Replication Seminar: Regression Discontinuity Analysis

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Here, we replicate Abou-Chadi, T., & Krause, W. (2018). The causal effect of radical right success on mainstream parties' policy positions: A regression discontinuity approach. British Journal of Political Science, 1-19. https://doi.org/10.1017/S0007123418000029

Data replication sets are available in Harvard Dataverse at https://dx.doi.org/10.7910/DVN/KYSD5S and online appendices at https://doi.org/10.1017/S0007123418000029.

Let us prep our environment and load some functions programmed by the authors

```r
library(tidyverse)
library(here)
library(magrittr)
source( here::here('Abou-ChadiKrause2018/rrp_rdd_functions.R' ))
```

Here is what I did to read transform the provided tab separated data into an RData file

```r
# ds <- read_tsv(here("Abou-ChadiKrause2018",'rrp_rdd.tab'))
# ds$er.in <- as.factor(ds$er.in)
# ds$er.in_l <- as.factor(ds$er.in_l)
# save(ds, file=here("Abou-ChadiKrause2018",'rrp_rdd.RData'))
```

So that we can follow their procedure (as reported in `rrp_rdd_log.pdf` or `rrp_rdd.r`)

```r
load( here::here('Abou-ChadiKrause2018/rrp_rdd.RData' ))
```

Inspecting data.

While this should have generally been done at the beginning, we will make use of the `libary(Hmisc)` package to label and describe the data.

```r
library(Hmisc)
```

Let us create a vector of labels (from `rrp_rdd.R`)

```r
labelvector <- c("iso2 character country code",
                 "election date",
                 "CMP-code mainstream party",
                 "name of mainstream party",
                 "party family of mainstream party (CMP-coding)",
                 "electoral threshold", "electoral threshold (lagged)",
                 "radical right party vote share (centerd on electoral threshold)",
                 "radical right party vote share (centerd on electoral threshold, lagged)",
```

```
                  "radical right parliamentary presence (binary indicator)",
                  "radical right parliamentary presence (binary indicator, lagged)",
                  "rile score (according to Lowe et al. 2011)",
                  "multiculturalism positive (CMP coding)",
                  "multiculturalism negative (CMP coding)",
                  "cultural protectionism score (Lowe et al. 2011, first difference)",
                  "per608 score (first difference)",
                  "cultural protectionism score (Kim and Fording 2003, first difference)",
                  "cultural protectionism score (Alonso and da Fonseca 2012, first difference)",
                  "cultural protectionism score (Meguid 2008, first difference)",
                  "environment protection score (Lowe et al. 2011, first difference)")
```

Now, let us bind variable names and labels, to print a table (using `kable()` from the `knitr` package) showingus what variables we are dealing with

```
cbind(VariableName=names(ds),VariableDescription=labelvector) %>%
  knitr::kable(caption = "Variables in Abou-Chadi & Krause (2018)")
```

Table 1: Variables in Abou-Chadi & Krause (2018)

VariableName	VariableDescription
iso2c	iso2 character country code
edate	election date
party	CMP-code mainstream party
partyname	name of mainstream party
parfam	party family of mainstream party (CMP-coding)
thrs	electoral threshold
thrs_l	electoral threshold (lagged)
er.v.c	radical right party vote share (centerd on electoral threshold)
er.v.c_l	radical right party vote share (centerd on electoral threshold, lagged)
er.in	radical right parliamentary presence (binary indicator)
er.in_l	radical right parliamentary presence (binary indicator, lagged)
rile.logit	rile score (according to Lowe et al. 2011)
per607	multiculturalism positive (CMP coding)
per608	multiculturalism negative (CMP coding)
multic.logit_fd	cultural protectionism score (Lowe et al. 2011, first difference)
per608_fd	per608 score (first difference)
multic.ratio_fd	cultural protectionism score (Kim and Fording 2003, first difference)
af.bipolar_fd	cultural protectionism score (Alonso and da Fonseca 2012, first difference)
meguid.bipolar_fd	cultural protectionism score (Meguid 2008, first difference)
env.logit_fd	environment protection score (Lowe et al. 2011, first difference)

Then, let us summarise the data by `summary()` (remember also `head()` and `str()` can provide us with an idea of the data)

