Plotting marginal effects and computing DAME with R: Examples

Supplement to: Zhirnov, Andrei, Mert Moral, and Evgeny Sedashov. 2022. "Taking Distributions Seriously: On the Interpretation of the Estimates of Interactive Nonlinear Models." Political Analysis (Conditional Acceptance)

21 January, 2022

Contents

Required packages

This document illustrates how one can use the `DAME` package to replicate the calculations presented in Zhirnov, Moral, and Sedashov (2022). The current version of the `DAME` package can be installed from GitHub using `devtools::install_github`:

```
library(devtools)
install_github("andreizhirnov/DAME")
library(DAME)
```

The version of this package used to generate this document can be installed using its v1.0.0 release:

```
install_github("andreizhirnov/DAME@v1.0.0")
```

`DAME` depends on `stats` (R Core Team 2021), `methods` (R Core Team 2021), and `MASS` (Ripley 2021) for calculations, and `ggplot2` (Wickham et al. 2021) for plotting.

In this document, we also refer to the `foreign` (R Core Team 2020) and `dataverse` (Kuriwaki et al. 2021) packages to download the below-mentioned datasets, `glmmTMB` (Magnusson et al. 2021) to estimate multi-level models, `sandwich` (Zeileis and Lumley 2021) to compute robust variance-covariance matrices, and `ggExtra` (Attali and Baker 2019) to add histograms to heatmaps and contour-plots.

Obtaining the datasets

We will need four datasets, which are included in the replication materials of the studies we replicated. These datasets are publicly available, and in this section, we show how you can obtain them.

Pre-electoral coalition formation (G)

The dataset was created by Sona Golder and used in her book (Golder 2006) on electoral alliances. It can be found on Matt Golder's web-page at http://mattgolder.com/files/interactions/. The following script can be used to download it using R:

```
library(foreign)
tmpdir <- tempdir()
download.file(url="http://mattgolder.com/files/interactions/interaction3.zip",
              file.path(tmpdir, "interaction3.zip"))
unzip(file.path(tmpdir, "interaction3.zip"), exdir = tmpdir )
dataset <- read.dta(file.path(tmpdir,"interaction3.dta"))
saveRDS(dataset, "G.rds")
```

Voter registration rules and turnout (N)

The dataset was originally used by Nagler (1991). It was made public by William D. Berry, Jacqueline H. R. DeMeritt, and Justin Esarey as part of the replication materials for Berry, DeMeritt, and Esarey (2010). The following script can be used to download it using R:

```
library(foreign)
tmpdir <- tempdir()
download.file(url="https://jdemeritt.weebly.com/uploads/2/2/7/7/22771764/bde.zip",
              file.path(tmpdir, "bde.zip"))
unzip(file.path(tmpdir, "bde.zip"), exdir = tmpdir )
dataset <- read.dta(file.path(tmpdir,"scobit.dta"))
saveRDS(dataset, "N.rds")
```

News media and party discipline (AJLW)

The datasets is part of the published replication materials for Arceneaux et al. (2016) and can be downloaded either directly from the Harvard Dataverse https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/27597 or using the `dataverse` package:

```
library(dataverse)
dataset <- get_dataframe_by_name(filename = "FoxNews_Master.tab",
                                 dataset="doi:10.7910/DVN/27597",
                                 server="dataverse.harvard.edu",
                                 original = TRUE,
                                 .f=  foreign::read.dta)
saveRDS(dataset, "AJLW.rds")
```

Foreign direct investment and labor protest (RT)

The datasets is part of the published replication materials for Robertson and Teitelbaum (2011) and can be downloaded from Emmanuel Teitelbaum's website: https://home.gwu.edu/~ejt/pages/Data.html. The following script can be used to download it using R:

```
library(foreign)
dataset <-
  read.dta("https://home.gwu.edu/~ejt/pages/Data_files/Robertson%20Teitelbaum%202011.dta")
saveRDS(dataset,"RT.rds")
```

Pre-electoral coalition formation (G)

Golder (2006) looks into the determinants of the pre-electoral coalition formation. One of the hypotheses is that "party system polarization increases the likelihood of pre-electoral coalitions when the electoral system is sufficiently disproportional" (p. 87). Using a dataset of party dyads in examined elections (G), the study estimates a model that predicts whether a particular party dyad enters the same alliance and includes polarization, effective electoral threshold (as a measure of the restrictiveness of the electoral system), and their interaction term as the predictors.

Estimate the main model

The probit model with an interaction term can be estimated using `stats::glm()` function:

```
dt <- readRDS("G.rds")
dt <- subset(dt, complete.cases(dt[c("pec","polarization","threshold","seatshare",
                                     "incompatibility","asymmetry")]))
m <- glm(pec ~ polarization*threshold + seatshare + I(seatshare^2) + incompatibility +
           asymmetry + asymmetry:seatshare, data=dt, family=binomial(link="probit"))
summary(m)
```

```
##
## Call:
## glm(formula = pec ~ polarization * threshold + seatshare + I(seatshare^2) +
##     incompatibility + asymmetry + asymmetry:seatshare, family = binomial(link = "probit"),
##     data = dt)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.1265  -0.3457  -0.2690  -0.2150   2.9468
##
## Coefficients:
##                         Estimate Std. Error z value Pr(>|z|)
## (Intercept)            -2.1005362  0.2040356 -10.295  < 2e-16 ***
## polarization           -0.0014849  0.0026606  -0.558 0.576757
## threshold               0.0206984  0.0060720   3.409 0.000652 ***
```

```
## seatshare               0.0430151  0.0085270   5.045 4.55e-07 ***
## I(seatshare^2)         -0.0004475  0.0000825  -5.425 5.81e-08 ***
## incompatibility        -0.0053749  0.0020063  -2.679 0.007382 **
## asymmetry               0.0208886  0.2356696   0.089 0.929372
## polarization:threshold  0.0002361  0.0001449   1.629 0.103225
## seatshare:asymmetry    -0.0244723  0.0068860  -3.554 0.000380 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1464.6  on 3494  degrees of freedom
## Residual deviance: 1341.4  on 3486  degrees of freedom
## AIC: 1359.4
##
## Number of Fisher Scoring iterations: 6
```

To replicate the original analysis, this model needs to include party-specific random effects. We can include those using `glmmTMB()` function from the `glmmTMB` package. You could achieve very similar results with `lme4`, which, however, has more limited functionality and is a bit slower than `glmmTMB` for estimating the models we show in this document.

```r
library(glmmTMB)
m2 <- glmmTMB(pec ~ polarization*threshold + seatshare + I(seatshare^2) + incompatibility +
                asymmetry + asymmetry:seatshare + (1|ident),
                  data=dt,
                  family=binomial(link="probit"))

summary(m2)
```

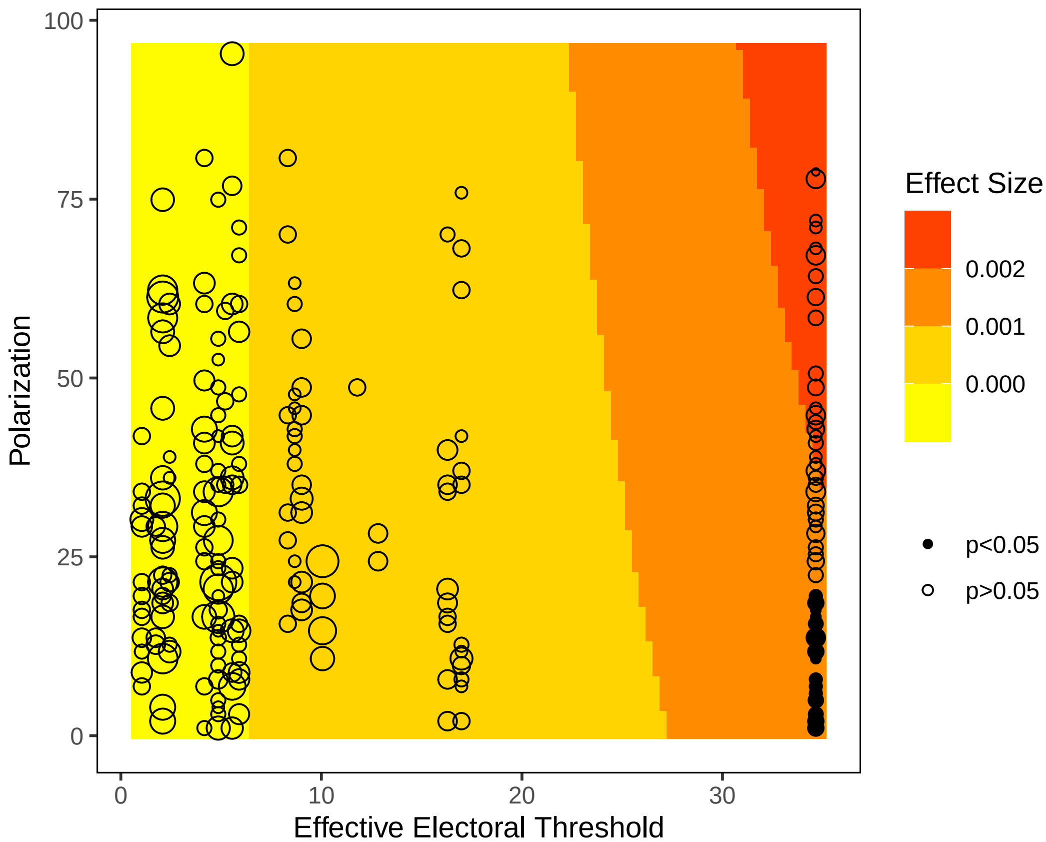
```
##  Family: binomial  ( probit )
## Formula:
## pec ~ polarization * threshold + seatshare + I(seatshare^2) +
##     incompatibility + asymmetry + asymmetry:seatshare + (1 |      ident)
## Data: dt
##
##      AIC      BIC   logLik deviance df.resid
##   1251.3   1312.9   -615.7   1231.3     3485
##
## Random effects:
##
## Conditional model:
##  Groups Name        Variance Std.Dev.
##  ident  (Intercept) 0.619    0.7868
## Number of obs: 3495, groups:  ident, 278
##
## Conditional model:
##                          Estimate Std. Error z value Pr(>|z|)
## (Intercept)            -2.4302284  0.3196440  -7.603 2.90e-14 ***
## polarization           -0.0028516  0.0055633  -0.513  0.60825
## threshold               0.0191869  0.0109901   1.746  0.08084 .
## seatshare               0.0511005  0.0114988   4.444 8.83e-06 ***
## I(seatshare^2)         -0.0005592  0.0001096  -5.102 3.37e-07 ***
## incompatibility        -0.0067494  0.0025283  -2.670  0.00759 **
## asymmetry              -0.1017402  0.3018679  -0.337  0.73609
```

```
## polarization:threshold  0.0005055  0.0002899   1.744  0.08116 .
## seatshare:asymmetry    -0.0287526  0.0089265  -3.221  0.00128 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Plotting marginal effects of polarization

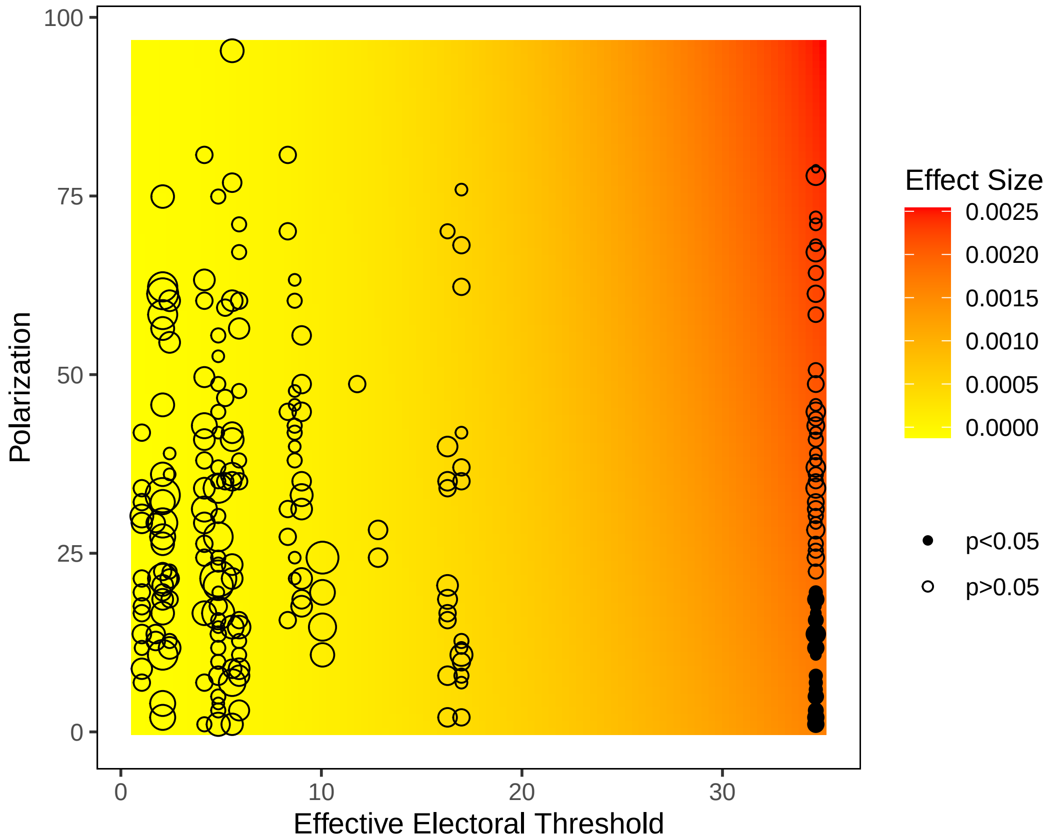
Making a contour-plot to illustrate marginal effects from a simple probit is straightforward with the `plot_me()` function provided that the model is estimated with a call to the `glm()` function. We need to specify the object with the model estimates (`m`), the name of the variable whose marginal effect we seek to estimate (`polarization`) and the conditioning variable (`threshold`).

