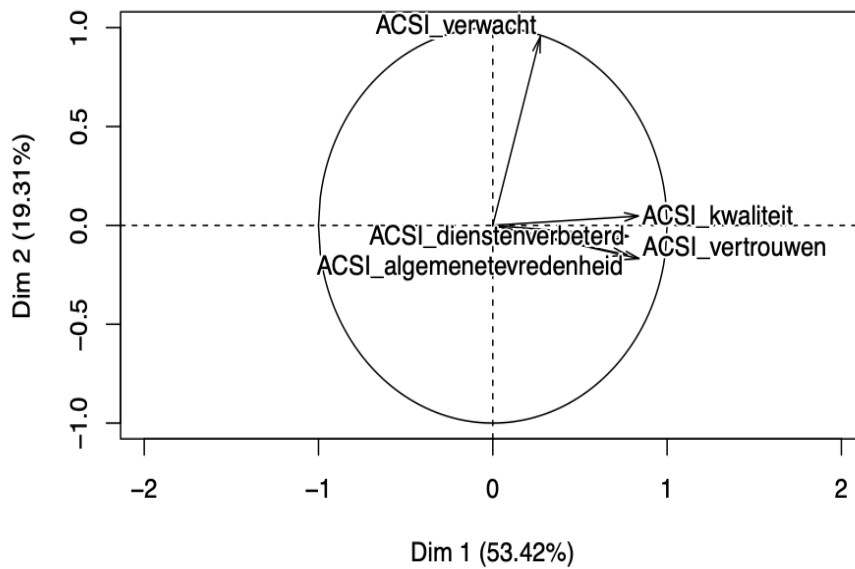
Principal Component Analysis of Dependent Variable

```
pca <- PCA(modeldata[4:8])
```

Individuals factor map (PCA)
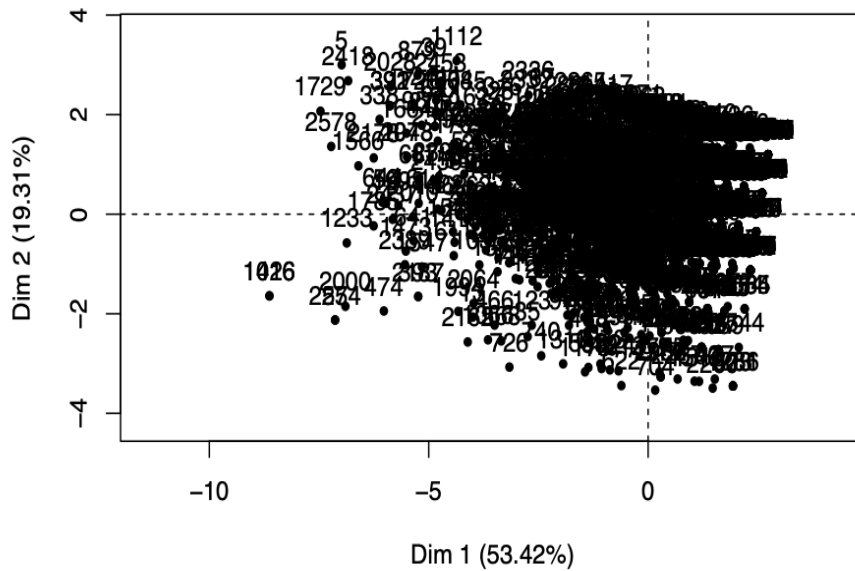
Variables factor map (PCA)


```
pca$eig
```

```
##         eigenvalue percentage of variance cumulative percentage of variance
```

```
## comp 1  2.6710441           53.420883              53.42088
## comp 2  0.9654697           19.309393              72.73028
## comp 3  0.6708285           13.416570              86.14685
## comp 4  0.3563752            7.127503              93.27435
## comp 5  0.3362825            6.725651             100.00000
```

```
modeldata$satisfaction_PCA <- pca$ind$coord[,1]
modeldata$satisfaction_PCA2 <- pca$ind$coord[,2]
```

Estimation of a model with only the Treatment variable

Treatment Variable reflects whether performance information provided (1) or not (0)

model	
$Y \sim Normal(\mu, \sigma)$	[likelihood]
$\mu_i = \alpha + \beta x_i$	[linear model]
$\alpha \sim Normal(50, 100)$	[α prior]
$\beta T \sim Normal(0, 1)$	[βT prior]
$\sigma \sim Unif(0, 10)$	[σT prior]

```
m1 <- rethinking::map(
  alist(
    satisfaction_PCA ~ dnorm(mu, sigma) ,
    mu <- a + bT*Versie,
    a ~ dnorm (50,100) ,
    bT ~ dnorm (0,1) ,
    sigma ~ dunif (0,10)
  ),
  data = modeldata )

precis(m1, prob = 0.95)
```

```
##        Mean StdDev  2.5% 97.5%
## a      0.00   0.04 -0.08  0.09
## bT    -0.01   0.06 -0.13  0.12
## sigma  1.63   0.02  1.59  1.68
```

```
WAIC(m1)
```

```
## [ 100 / 1000 ]
[ 200 / 1000 ]
[ 300 / 1000 ]
[ 400 / 1000 ]
[ 500 / 1000 ]
[ 600 / 1000 ]
[ 700 / 1000 ]
[ 800 / 1000 ]
[ 900 / 1000 ]
[ 1000 / 1000 ]
```

```
## [1] 9913.764
## attr(,"lppd")
## [1] -4952.467
```
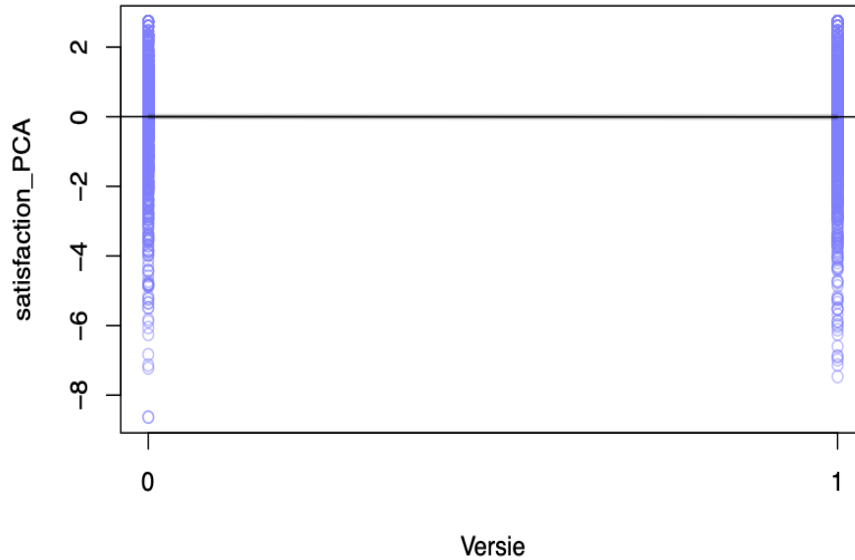
```
## attr(,"pWAIC")
## [1] 4.414845
## attr(,"se")
## [1] 106.4095
```

WAIC: first value is WAIC value

Plotting the model

```r
# mu is a matrix with 1000 samples (rows) from the posterior that compute average for values on X axis
version.seq <- c(0,1)

mu <- link(m1, data = data.frame(Versie = version.seq))
```

```
## [ 100 / 1000 ]
[ 200 / 1000 ]
[ 300 / 1000 ]
[ 400 / 1000 ]
[ 500 / 1000 ]
[ 600 / 1000 ]
[ 700 / 1000 ]
[ 800 / 1000 ]
[ 900 / 1000 ]
[ 1000 / 1000 ]
```

```r
str(mu)
```

```
##  num [1:1000, 1:2] -0.07601 -0.04874 0.01906 -0.00609 0.12497 ...
```

```r
# summarize the distribution of mu
mu.mean <- apply( mu , 2 , mean )
mu.HPDI <- apply( mu , 2 , HPDI , prob=0.95 )


# plot raw data
# fading out points to make line and interval more visible
plot( satisfaction_PCA ~ Versie , data=modeldata , col=col.alpha(rangi2,0.5), xaxt="n")
abline ( a = coef(m1)["a"], b=coef(m1)["bT"])
axis(1, at=c(0,1),labels=c(0,1))

# plot the MAP line, aka the mean mu for each weight
lines( version.seq , mu.mean )

# plot a shaded region for 99% HPDI
shade( mu.HPDI , version.seq )
```

Estimation of a model with an interaction effect for Party identification.

The model estimates satisfaction (Y) as function of the treatment T (no performance info (0) performance info (1) and the party preference P (opposition party (0), ruling party (1). The slope γ_i represents the treatment effect (slope) as a function of the party preference.

model	
$Y \sim Normal(\mu, \sigma)$	[likelihood]
$\mu_i = \alpha + \gamma_i T_i + \beta_P P_i$	[linear model]
$\gamma_i = \beta_T + \beta_{PT} P_i$	[linear model of the slope]
$\alpha \sim Normal(50, 100)$	[α prior]
$\beta T \sim Normal(0, 1)$	[βT prior]
$\beta P \sim Normal(0, 1)$	[βP prior]
$\beta TP \sim Normal(0, 1)$	[βTP prior]
$\sigma \sim Unif(0, 10)$	[σT prior]

```r
m2 <- rethinking::map(
  alist(
    satisfaction_PCA ~ dnorm(mu, sigma) ,
    mu <- a + gamma*Versie +bP*rulingparty ,
    gamma <- bT + bTP*rulingparty ,
    a ~ dnorm (50,100) ,
    bT ~ dnorm (0,1) ,
    bP ~ dnorm (0,1) ,
    bTP ~ dnorm (0,1) ,
    sigma ~ dunif (0,10)
  ),
  data = modeldata )

precis(m2, prob = 0.95)
```

```
##         Mean StdDev  2.5% 97.5%
## a      -0.51   0.07 -0.64 -0.38
## bT     -0.08   0.10 -0.27  0.11
## bP      0.86   0.09  0.69  1.03
## bTP     0.12   0.12 -0.13  0.36
## sigma   1.57   0.02  1.53  1.61
```

```
WAIC(m2)
```

```
## [ 100 / 1000 ]
[ 200 / 1000 ]
[ 300 / 1000 ]
[ 400 / 1000 ]
[ 500 / 1000 ]
[ 600 / 1000 ]
[ 700 / 1000 ]
[ 800 / 1000 ]
[ 900 / 1000 ]
[ 1000 / 1000 ]
```

```
## [1] 9711.607
## attr(,"lppd")
## [1] -4849.605
## attr(,"pWAIC")
## [1] 6.198433
## attr(,"se")
## [1] 104.0835
```