```
library(ggplot2)
plot_me(model = m, x = "polarization", over = "threshold") +
  scale_fill_steps(low="yellow",high="red", n.breaks=4) +
  labs(x="Effective Electoral Threshold", y="Polarization")
```



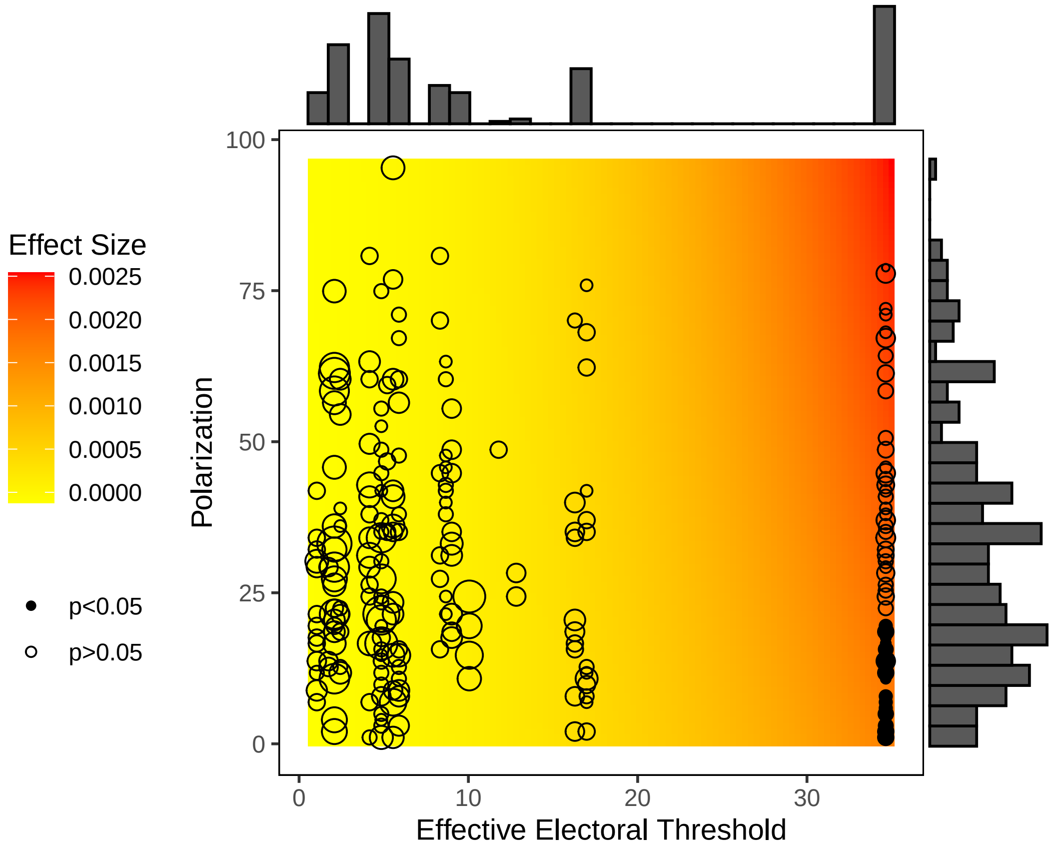
Notice that to adjust the axis labels and specify the type of the color ramp, we use the standard `ggplot2` syntax. Here, `scale_fill_steps()` breaks down the continuous color values into the number of categories specified with the `n.breaks` option. To create a heatmap, we need to replace `scale_fill_steps()` with `scale_fill_gradient()`:

```
(g <- plot_me(model = m, x = "polarization", over = "threshold") +
  scale_fill_gradient(low="yellow", high="red") +
  labs(x="Effective Electoral Threshold", y="Polarization"))
```



We can use `ggMarginal()` from the `ggExtra` package to attach histograms with marginal distributions of the main covariates to the heatmap:

```
gt <- g + theme(legend.position="left")
ggExtra::ggMarginal(gt, type="histogram", data=dt, x=threshold, y=polarization)
```

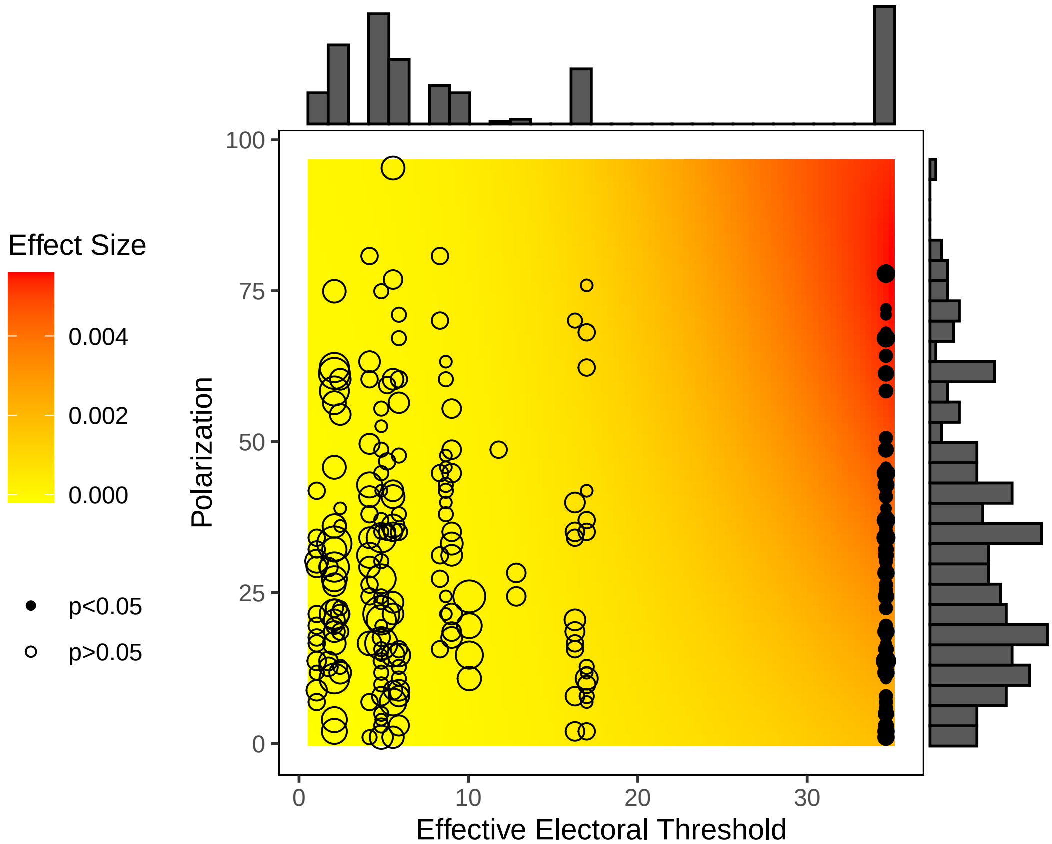


DAME works best with model estimates from `glm()`. When the model estimates are produced with the `lme4` or `glmmTMB` package, we must specify the components directly. We can extract the coefficients and variance-covariance matrix corresponding to the fixed effects using the `glmmTMB::fixef()` and `stats::vcov()` functions.

```
coef <- fixef(m2)$cond
vc <- vcov(m2)$cond
```

Since we will be setting the covariates (other than the main ones) to their central values, we can ignore the random component of the intercept, effectively setting the random effects to zero. To bring these calculations closer to what is shown in the paper, we will use simulations to produce standard errors by setting `mc=TRUE`:

```
g <- plot_me(formula = pec ~ polarization*threshold + seatshare + I(seatshare^2) +
               incompatibility + asymmetry + asymmetry:seatshare,
        data=dt,
        coefficients=coef,
        vcov=vc,
        link="probit",
        x = "polarization", over = "threshold", mc=TRUE)
gt <- g + scale_fill_gradient(low="yellow", high="red") +
  labs(x="Effective Electoral Threshold", y="Polarization") +
  theme(legend.position="left")
ggExtra::ggMarginal(gt, type="histogram", data=dt, x=threshold, y=polarization)
```



Computing and plotting DAME of polarization

To compute the distribution-weighted average marginal effects of `polarization`, we can resort to the `dame()` function:

```
(d <- dame(model=m, x="polarization", over="threshold", nbins=10))
```

```
##             est           se           lb           ub bin_id
## 1 -7.854570e-05 0.0001810035 -0.0004333061 0.0002762147    2.0
## 2 -5.534738e-05 0.0001512690 -0.0003518292 0.0002411345    2.6
## 3 -3.853787e-05 0.0002061198 -0.0004425253 0.0003654495    4.8
## 4 -2.078844e-05 0.0002244287 -0.0004606606 0.0004190837    5.6
## 5  4.329523e-06 0.0002087581 -0.0004048289 0.0004134880    5.9
## 6  6.396721e-05 0.0001744165 -0.0002778829 0.0004058173    8.9
## 7  8.938963e-04 0.0005087583 -0.0001032517 0.0018910442   35.0
```

The `nbins` option allows us to create 10 bins with approximately the same number of observations.

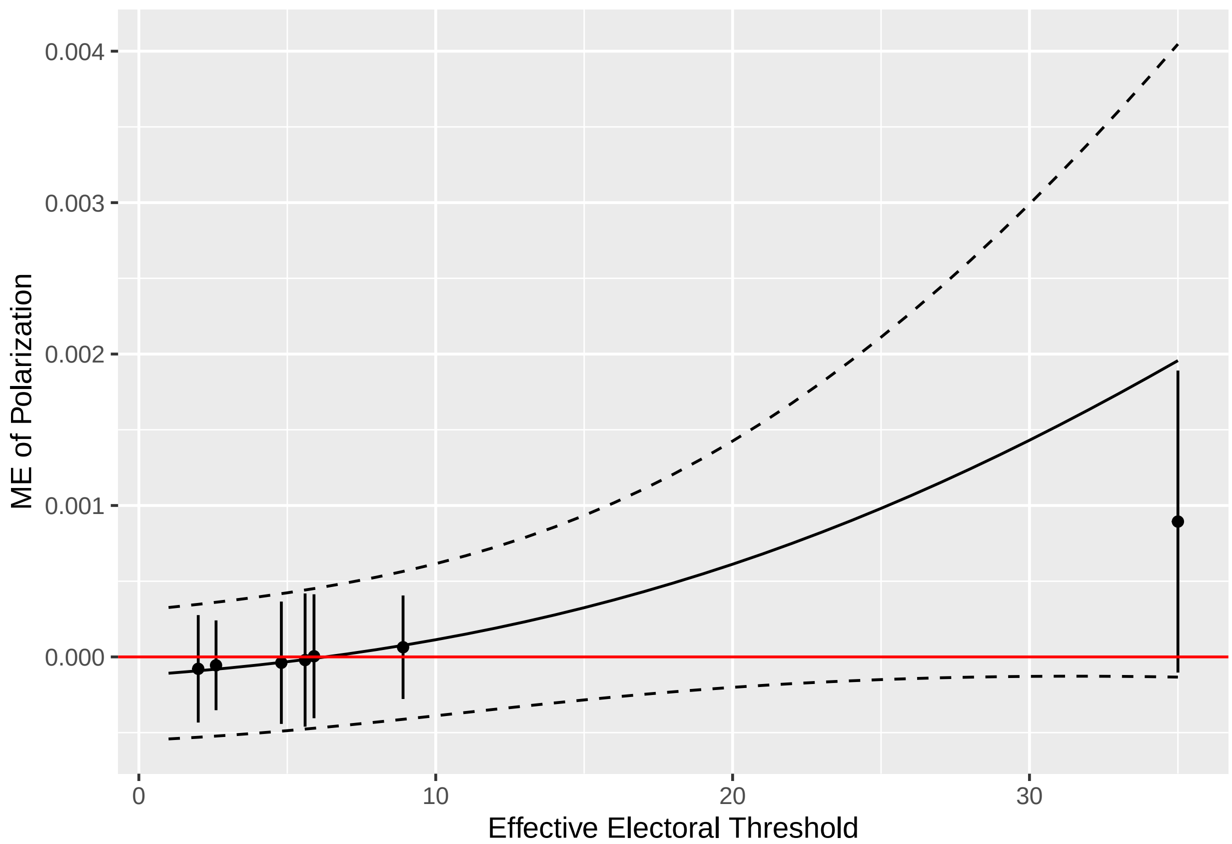
Likewise, we use `mem()` to compute the marginal effect of `polarization` at its mean:

```
mem <- mem(model=m, x="polarization", at=list("threshold"=seq(from=1,to=35, by=1)))
```

Putting both DAME and MEM on a single plot:

```
ggplot(data=d, aes(x=bin_id, y=est, ymin=lb, ymax=ub)) +
  geom_point() +
  geom_linerange() +
  geom_line(aes(x=threshold, y=est), data=mem) +
  geom_line(aes(x=threshold, y=lb), data=mem, linetype="dashed") +
```

```
  geom_line(aes(x=threshold, y=ub), data=mem, linetype="dashed") +
  geom_hline(yintercept=0, color="red") +
  labs(x="Effective Electoral Threshold", y="ME of Polarization")
```



How should we deal with a model with random effects? When the estimates are produced with `glmmTMB`, we can easily recover the estimates for the group-specific values of the random effects (but not their sampling distribution).

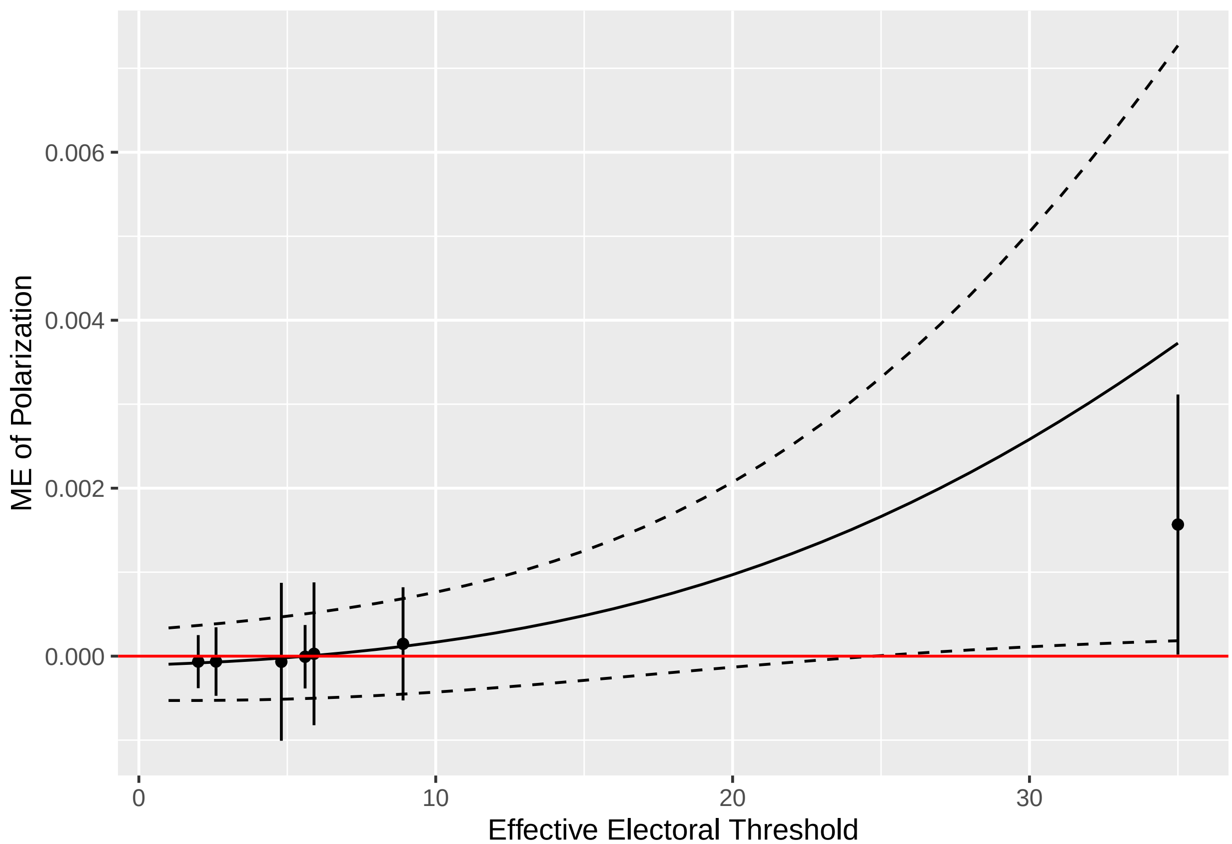
```
re <- ranef(m2)$cond$ident
dt$reff <- re[as.character(dt$ident),"(Intercept)"]
```

To take into account the differential intercepts for each of the groups, we will treat random intercepts as offsets to the linear prediction and include them in the model formula:

```
d <- dame(formula = pec ~ polarization*threshold + seatshare + I(seatshare^2) +
            incompatibility + asymmetry + asymmetry:seatshare + offset(reff) ,
        data=dt,
        coefficients=coef,
        vcov=vc,
        link="probit",
        x="polarization", over="threshold", nbins=10)
mem <- mem(formula = pec ~ polarization*threshold + seatshare + I(seatshare^2) +
             incompatibility + asymmetry + asymmetry:seatshare + offset(reff),
        data=dt,
        coefficients=coef,
        vcov=vc,
        link="probit",
```

```
       x="polarization",
       at=list("threshold"=seq(from=1,to=35, by=1)))

# plot them
ggplot(data=d, aes(x=bin_id, y=est, ymin=lb, ymax=ub)) +
  geom_point() +
  geom_linerange() +
  geom_line(aes(x=threshold, y=est), data=mem) +
  geom_line(aes(x=threshold, y=lb), data=mem, linetype="dashed") +
  geom_line(aes(x=threshold, y=ub), data=mem, linetype="dashed") +
  geom_hline(yintercept=0, color="red") +
  labs(x="Effective Electoral Threshold", y="ME of Polarization")
```



Voter registration rules and turnout (N)

Nagler (1991) examines the interactive effect of education and the restrictiveness of electoral registration rules on turnout. The latter is measured using the number of days before the election when the registration closes. This variable takes on the value of 0 when the voters are allowed to register on the election day, and 30 means that the registration closes 30 days before the election day. The main hypothesis is conditional: more restrictive registration rules primarily hurt less educated individuals.

Load the data and estimate the model

This expectation is captured using a probit model including an interaction term of `closing` and `neweduc`, as well as an intraction term of `closing` and `neweduc` squared.

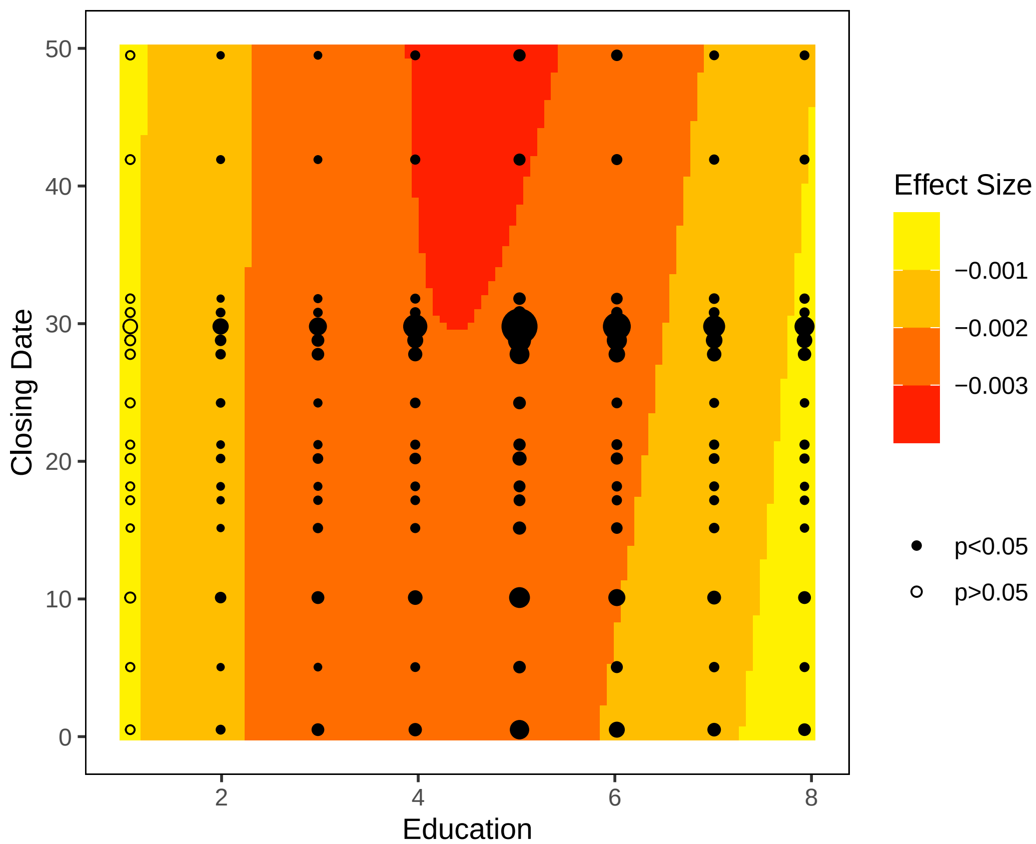
```r
dt <- readRDS("N.rds")
dt <- subset(dt, newvote %in% 0:1, select=c("state","newvote","closing","neweduc",
                                            "age","south","gov"))
m <- glm(newvote ~ closing*neweduc + closing*I(neweduc^2) + age + I(age^2) + south + gov,
         data=dt,
         family=binomial(link="probit"))
summary(m)
```

```
##
## Call:
## glm(formula = newvote ~ closing * neweduc + closing * I(neweduc^2) +
##     age + I(age^2) + south + gov, family = binomial(link = "probit"),
##     data = dt)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.8318  -1.0797   0.6029   0.8729   2.2440
##
## Coefficients:
##                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -2.743e+00  1.077e-01 -25.479  < 2e-16 ***
## closing               6.243e-04  3.721e-03   0.168   0.8668
## neweduc               2.645e-01  4.184e-02   6.322 2.59e-10 ***
## I(neweduc^2)          5.069e-03  4.196e-03   1.208   0.2270
## age                   6.966e-02  1.311e-03  53.143  < 2e-16 ***
## I(age^2)             -5.061e-04  1.352e-05 -37.437  < 2e-16 ***
## south                -1.155e-01  1.097e-02 -10.525  < 2e-16 ***
## gov                   3.431e-03  1.162e-02   0.295   0.7678
## closing:neweduc      -3.173e-03  1.509e-03  -2.103   0.0355 *
## closing:I(neweduc^2)  2.774e-04  1.518e-04   1.827   0.0677 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 126410  on 99675  degrees of freedom
## Residual deviance: 111631  on 99666  degrees of freedom
## AIC: 111651
##
## Number of Fisher Scoring iterations: 4
```

Plotting marginal effects of registration closing date

We can use the `plot_me()` function to draw a contour-plot for the marginal effects of registration closing date. Since `closing` can only take on integer values, it makes more sense here to use the first-difference method for calculating the marginal effect. Thus, we set `discrete=TRUE` and use 1-day increments.