Plotting the interaction effects

First, calculate posterior mean line and interval

```
version.seq <- c(0,1)
mu.Party <- link( m2 , data=data.frame(rulingparty=1,Versie=version.seq) )
```

```
## [ 100 / 1000 ]
[ 200 / 1000 ]
[ 300 / 1000 ]
[ 400 / 1000 ]
[ 500 / 1000 ]
[ 600 / 1000 ]
[ 700 / 1000 ]
[ 800 / 1000 ]
[ 900 / 1000 ]
[ 1000 / 1000 ]
```

```
mu.Party.mean <- apply( mu.Party , 2 , mean )
mu.Party.PI <- apply( mu.Party , 2 , PI , prob=0.95 )
mu.NotParty <- link( m2 , data=data.frame(rulingparty=0,Versie=version.seq) )
```

```
## [ 100 / 1000 ]
[ 200 / 1000 ]
[ 300 / 1000 ]
[ 400 / 1000 ]
```

```
[ 500 / 1000 ]
[ 600 / 1000 ]
[ 700 / 1000 ]
[ 800 / 1000 ]
[ 900 / 1000 ]
[ 1000 / 1000 ]
```

```
mu.NotParty.mean <- apply( mu.NotParty , 2 , mean )
mu.NotParty.PI <- apply( mu.NotParty , 2 , PI , prob=0.95 )
```

Next, make plot

```
# plot Party support for ruling party with regression
d.P1 <- modeldata[modeldata$rulingparty==1,]
plot( satisfaction_PCA ~ Versie , data=d.P1 ,
    col=rangi2 , ylab="Satisfaction" ,
    xlab="Treatment", xaxt = "n" )
mtext( "Vote for coalition" , 3 )
lines( version.seq , mu.Party.mean , col=rangi2 )
shade( mu.Party.PI , version.seq , col=col.alpha(rangi2,0.3) )
axis(1, at=c(0,1),labels=c(0,1))
```
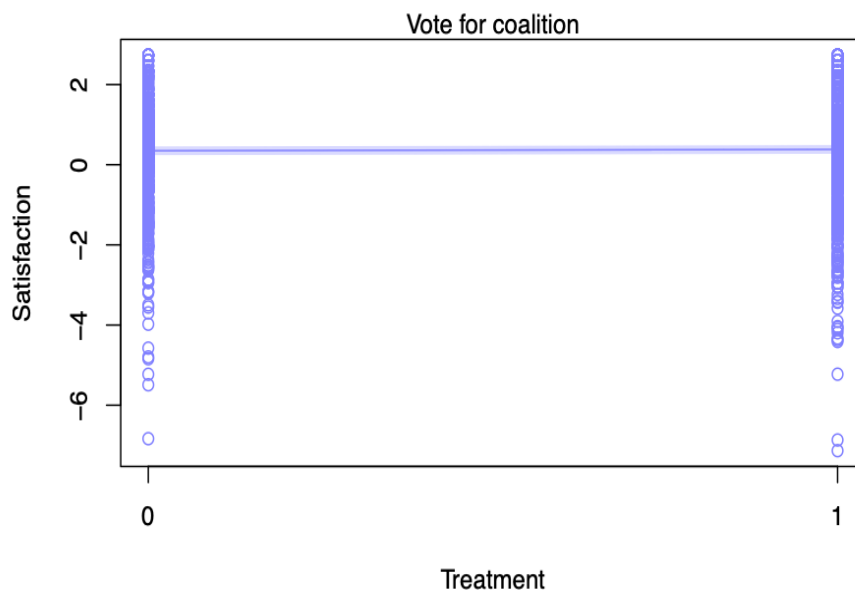

Vote for coalition

```
# plot no support for ruling party with regression
d.P0 <- modeldata[modeldata$rulingparty==0,]
plot( satisfaction_PCA ~ Versie , data=d.P0 ,
    col=rangi2 , ylab="Satisfaction" ,
    xlab="Treatment", xaxt = "n" )
mtext( "No vote for coalition" , 3 )
lines( version.seq , mu.NotParty.mean , col=rangi2 )
shade( mu.NotParty.PI , version.seq , col=col.alpha(rangi2,0.3) )
axis(1, at=c(0,1),labels=c(0,1))
```

No vote for coalition

Treatment
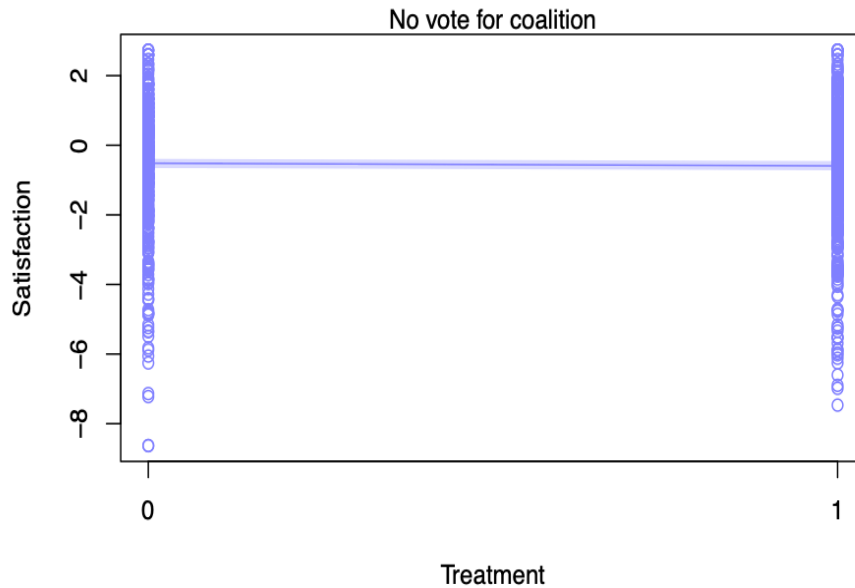
Finally, calculate and plot Uncertainty around these point estimates

```
# samples from the posterior to calculate gamma's for Party (1) and NotParty (0)
post <- extract.samples(m2)
gamma.Party <- post$bT + post$bTP*1
gamma.NotParty <- post$bT

# mean = same as hand calculated
mean(gamma.Party)
```

```
## [1] 0.03505784
```

```
mean( gamma.NotParty)
```

```
## [1] -0.08479973
```

```
# plot

dens ( gamma.Party, xlim = c(-0.5,0.5), ylim= c(0,6),
      xlab="slope of treatment ~ satisfaction for majority voters (bleu) and opposition voters (black)"
dens ( gamma.NotParty, add = TRUE)
```
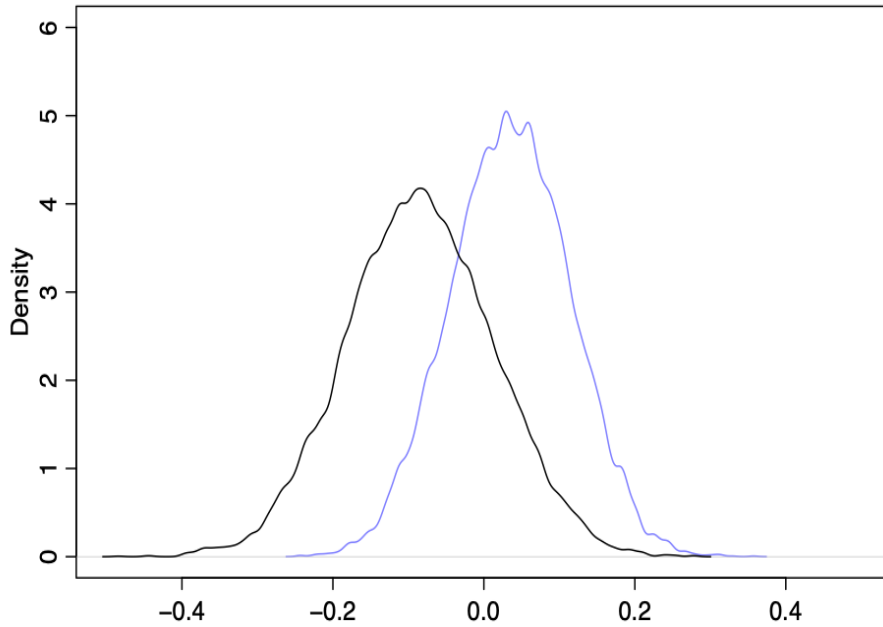
slope of treatment ~ satisfaction for majority voters (bleu) and opposition voters (black

```
#difference in slope. What is the probability that the slope within the supportrs of the majority (Party
```

```
diff <- gamma.Party - gamma.NotParty
sum (diff < 0)/length(diff)
```
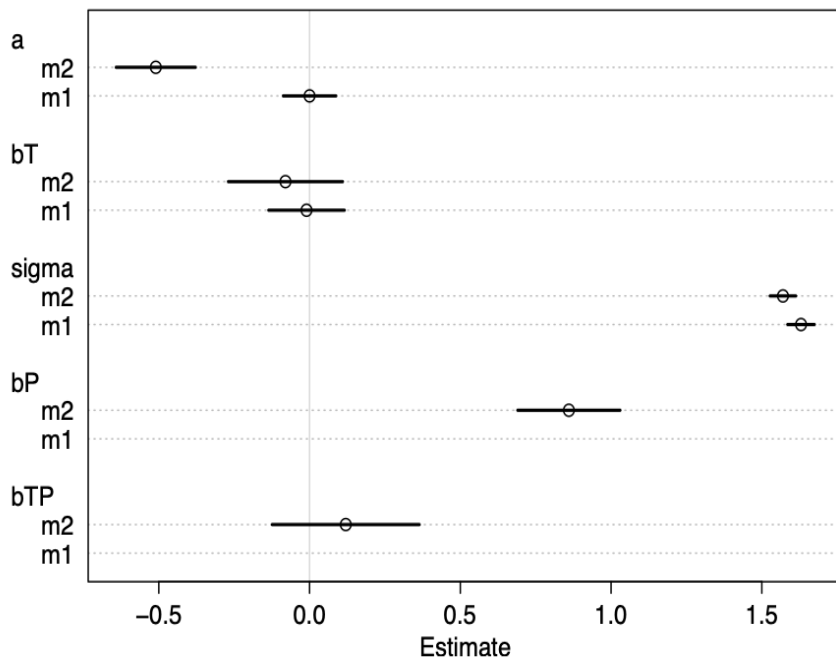
```
## [1] 0.1669
```

compare models

```
comparison <- compare(m1,m2)
comparison
```

```
##      WAIC pWAIC dWAIC weight     SE    dSE
## m2 9711.9   6.4   0.0      1 104.01     NA
## m1 9913.2   4.1 201.3      0 106.21  28.06
```

```
plot(comparison, SE=TRUE, dSE=TRUE)
```

```
plot(coeftab(m1,m2))
```