```r
plot_me(model = m, x = "closing", over = "neweduc", discrete = TRUE, discrete_step = 1) +
  scale_fill_steps(low="red", high="yellow", n.breaks=4) +
  labs(y="Closing Date", x="Education")
```

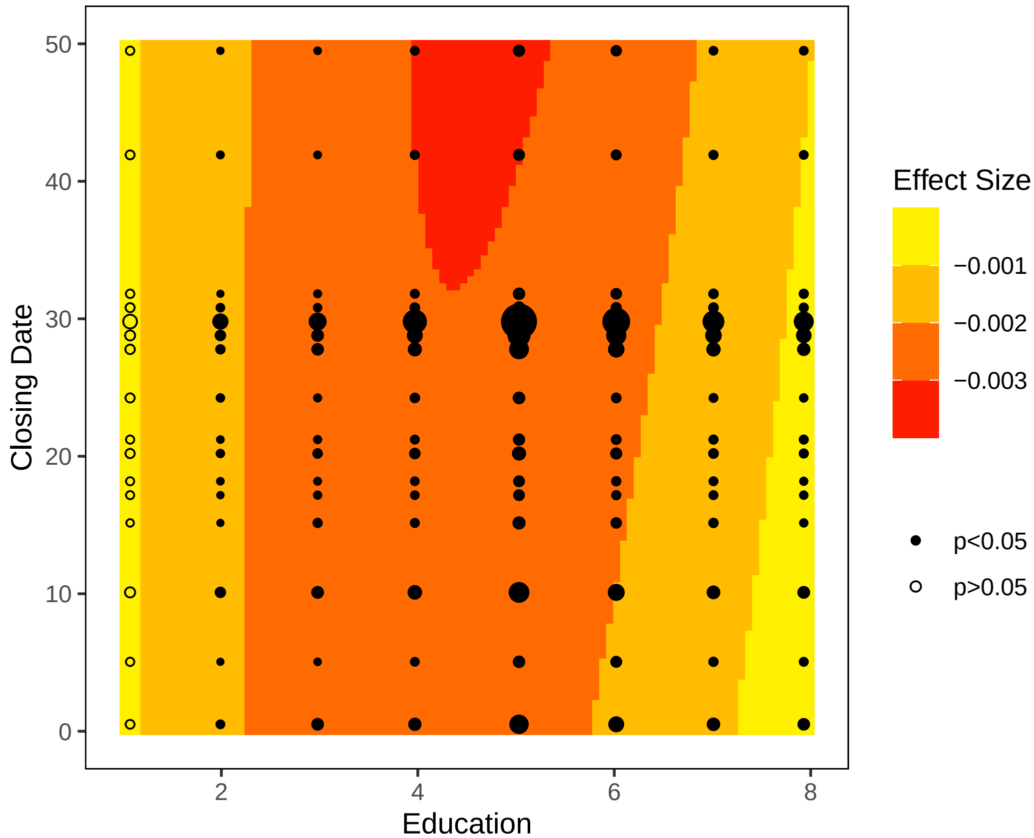


To set the dummy variables `south` and `gov` to their modes (rather than means), we can either use the `at` option or convert them to factors before the estimation. To use the `at` option, create a list with medians (which are almost always equal to modes for dummy variables):

```
(medians <- lapply(dt[c("south","gov")], median))
```

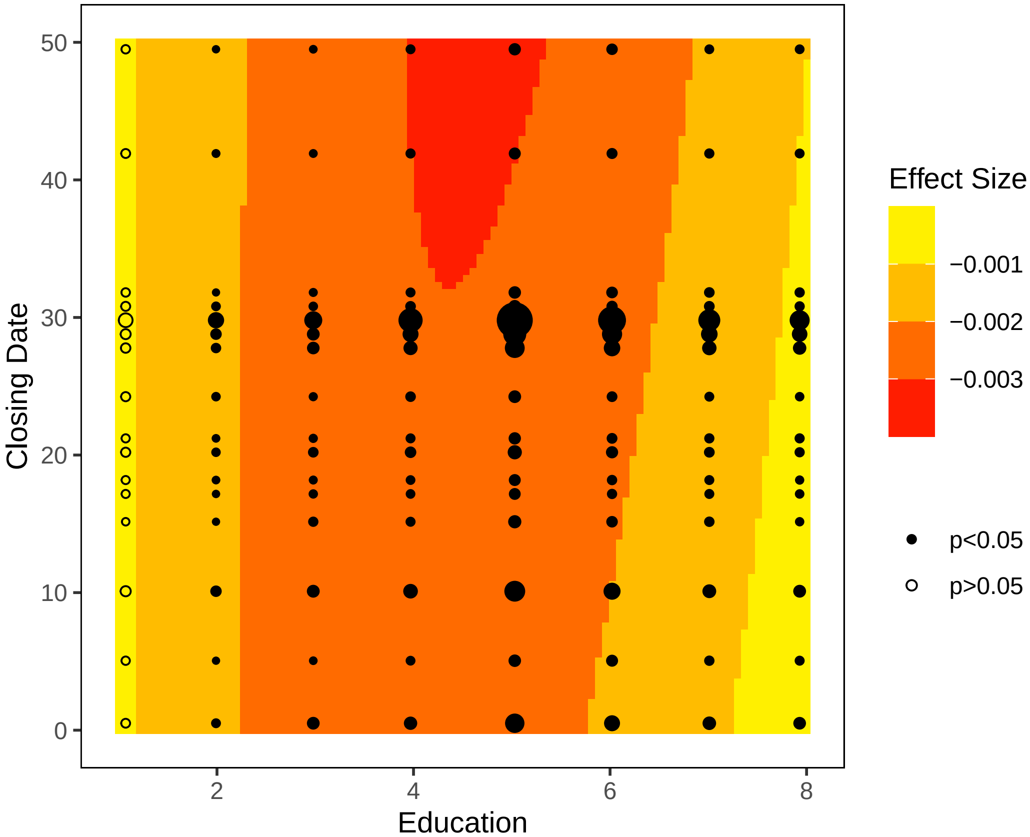
```
## $south
## [1] 0
##
## $gov
## [1] 0
```

```
plot_me(model = m, x = "closing", over = "neweduc", discrete = TRUE, discrete_step = 1, at=medians) +
  scale_fill_steps(low="red", high="yellow", n.breaks=4) +
  labs(y="Closing Date", x="Education")
```



Alternatively, we could generate factor variables and use them instead of `south` and `gov`: in this case `plot_me()` will automatically use modes instead of means:

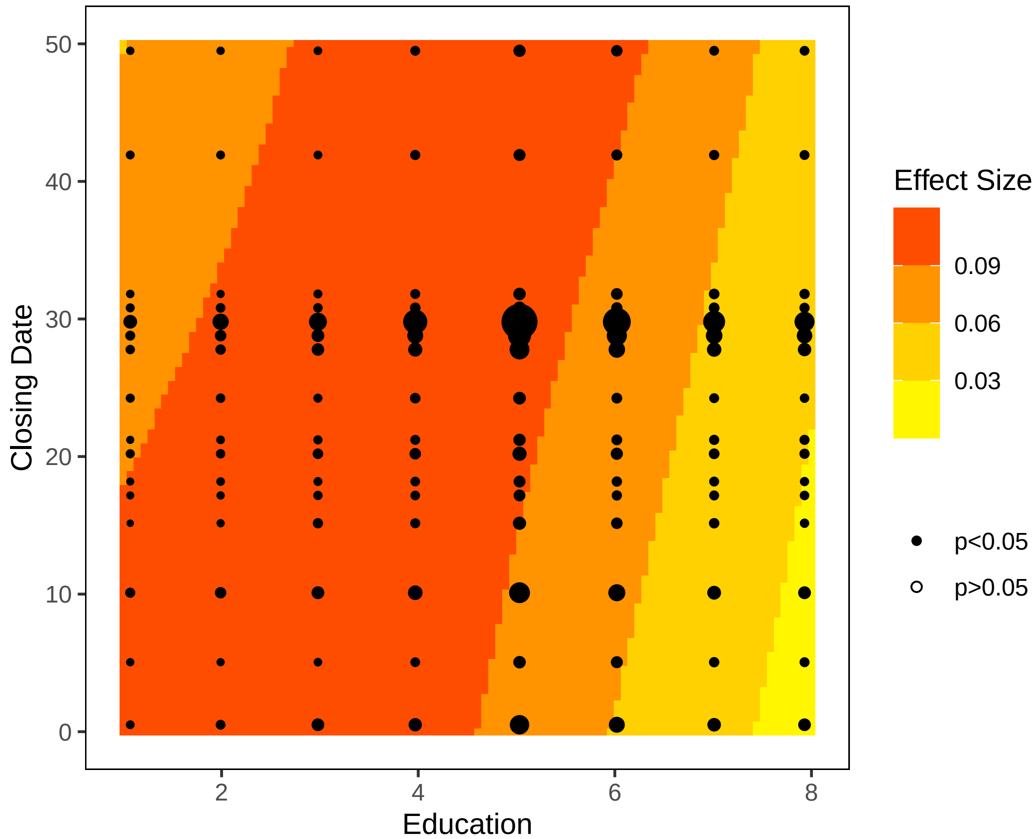
```
dt <- within(dt, {
  south.f <- factor(south, levels=0:1)
  gov.f <- factor(gov, levels=0:1)
})
m2 <- glm(newvote ~ closing*neweduc + closing*I(neweduc^2) + age + I(age^2) + south.f + gov.f,
          data=dt,
          family=binomial(link="probit"))
plot_me(model = m2, x = "closing", over = "neweduc", discrete = TRUE, discrete_step = 1) +
  scale_fill_steps(low="red", high="yellow", n.breaks=4) +
  labs(y="Closing Date", x="Education")
```



Plotting marginal effects of education

When computing the marginal effect of education, we might benefit from keeping the same orientation of axes as before. To do so, we can use the `coord_flip()` function from `ggplot2`.