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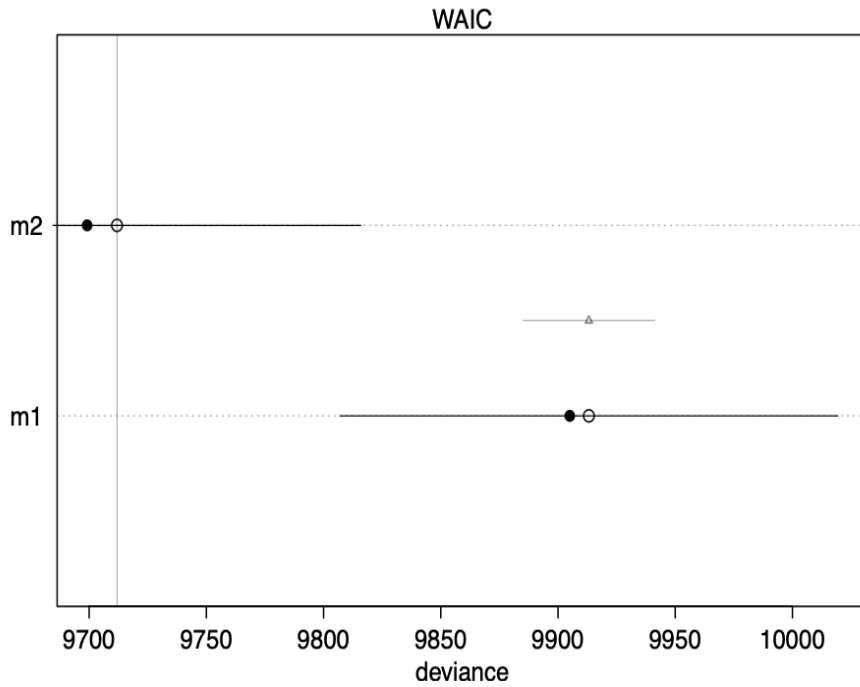
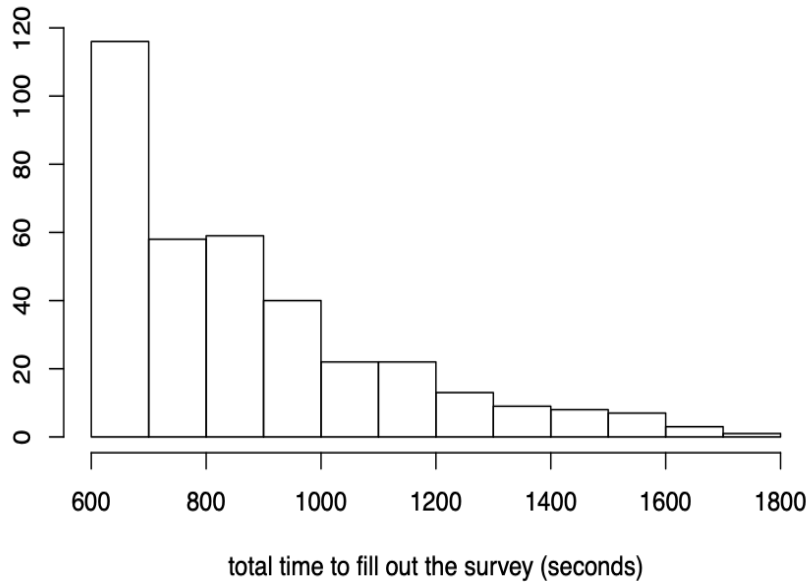# Exposuredata based on online surveys

Data Wrangling and Variables

```
exposuredata_0 <- filter(modeldata, !is.na(modeldata$Duration__in_seconds_))

hist(exposuredata_0$Duration__in_seconds_, xlab = "total time to fill out the survey (seconds)", ylab =
```


total time to fill out the survey (seconds)
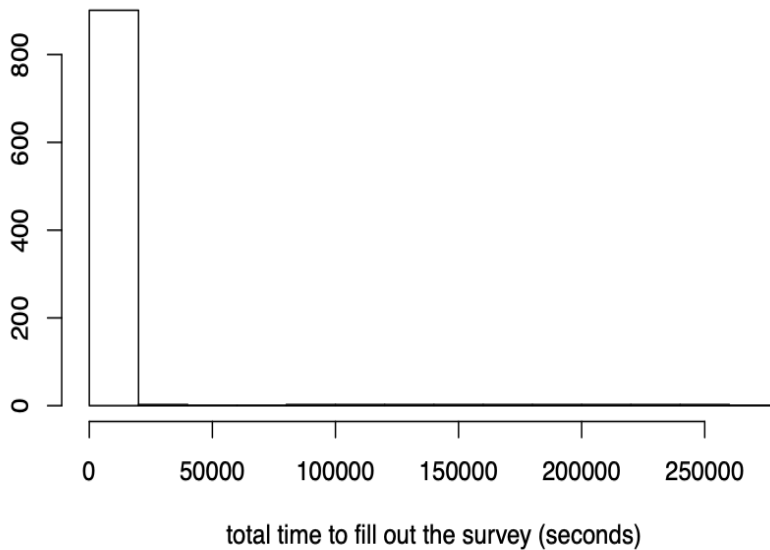
```
exposuredata <- filter(exposuredata_0, Duration__in_seconds_ < 1800)%>%
  filter(Duration__in_seconds_ > 600)

hist(exposuredata$Duration__in_seconds_, xlab = "total time to fill out the survey (seconds)", ylab = "
```

total time to fill out the survey (seconds)

```
summary(exposuredata)
```

Estimation of a model with only the treatment variable

Treatment Variable reflects whether ˆerformance information provided (1) or not (0)

model	
$Y \sim Normal(\mu, \sigma)$	[likelihood]
$\mu_i = \alpha + \beta x_i$	[linear model]
$\alpha \sim Normal(50, 100)$	[α prior]
$\beta T \sim Normal(0, 1)$	[βT prior]
$\sigma \sim Unif(0, 10)$	[σT prior]

```
m1 <- rethinking::map(
  alist(
    satisfaction_PCA ~ dnorm(mu, sigma) ,
    mu <- a + bT*Versie,
    a ~ dnorm (50,100) ,
    bT ~ dnorm (0,1) ,
    sigma ~ dunif (0,10)
  ),
  data = exposuredata )

precis(m1, prob = 0.95)

##        Mean StdDev  2.5% 97.5%
## a     -0.21   0.12 -0.45  0.04
## bT     0.02   0.17 -0.32  0.35
## sigma  1.64   0.06  1.52  1.76
```

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```
WAIC(m1)
```

```
## [ 100 / 1000 ]
[ 200 / 1000 ]
[ 300 / 1000 ]
[ 400 / 1000 ]
[ 500 / 1000 ]
[ 600 / 1000 ]
[ 700 / 1000 ]
[ 800 / 1000 ]
[ 900 / 1000 ]
[ 1000 / 1000 ]
```

```
## [1] 1375.849
## attr(,"lppd")
## [1] -684.0551
## attr(,"pWAIC")
## [1] 3.86919
## attr(,"se")
## [1] 35.32481
```

WAIC: first value is WAIC value

Plotting the model

```
# mu is a matrix with 1000 samples (rows) from the posterior that compute average for values on X axis
version.seq <- c(0,1)

mu <- link(m1, data = data.frame(Versie = version.seq))
```

```
## [ 100 / 1000 ]
[ 200 / 1000 ]
[ 300 / 1000 ]
[ 400 / 1000 ]
[ 500 / 1000 ]
[ 600 / 1000 ]
[ 700 / 1000 ]
[ 800 / 1000 ]
[ 900 / 1000 ]
[ 1000 / 1000 ]
```

```
str(mu)
```

```
##   num [1:1000, 1:2] -0.374 -0.0166 -0.089 -0.1779 -0.0994 ...
# summarize the distribution of mu
mu.mean <- apply( mu , 2 , mean )
mu.HPDI <- apply( mu , 2 , HPDI , prob=0.95 )


# plot raw data
# fading out points to make line and interval more visible
plot( satisfaction_PCA ~ Versie , data=exposuredata , col=col.alpha(rangi2,0.5), xaxt="n")
abline ( a = coef(m1)["a"], b=coef(m1)["bT"])
axis(1, at=c(0,1),labels=c(0,1))
```
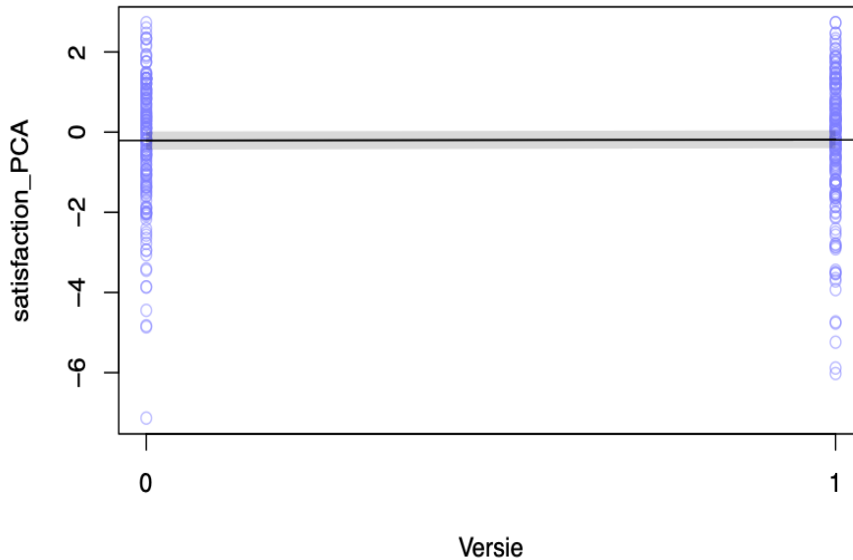
```
# plot the MAP line, aka the mean mu for each weight
lines( version.seq , mu.mean )

# plot a shaded region for 99% HPDI
shade( mu.HPDI , version.seq )
```


Estimation of a model with an interaction effect for Party identification.

The model estimates satisfaction (Y) as function of the treatment T (no performance info (0) performance info (1) and the party preference P (opposition party (0), ruling party (1). The slope γ_i represents the treatment effect (slope) as a function of the party preference.

model	
$Y \sim Normal(\mu, \sigma)$	[likelihood]
$\mu_i = \alpha + \gamma_i T_i + \beta_P P_i$	[linear model]
$\gamma_i = \beta_T + \beta_{PT} P_i$	[linear model of the slope]
$\alpha \sim Normal(50, 100)$	[α prior]
$\beta T \sim Normal(0, 1)$	[βT prior]
$\beta P \sim Normal(0, 1)$	[βP prior]
$\beta TP \sim Normal(0, 1)$	[βTP prior]
$\sigma \sim Unif(0, 10)$	[σT prior]

```
m2 <- rethinking::map(
  alist(
    satisfaction_PCA ~ dnorm(mu, sigma) ,
    mu <- a + gamma*Versie +bP*rulingparty ,
    gamma <- bT + bTP*rulingparty ,
    a ~ dnorm (50,100) ,
    bT ~ dnorm (0,1) ,
```

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```
    bP ~ dnorm (0,1) ,
    bTP ~ dnorm (0,1) ,
    sigma ~ dunif (0,10)
  ) ,
  data = exposuredata )
```

```
precis(m2, prob = 0.95)
```

```
##          Mean StdDev  2.5% 97.5%
## a      -0.49   0.15 -0.79 -0.19
## bT     -0.16   0.20 -0.56  0.24
## bP      0.64   0.23  0.20  1.09
## bTP     0.59   0.31 -0.02  1.20
## sigma   1.56   0.06  1.45  1.67
```

```
WAIC(m2)
```

```
## [ 100 / 1000 ]
[ 200 / 1000 ]
[ 300 / 1000 ]
[ 400 / 1000 ]
[ 500 / 1000 ]
[ 600 / 1000 ]
[ 700 / 1000 ]
[ 800 / 1000 ]
[ 900 / 1000 ]
[ 1000 / 1000 ]
```

```
## [1] 1344.835
## attr(,"lppd")
## [1] -667.0817
## attr(,"pWAIC")
## [1] 5.335948
## attr(,"se")
## [1] 34.4176
```