```
plot_me(model = m, x ="neweduc" , over = "closing", discrete = TRUE, discrete_step = 1, at=medians) +
  scale_fill_steps(low="yellow", high="red", n.breaks=4) +
  labs(y="Education", x="Closing Date") +
  coord_flip()
```

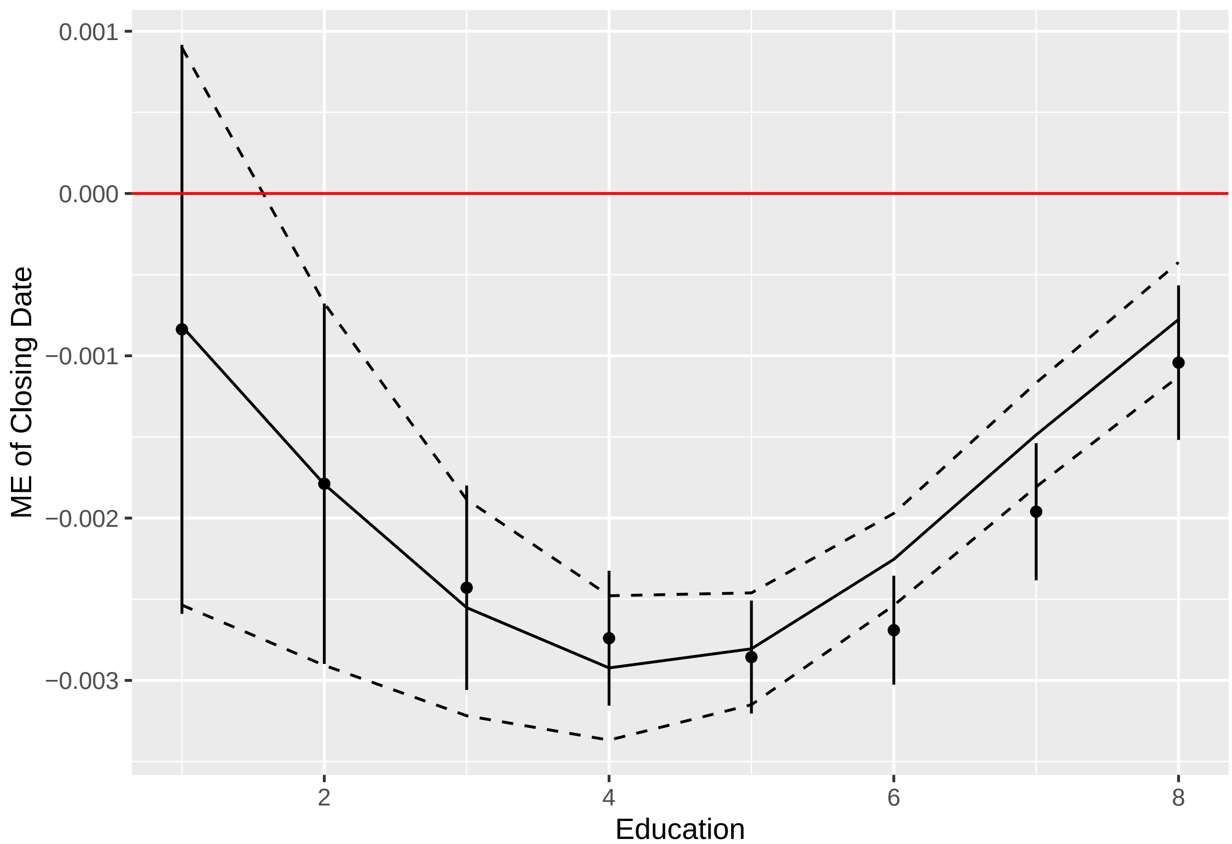


Computing and plotting DAME of registration closing date

Turning to DAME, we can use a similar syntax as before and, since `neweduc` takes only 8 unique values, we can bin the observations by the unique values of this variable (`use_distinct_values=TRUE`).

```
d <- dame(model=m, x="closing", over="neweduc",
          discrete=TRUE, discrete_step=1,
          use_distinct_values = TRUE)
mem <- mem(model=m, x="closing",
           discrete=TRUE, discrete_step=1,
           at=c(medians, list("neweduc"=sort(unique(dt$neweduc)))))

ggplot(data=d, aes(x=bin_id, y=est, ymin=lb, ymax=ub)) +
  geom_point() +
  geom_linerange() +
  geom_line(aes(x=neweduc, y=est), data=mem) +
  geom_line(aes(x=neweduc, y=lb), data=mem, linetype="dashed") +
  geom_line(aes(x=neweduc, y=ub), data=mem, linetype="dashed") +
  geom_hline(yintercept=0, color="red") +
  labs(x="Education", y="ME of Closing Date")
```

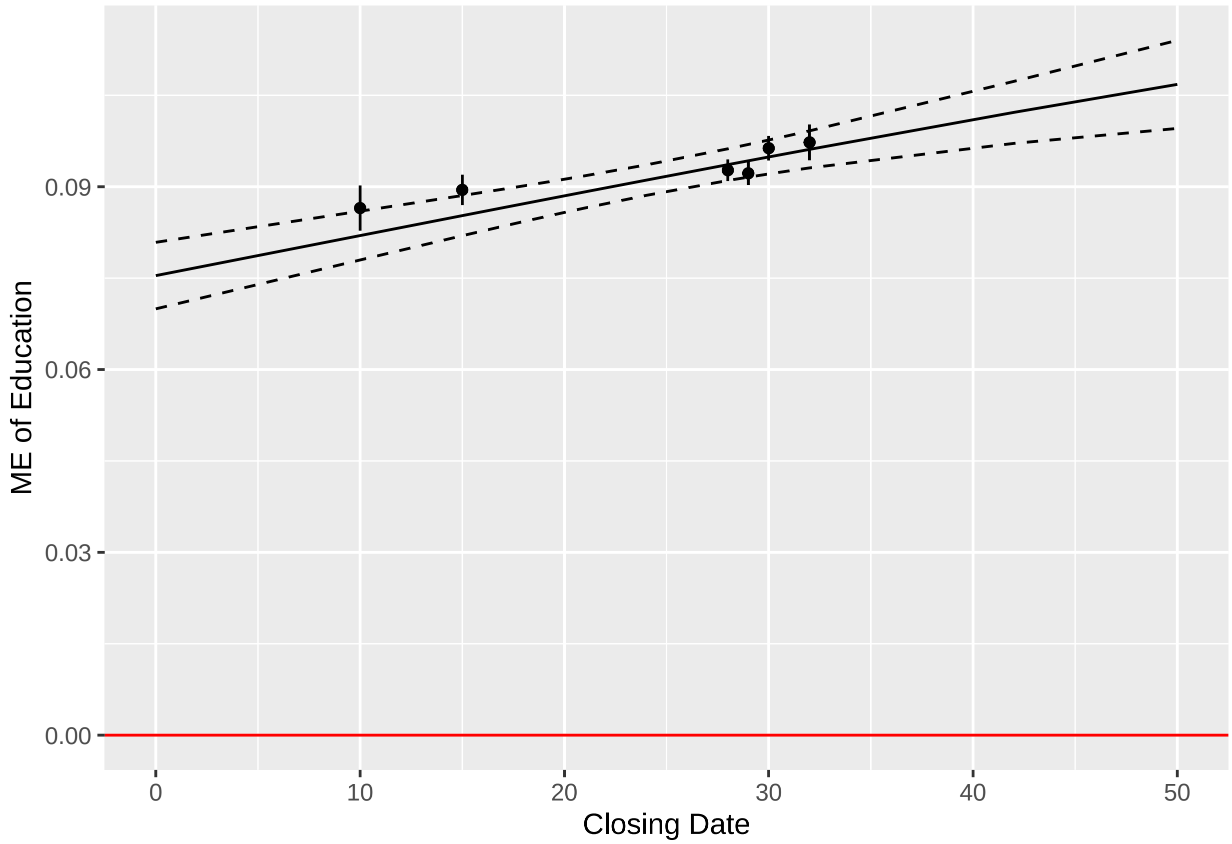


Computing and plotting DAME of education

Change the `x`, `over`, and the values of the running variable to plot the DAME of education:

```
d <- dame(model=m, x="neweduc", over="closing",
          discrete=TRUE, discrete_step=1)
mem <- mem(model=m, x="neweduc", discrete=TRUE, discrete_step=1,
           at=c(medians, list("closing"=sort(unique(dt$closing)))))

ggplot(data=d, aes(x=bin_id, y=est, ymin=lb, ymax=ub)) +
  geom_point() +
  geom_linerange() +
  geom_line(aes(x=closing, y=est), data=mem) +
  geom_line(aes(x=closing, y=lb), data=mem, linetype="dashed") +
  geom_line(aes(x=closing, y=ub), data=mem, linetype="dashed") +
  geom_hline(yintercept=0, color="red") +
  labs(x="Closing Date", y="ME of Education")
```



News media and party discipline (AJLW)

Arceneaux et al. (2016) view Congressmen as facing a choice between voting with the party and more closely following the preferences of their constituencies. In this theory, politicians are expected to vote with their party when they can afford to do so when the next election is sufficiently far, their district is safe, or they can shape the public opinion in their districts. The article presents several hypotheses about the interactive effects of these factors; in the interest of space, we focus here only on the interaction between competitiveness and the proximity of the next election.

Load the data and estimate the model

To examine the interactive effect of district competitiveness and the proximity of the next election, following Arceneaux et al. (2016), we subset the data and examine the Republicans from the districts in which Fox News was present (this is another explanatory variable in the authors' study) and build a model explaining whether a Congressman voted with their party and including a full interaction term of the polynomial of the number of days until the next election and the Democratic vote share in the preceding election in the representative's district (the larger this share, the more competitive the district).

Before estimating this model, we need to convert the dummy variables representing different types of votes into a single factor variable. This will make it easier to include them in the model and find their central values.

```
dt <- readRDS("AJLW.rds")

# create a factor variable with the vote type
dt$votetype <- "MiscProcedure"
```

```r
for (v in  c("Amend", "OtherPass", "ProPart", "RegPass", "Susp")) {
  dt$votetype[which(dt[[v]]==1)] <- v
}

dt <- subset(dt, PresencePartyUnity==1 & Republican==1 & FoxNews==1,
             select=c("id","dist2","PartyVote","daystoelection","dv","Retirement",
                      "seniorit","qualchal_lag","qualchal","spendgap_lag","spendgap",
                      "distpart_lag","votetype"))
dt <- within(dt, {
  dvprop <- dv/100
  votetype <- relevel(factor(votetype), ref="MiscProcedure")
  qualchal_lag.f <- factor(qualchal_lag, levels=0:1)
  qualchal.f <- factor(qualchal, levels=0:1)
  Retirement.f <- factor(Retirement, levels=0:1)
  })
dt <- na.omit(dt)

m <- glm(PartyVote ~ dvprop*(daystoelection + I(daystoelection^2) + I(daystoelection^3)) +
           Retirement.f + seniorit + qualchal_lag.f + qualchal.f + spendgap_lag + spendgap +
           distpart_lag + votetype,
         data=dt,
         family=binomial)
summary(m)
```

```
##
## Call:
## glm(formula = PartyVote ~ dvprop * (daystoelection + I(daystoelection^2) +
##     I(daystoelection^3)) + Retirement.f + seniorit + qualchal_lag.f +
##     qualchal.f + spendgap_lag + spendgap + distpart_lag + votetype,
##     family = binomial, data = dt)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.0597   0.2351   0.3521   0.6106   1.0482
##
## Coefficients:
##                              Estimate Std. Error z value Pr(>|z|)
## (Intercept)                -7.374e-02  4.802e-01  -0.154   0.8780
## dvprop                      9.986e-01  1.251e+00   0.799   0.4246
## daystoelection             -5.359e-03  5.009e-03  -1.070   0.2847
## I(daystoelection^2)         1.575e-05  1.630e-05   0.966   0.3339
## I(daystoelection^3)        -1.502e-08  1.605e-08  -0.935   0.3496
## Retirement.f1               1.015e+00  2.556e-01   3.973 7.08e-05 ***
## seniorit                   -3.401e-02  3.634e-03  -9.361  < 2e-16 ***
## qualchal_lag.f1             2.340e-01  3.581e-02   6.534 6.40e-11 ***
## qualchal.f1                -1.628e-01  3.749e-02  -4.342 1.41e-05 ***
## spendgap_lag                1.669e-02  8.401e-03   1.987   0.0469 *
## spendgap                   -4.771e-02  9.783e-03  -4.877 1.08e-06 ***
## distpart_lag                6.657e+00  2.566e-01  25.946  < 2e-16 ***
## votetypeAmend              -2.204e+00  9.322e-02 -23.641  < 2e-16 ***
## votetypeOtherPass          -9.420e-01  1.192e-01  -7.904 2.70e-15 ***
## votetypeProPart            -2.191e-01  1.005e-01  -2.181   0.0292 *
## votetypeRegPass            -1.228e+00  1.004e-01 -12.229  < 2e-16 ***
## votetypeSusp               -1.044e+00  1.431e-01  -7.299 2.91e-13 ***
```