Plotting the interaction effects

First, calculate posterior mean line and interval

```
version.seq <- c(0,1)
mu.Party <- link( m2 , data=data.frame(rulingparty=1,Versie=version.seq) )
```

```
## [ 100 / 1000 ]
[ 200 / 1000 ]
[ 300 / 1000 ]
[ 400 / 1000 ]
[ 500 / 1000 ]
[ 600 / 1000 ]
[ 700 / 1000 ]
[ 800 / 1000 ]
[ 900 / 1000 ]
[ 1000 / 1000 ]
```

```
mu.Party.mean <- apply( mu.Party , 2 , mean )
mu.Party.PI <- apply( mu.Party , 2 , PI , prob=0.95 )
mu.NotParty <- link( m2 , data=data.frame(rulingparty=0,Versie=version.seq) )
```
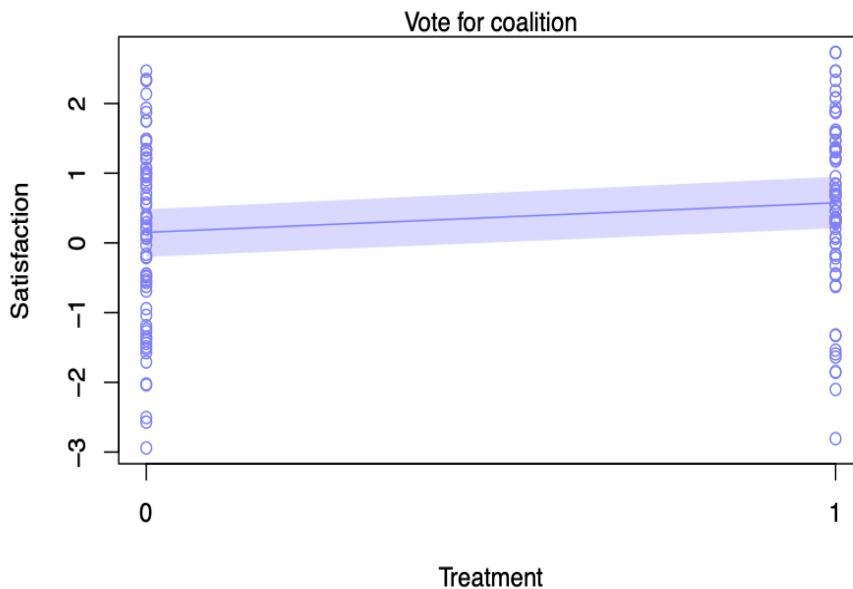
```
## [ 100 / 1000 ]
[ 200 / 1000 ]
[ 300 / 1000 ]
[ 400 / 1000 ]
[ 500 / 1000 ]
[ 600 / 1000 ]
[ 700 / 1000 ]
[ 800 / 1000 ]
[ 900 / 1000 ]
[ 1000 / 1000 ]
```

```
mu.NotParty.mean <- apply( mu.NotParty , 2 , mean )
mu.NotParty.PI <- apply( mu.NotParty , 2 , PI , prob=0.95 )
```

Next, make plot

```
# plot Party support for ruling party with regression
d.P1 <- exposuredata[exposuredata$rulingparty==1,]
plot( satisfaction_PCA ~ Versie , data=d.P1 ,
    col=rangi2 , ylab="Satisfaction" ,
    xlab="Treatment", xaxt = "n" )
mtext( "Vote for coalition" , 3 )
lines( version.seq , mu.Party.mean , col=rangi2 )
shade( mu.Party.PI , version.seq , col=col.alpha(rangi2,0.3) )
axis(1, at=c(0,1),labels=c(0,1))
```
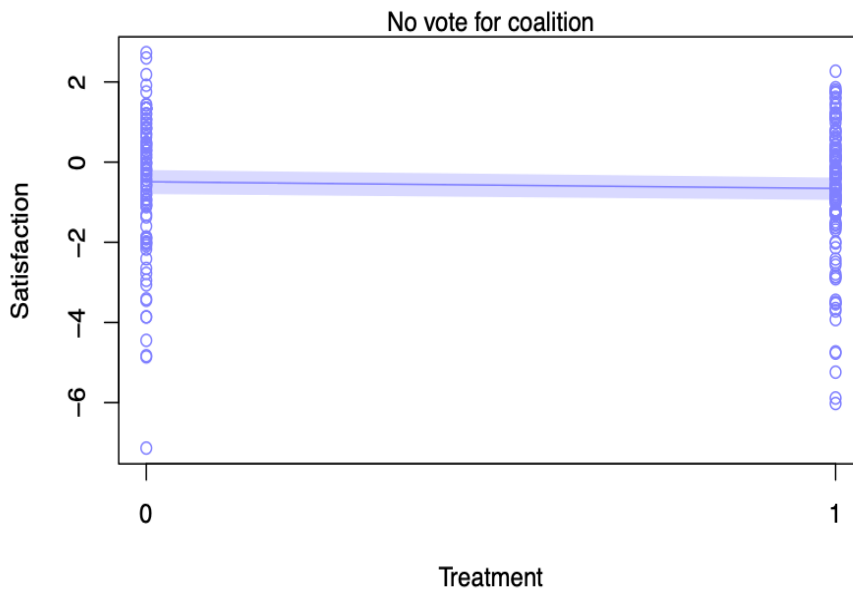


```
# plot no support for ruling party with regression
d.P0 <- exposuredata[exposuredata$rulingparty==0,]
plot( satisfaction_PCA ~ Versie , data=d.P0 ,
```

```
      col=rangi2 , ylab="Satisfaction" ,
      xlab="Treatment", xaxt = "n" )
mtext( "No vote for coalition" , 3 )
lines( version.seq , mu.NotParty.mean , col=rangi2 )
shade( mu.NotParty.PI , version.seq , col=col.alpha(rangi2,0.3) )
axis(1, at=c(0,1),labels=c(0,1))
```


No vote for coalition

Slope at the MAP values for posterior means for coalition voters

γ = -0.08 + 0.01 = -0.07

Slope at the MAP values for posterior means for opposition voters

γ = -0.08

Finally, calculate and plot Uncertainty around these point estimates

```
# samples from the posterior to calculate gamma's for Party (1) and NotParty (0)
post <- extract.samples(m2)
gamma.Party <- post$bT + post$bTP*1
gamma.NotParty <- post$bT

# mean = same as hand calculated
mean(gamma.Party)
```
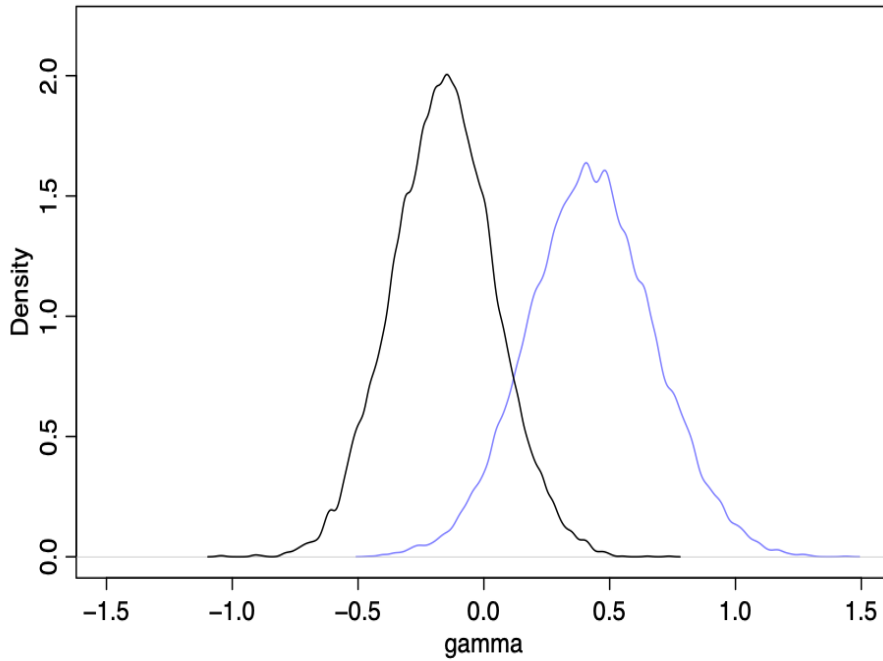
```
## [1] 0.4289928
```

```
mean( gamma.NotParty)
```

```
## [1] -0.1596126
```

```
# plot

dens ( gamma.Party, xlim = c(-1.5,1.5), ylim= c(0,2.2),
       xlab="gamma", col=rangi2)
```

```
dens ( gamma.NotParty, add = TRUE)
```



```
#difference in slope. What is the probability that the slope within the supportrs of the majority (Part;

diff <- gamma.Party - gamma.NotParty
sum (diff < 0)/length(diff)
```
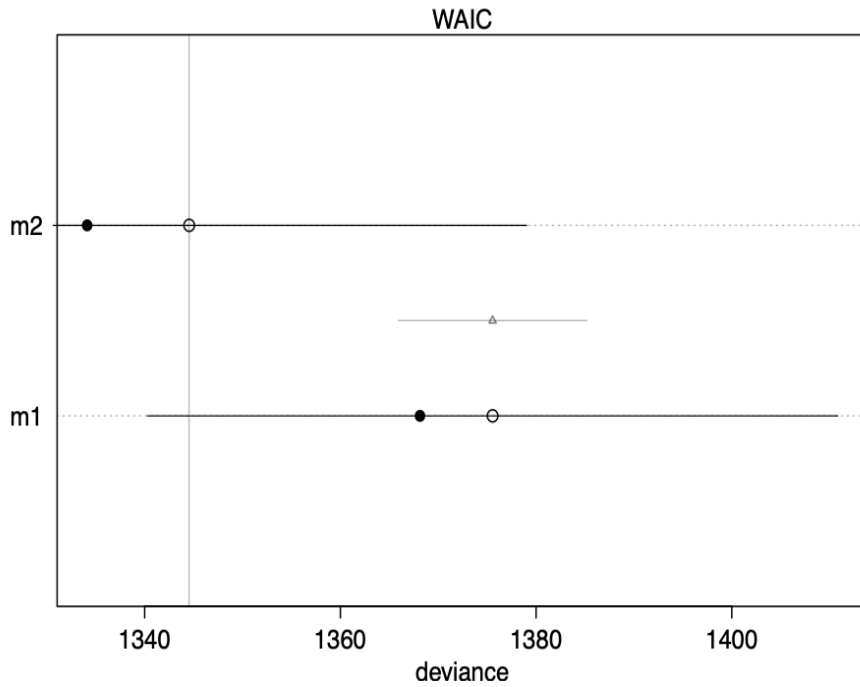
```
## [1] 0.0307
```

compare models

```
comparison <- compare(m1,m2)
comparison
```

```
##      WAIC pWAIC dWAIC weight    SE   dSE
## m2 1344.6   5.2     0      1 34.49    NA
## m1 1375.6   3.7    31      0 35.28  9.64
```

```
plot(comparison, SE=TRUE, dSE=TRUE)
```

```
plot(coeftab(m1,m2))
```