```
## dvprop:daystoelection       1.105e-02  1.442e-02   0.767   0.4434
## dvprop:I(daystoelection^2) -4.476e-05  4.710e-05  -0.950   0.3419
## dvprop:I(daystoelection^3)  5.757e-08  4.655e-08   1.237   0.2161
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 43732  on 57085  degrees of freedom
## Residual deviance: 38692  on 57066  degrees of freedom
## AIC: 38732
##
## Number of Fisher Scoring iterations: 6
```

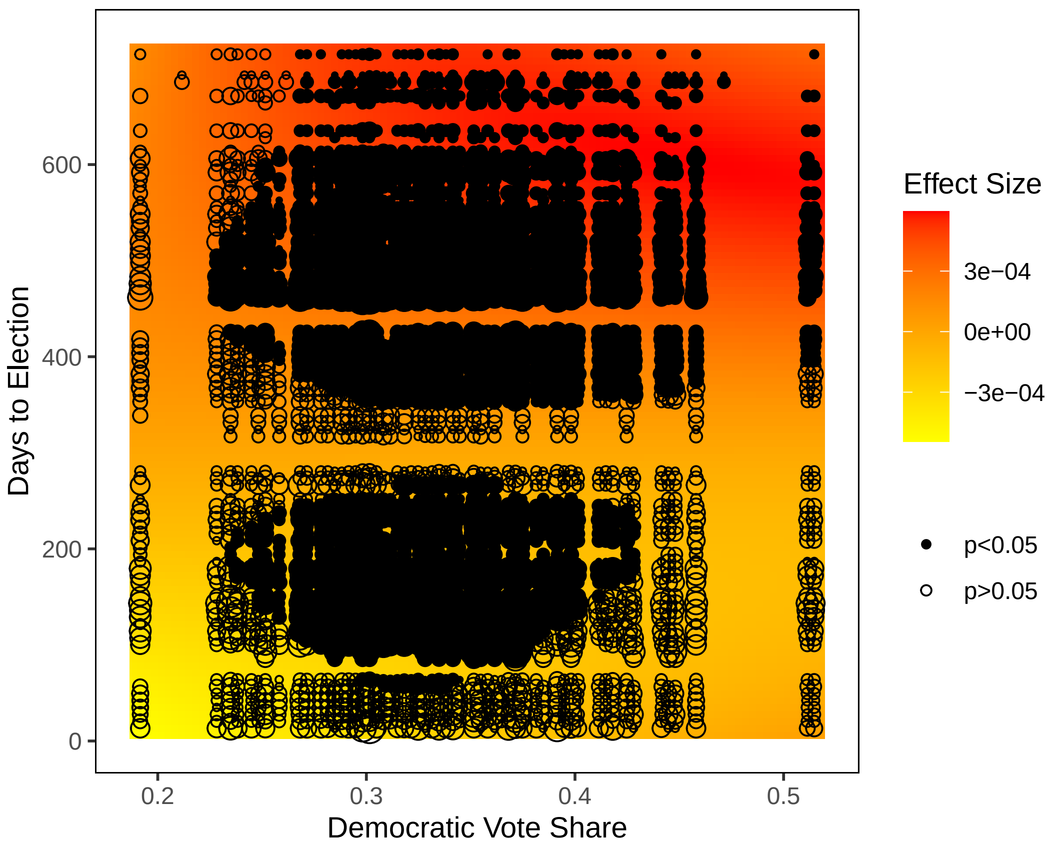
The observations are clustered by districts. Thus, we need to compute a cluster-robust variance-covariance matrix:

```
vc <- sandwich::vcovCL(m, cluster= ~ dist2 )
```

Plotting marginal effects of election proximity

We use the `plot_me()` function to make a heatmap for the marginal effects of election proximity.

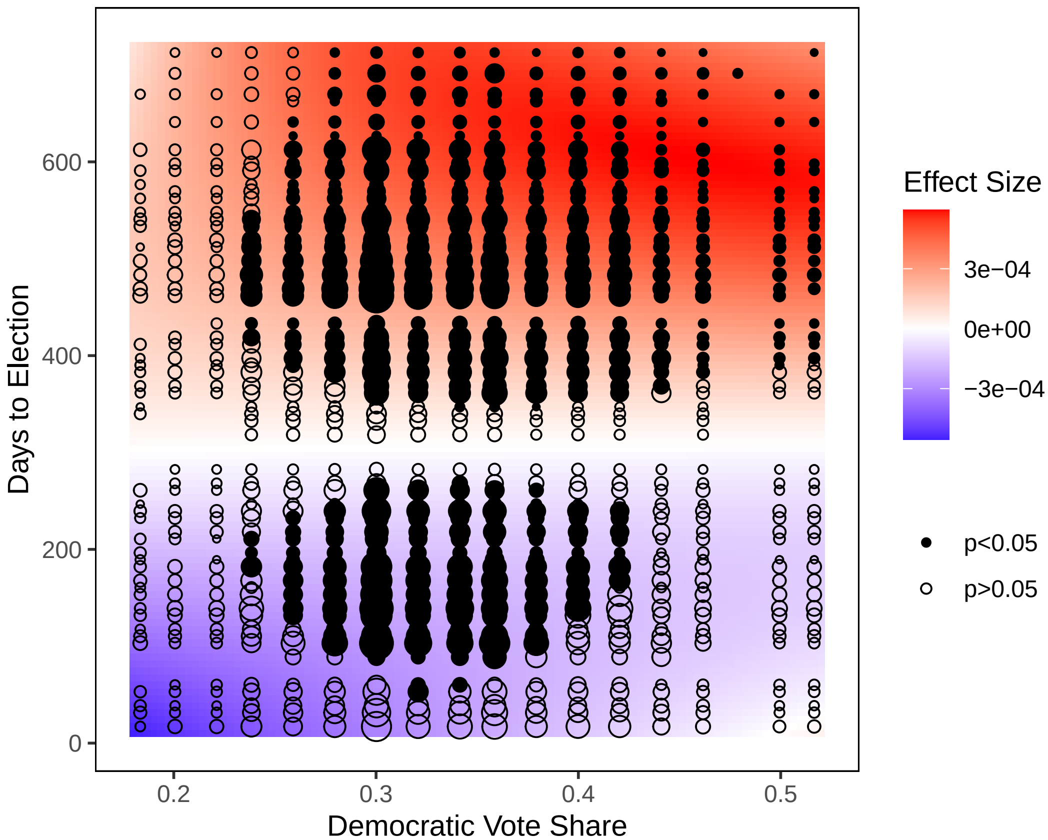
```
plot_me(model = m, x = "daystoelection", over = "dvprop", vcov=vc) +
  scale_fill_gradient(low="yellow", high="red") +
  labs(y="Days to Election", x="Democratic Vote Share")
```



Two modifications are needed here. First, since about half of these effects are positive, we need to use a divergent palette so that the intensity would represent the magnitude of the effect, and the hue would represent the direction. We can use the `scale_fill_gradient2()` function to specify the endpoints and midpoint of the color scale.

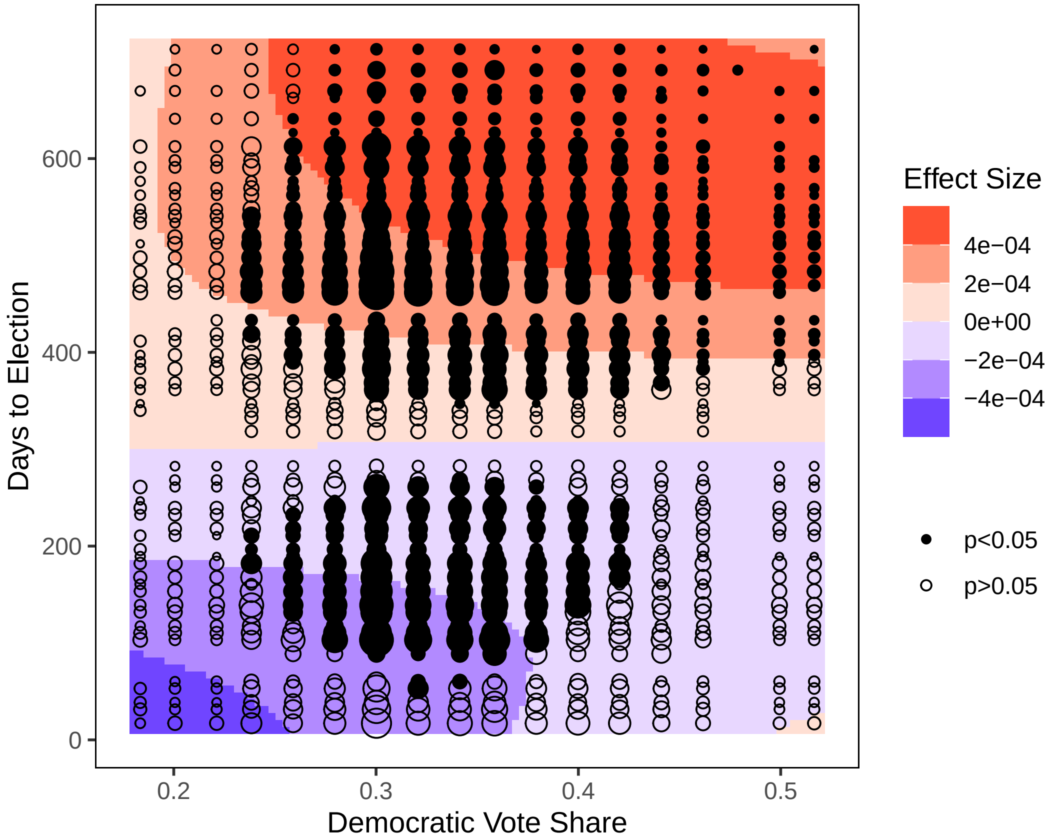
Second, to reduce the number of markers and subsequent overplotting, we can round the values shown on the axes:

```
newdt <- within(dt, {
  daystoelection <- round(daystoelection, -1) ## round to the nearest multiple of 10
  dvprop <- round(dvprop/0.02)*0.02 ## round to the nearest multiple of 0.02
})
plot_me(model = m, data=newdt, x = "daystoelection", over = "dvprop", vcov=vc) +
  scale_fill_gradient2(low="blue", mid="white", high="red") +
  labs(y="Days to Election", x="Democratic Vote Share")
```



To obtain a contour-plot with a divergent scale, replace `scale_fill_gradient2()` with `scale_fill_steps2()`:

```
plot_me(model = m, data=newdt, x = "daystoelection", over = "dvprop", vcov=vc) +
  scale_fill_steps2(low="blue", mid="white", high="red", n.breaks=7) +
  labs(y="Days to Election", x="Democratic Vote Share")
```

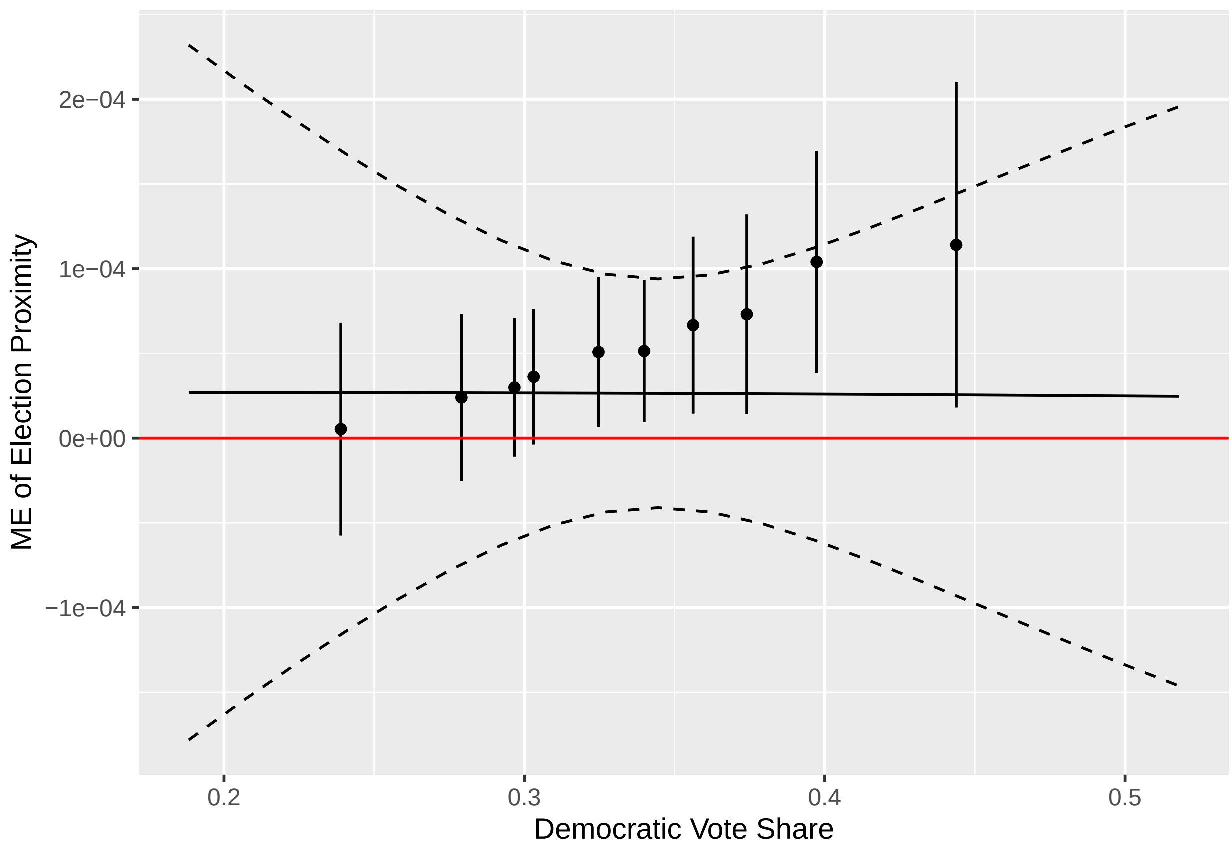


Computing and plotting DAME of election proximity

Do not forget to specify the variance-covariance matrix when computing DAME and MEM:

```
d <- dame(model=m, x="daystoelection", over="dvprop", vcov=vc)
ra.over <- seq(min(dt$dvprop, na.rm=TRUE), max(dt$dvprop, na.rm=TRUE), length.out=20)
mem <- mem(model=m, x="daystoelection", vcov=vc,
           at=list("dvprop"=ra.over))

ggplot(data=d, aes(x=bin_id, y=est, ymin=lb, ymax=ub)) +
  geom_point() +
  geom_linerange() +
  geom_line(aes(x=dvprop, y=est), data=mem) +
  geom_line(aes(x=dvprop, y=lb), data=mem, linetype="dashed") +
  geom_line(aes(x=dvprop, y=ub), data=mem, linetype="dashed") +
  geom_hline(yintercept=0, color="red") +
  labs(x="Democratic Vote Share", y="ME of Election Proximity")
```



Foreign direct investment and labor protest (RT)

Robertson and Teitelbaum (2011) study the response of the local labor to foreign direct investment. The article argues that FDI flows lead to more labor protests, and this effect is more substantial when there are fewer democratic means for resolving such conflicts.

Load the data and estimate the model

Since the dependent variable is a count of protests, we use a negative binomial regression. The right-hand side of the model equation includes an interaction of political regime (Polity 2 score) and the natural log of FDI flow. We expect the latter's effect to be conditional on the values of the former.

```
dt <- readRDS("RT.rds")
current_vals <- dt[,c("isocode","year","dispute","open_penn","l_gdp_pc_penn","gdp_grth",
                      "inflation_1","urban","xratchg","l_pop","time")]
lagged_vals <- within(dt, {
  year <- year + 1L
  l_l_flows <- l_flows
  l_polity2 <- polity2
  l_dispute <- dispute
})[c("isocode","year","l_l_flows","l_polity2","l_dispute")]
dt <- merge(current_vals, lagged_vals, by=c("isocode","year"))
dt <- na.omit(dt)

library(MASS)
m <- glm.nb(dispute ~ l_l_flows*l_polity2 + l_dispute + open_penn + l_gdp_pc_penn +
```

```
             gdp_grth + inflation_1 + urban + xratchg + l_pop + time,
        data=dt )
summary(m)
```

```
##
## Call:
## glm.nb(formula = dispute ~ l_l_flows * l_polity2 + l_dispute +
##     open_penn + l_gdp_pc_penn + gdp_grth + inflation_1 + urban +
##     xratchg + l_pop + time, data = dt, init.theta = 0.3997142679,
##     link = log)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.8660  -0.4005  -0.2286  -0.1056   6.3269
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)         -1.724e+01  1.950e+00  -8.839  < 2e-16 ***
## l_l_flows            1.508e-01  6.132e-02   2.460 0.013896 *
## l_polity2            1.872e-01  4.030e-02   4.645 3.40e-06 ***
## l_dispute            3.391e-01  3.205e-02  10.580  < 2e-16 ***
## open_penn           -5.637e-04  1.880e-03  -0.300 0.764346
## l_gdp_pc_penn        2.981e-01  1.829e-01   1.630 0.103171
## gdp_grth            -4.039e-04  1.755e-02  -0.023 0.981640
## inflation_1          9.812e-05  7.645e-05   1.284 0.199305
## urban                2.267e-02  6.359e-03   3.565 0.000364 ***
## xratchg             -7.718e-04  4.401e-03  -0.175 0.860797
## l_pop                6.341e-01  7.802e-02   8.127 4.38e-16 ***
## time                -1.171e-02  1.408e-02  -0.832 0.405371
## l_l_flows:l_polity2 -1.948e-02  6.104e-03  -3.192 0.001415 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for Negative Binomial(0.3997) family taken to be 1)
##
##     Null deviance: 1501.51  on 2347  degrees of freedom
## Residual deviance:  634.28  on 2335  degrees of freedom
## AIC: 1607.2
##
## Number of Fisher Scoring iterations: 1
##
##
##               Theta:  0.3997
##           Std. Err.:  0.0546
##
##  2 x log-likelihood:  -1579.1580
```

The article employs a more complicated version of this model with country-specific random effects. As earlier, we can estimate such a model with the `glmmTMB()` function from the `glmmTMB` package.

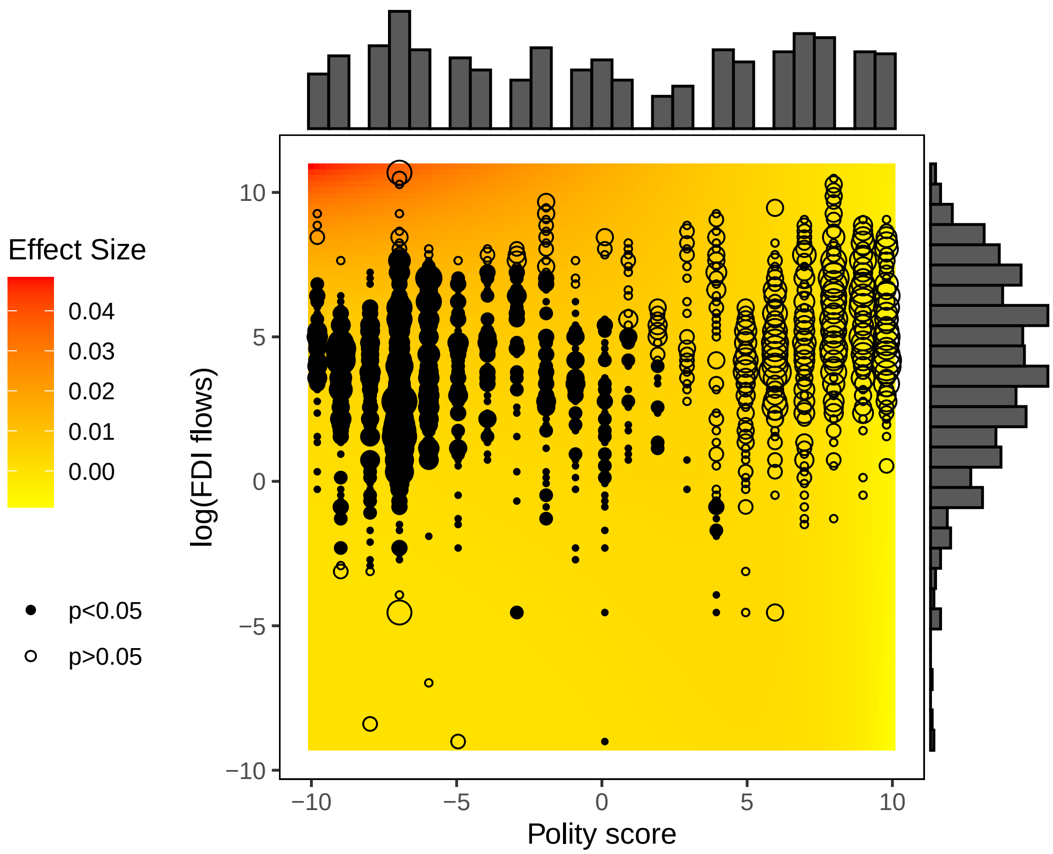
```
library(glmmTMB)
m2 <- glmmTMB(dispute ~ l_l_flows*l_polity2 + l_dispute + open_penn + l_gdp_pc_penn +
                gdp_grth + inflation_1 + urban + xratchg + l_pop + time + (1|isocode),
              family=nbinom1, data=dt)
summary(m2)
```

```
##  Family: nbinom1  ( log )
## Formula:
## dispute ~ l_l_flows * l_polity2 + l_dispute + open_penn + l_gdp_pc_penn +
##     gdp_grth + inflation_1 + urban + xratchg + l_pop + time +
##     (1 | isocode)
## Data: dt
##
##      AIC      BIC   logLik deviance df.resid
##   1484.7   1571.1   -727.3   1454.7     2333
##
## Random effects:
##
## Conditional model:
##  Groups  Name        Variance Std.Dev.
##  isocode (Intercept) 1.576    1.255
## Number of obs: 2348, groups:  isocode, 131
##
## Dispersion parameter for nbinom1 family (): 1.19
##
## Conditional model:
##                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -1.744e+01  3.236e+00  -5.390 7.07e-08 ***
## l_l_flows             3.382e-01  8.686e-02   3.894 9.87e-05 ***
## l_polity2             2.551e-01  6.007e-02   4.247 2.17e-05 ***
## l_dispute             5.996e-02  1.648e-02   3.637 0.000275 ***
## open_penn            -1.445e-03  3.568e-03  -0.405 0.685382
## l_gdp_pc_penn         9.334e-02  2.741e-01   0.340 0.733487
## gdp_grth             -2.570e-02  1.626e-02  -1.580 0.114100
## inflation_1           1.147e-04  6.852e-05   1.674 0.094076 .
## urban                 1.692e-02  1.094e-02   1.546 0.122083
## xratchg               1.383e-03  4.104e-03   0.337 0.736148
## l_pop                 6.491e-01  1.468e-01   4.422 9.80e-06 ***
## time                  2.143e-02  1.703e-02   1.258 0.208211
## l_l_flows:l_polity2 -2.973e-02  8.618e-03  -3.450 0.000560 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Plotting marginal effects of logged FDI flows

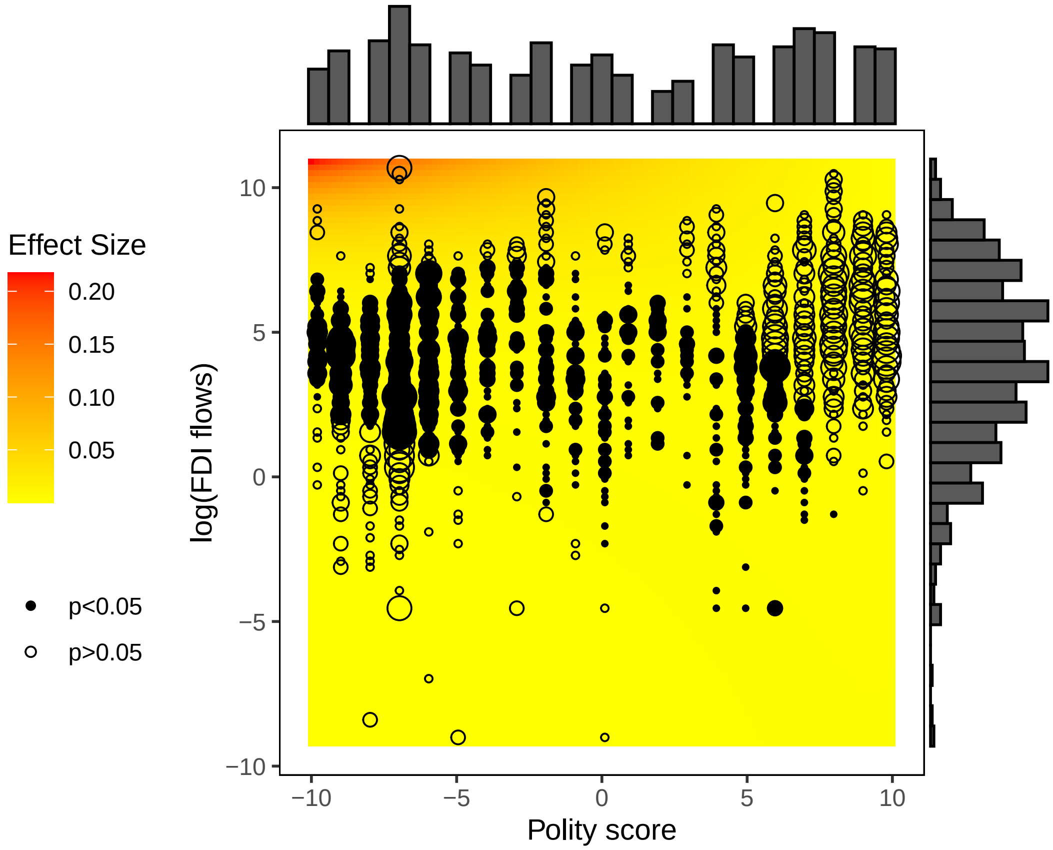
To plot the marginal effects from the negative binomial regression estimated using `glm.nb()`, we can use the standard syntax of `plot_me()`, with the exception of the dataset, which needs to be specified directly.

```
g <- plot_me(model = m, data=dt, x = "l_l_flows", over = "l_polity2")
gt <- g +
  scale_fill_gradient(low="yellow", high="red") +
  labs(x="Polity score", y="log(FDI flows)") +
  theme(legend.position="left")
ggExtra::ggMarginal(gt, type="histogram", data=dt, x=l_polity2, y=l_l_flows)
```



To plot a heatmap for the random effects model, we need to extract the coefficients and the variance-covariance matrix.

```
coef <- glmmTMB::fixef(m2)$cond
vc <- vcov(m2)$cond
g <- plot_me(formula = dispute ~ l_l_flows*l_polity2 + l_dispute + open_penn +
               l_gdp_pc_penn + gdp_grth + inflation_1 + urban + xratchg + l_pop + time,
        data=dt,
        coefficients=coef,
        vcov=vc,
        link="log",
        x = "l_l_flows", over = "l_polity2")
gt <- g +
  scale_fill_gradient(low="yellow", high="red") +
  labs(x="Polity score", y="log(FDI flows)") +
  theme(legend.position="left")
ggExtra::ggMarginal(gt, type="histogram", data=dt, x=l_polity2, y=l_l_flows)
```

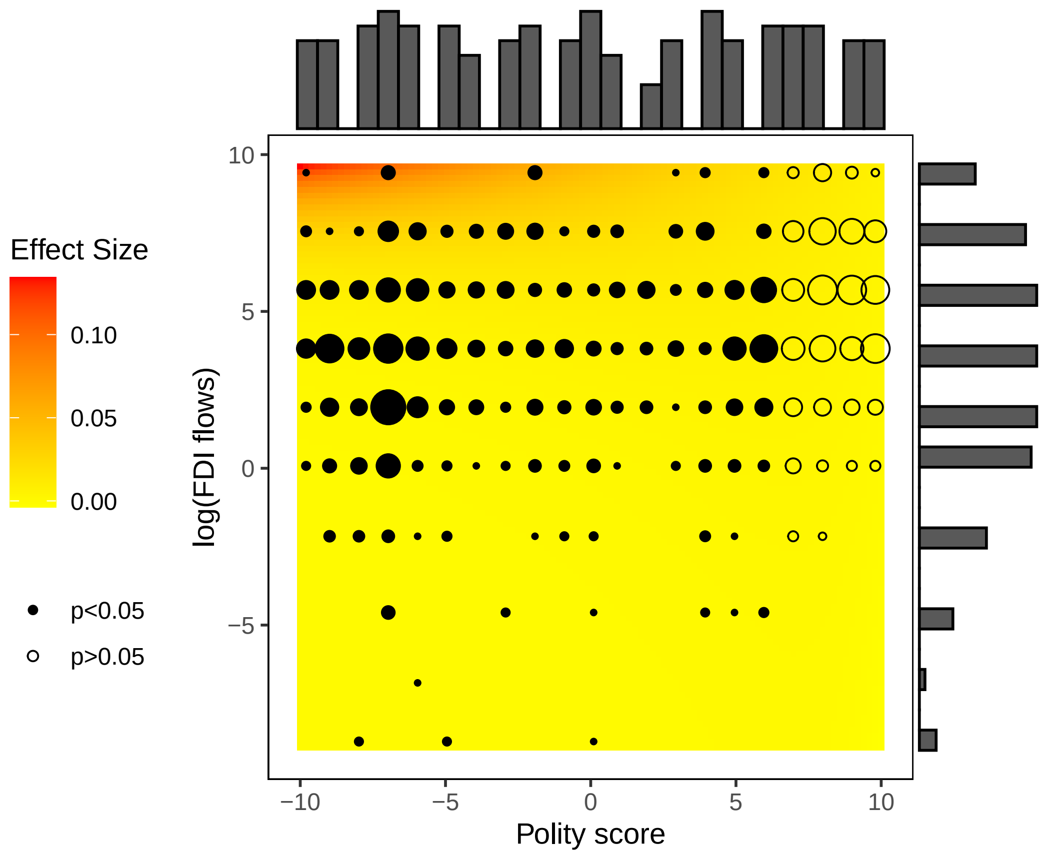


The figure in Zhirnov, Moral, and Sedashov (2022) uses binned values of logged FDI flows to reduce overplotting and applies simulations instead of the delta method for computing the standard errors. We can replicate these calculations in R by binning the values of `l_l_flows` and setting `mc=TRUE` in the `plot_me()` function (please note that the parameter estimates produced with `glmmTMB` and `lme4` are slightly different from Stata's estimates shown in the paper, which also leads to varied marginal effect estimates):

```
mcut <- cut(dt$l_l_flows, breaks=seq(from=-11.22, to=11.22, by=2))
binned <- tapply(dt$l_l_flows, INDEX=mcut, FUN=mean, na.rm=TRUE)
dt2 <- within(dt, {
  l_l_flows <- binned[mcut]
})

g <- plot_me(formula = dispute ~ l_l_flows*l_polity2 + l_dispute + open_penn +
               l_gdp_pc_penn + gdp_grth + inflation_1 + urban + xratchg + l_pop + time,
        data=dt2,
        coefficients=coef,
        vcov=vc,
        link="log",
        x = "l_l_flows", over = "l_polity2", mc=TRUE)

gt <- g +
  scale_fill_gradient(low="yellow", high="red") +
  labs(x="Polity score", y="log(FDI flows)") +
  theme(legend.position="left")
ggExtra::ggMarginal(gt, type="histogram", data=dt, x=l_polity2, y=l_l_flows)
```



Computing and plotting DAME of logged FDI flows

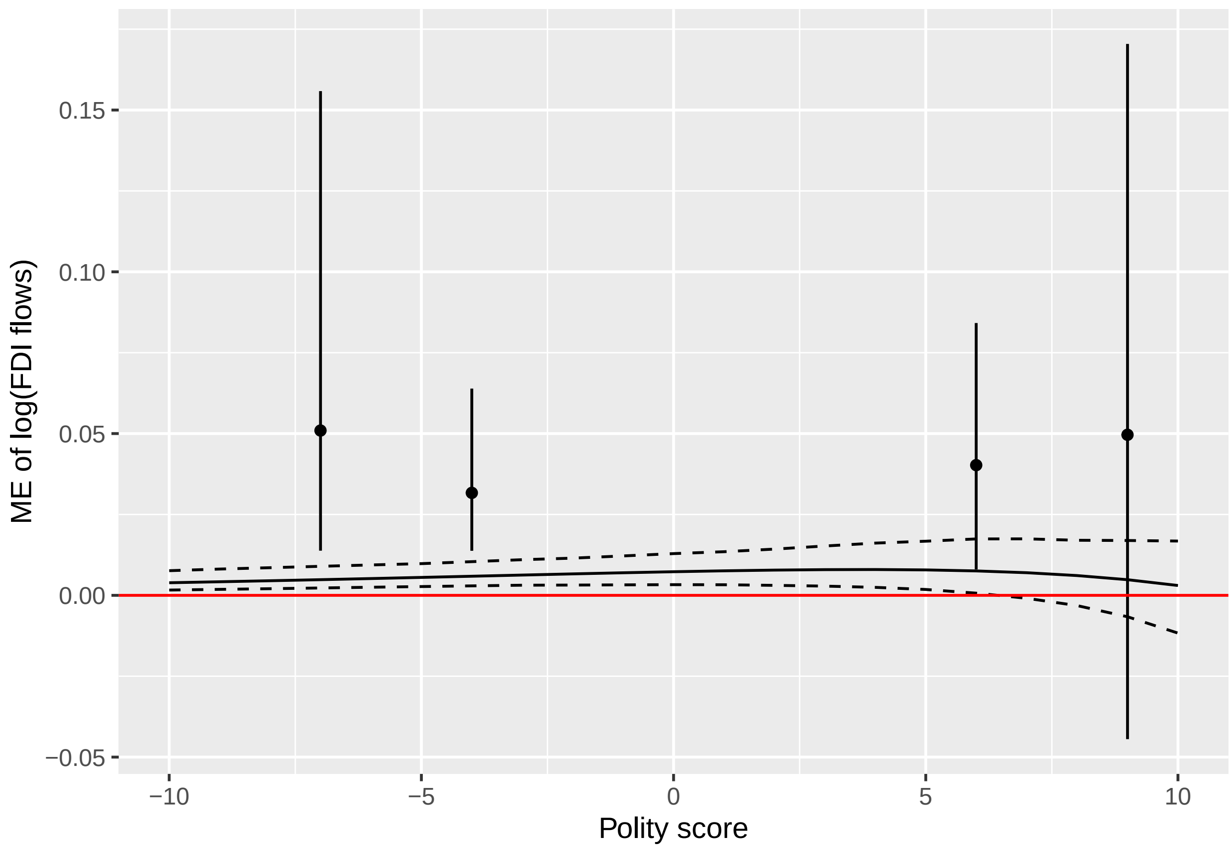
As earlier, we will include the group-specific components of intercepts as the offset.

```
re <- ranef(m2)$cond$isocode
dt$reff <- re[dt$isocode,"(Intercept)"]

d <- dame(formula = dispute ~ l_l_flows*l_polity2 + l_dispute + open_penn +
            l_gdp_pc_penn + gdp_grth + inflation_1 + urban + xratchg + l_pop +
            time + offset(reff),
        data=dt,
        coefficients=coef,
        vcov=vc,
        link="log",
        x="l_l_flows", over="l_polity2", nbins=4, mc=TRUE)
mem <- mem(formula = dispute ~ l_l_flows*l_polity2 + l_dispute + open_penn +
             l_gdp_pc_penn + gdp_grth + inflation_1 + urban + xratchg + l_pop +
             time + offset(reff),
        data=dt,
        coefficients=coef,
        vcov=vc,
        link="log", x="l_l_flows", mc=TRUE, at=list("l_polity2"=seq(from=-10,to=10, by=1)))

ggplot(data=d, aes(x=bin_id, y=est, ymin=lb, ymax=ub)) +
  geom_point() +
  geom_linerange() +
```

```
  geom_line(aes(x=l_polity2, y=est), data=mem) +
  geom_line(aes(x=l_polity2, y=lb), data=mem, linetype="dashed") +
  geom_line(aes(x=l_polity2, y=ub), data=mem, linetype="dashed") +
  geom_hline(yintercept=0, color="red") +
  labs(x="Polity score", y="ME of log(FDI flows)")
```



This document

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