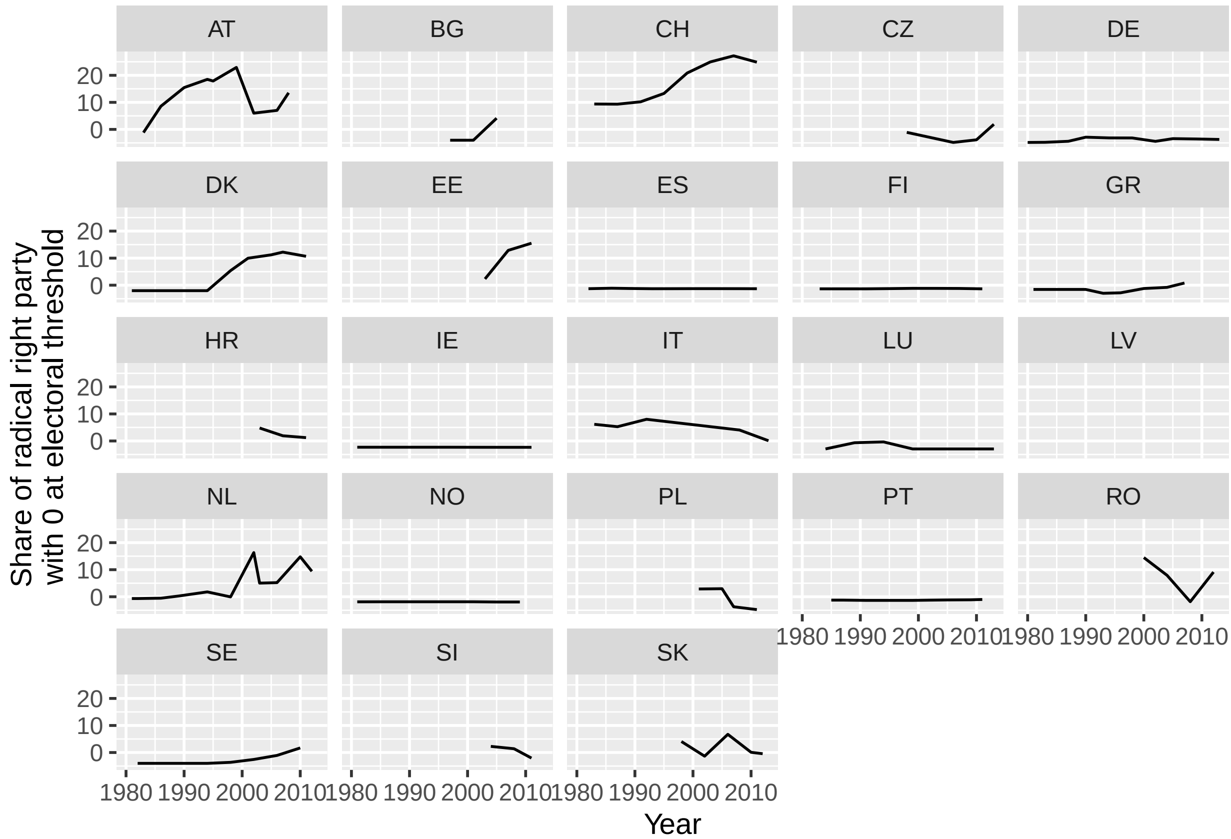
```
summary(ds)
```

```
##     iso2c               edate                party          partyname
##  Length:426         Min.   :1980-10-05   Min.   :11320   Length:426
##  Class :character   1st Qu.:1989-09-06   1st Qu.:14810   Class :character
##  Mode  :character   Median :1999-10-03   Median :34313   Mode  :character
##                     Mean   :1998-08-01   Mean   :40537
##                     3rd Qu.:2007-03-14   3rd Qu.:53320
##                     Max.   :2013-10-26   Max.   :97521
```

```
##
##      parfam          thrs            thrs_l          er.v.c
##  Min.   :10.00   Min.   :0.6409   Min.   :0.6409   Min.   :-4.824
##  1st Qu.:30.00   1st Qu.:1.3510   1st Qu.:1.3510   1st Qu.:-2.320
##  Median :40.00   Median :2.3200   Median :2.3200   Median :-1.280
##  Mean   :42.18   Mean   :2.7200   Mean   :2.6891   Mean   : 1.531
##  3rd Qu.:50.00   3rd Qu.:4.0000   3rd Qu.:4.0000   3rd Qu.: 2.733
##  Max.   :80.00   Max.   :5.0000   Max.   :5.0000   Max.   :27.205
##
##     er.v.c_l      er.in   er.in_l   rile.logit          per607
##  Min.   :-4.824   0:282   0:287   Min.   :-4.2627   Min.   :0.0000
##  1st Qu.:-2.337   1:144   1:139   1st Qu.:-0.6113   1st Qu.:0.0000
##  Median :-1.291                   Median :-0.1467   Median :0.1215
##  Mean   : 1.094                   Mean   :-0.1200   Mean   :0.5025
##  3rd Qu.: 2.271                   3rd Qu.: 0.3950   3rd Qu.:0.7252
##  Max.   :27.205                   Max.   : 3.4764   Max.   :5.4790
##                                   NA's   :2
##      per608        multic.logit_fd      per608_fd         multic.ratio_fd
##  Min.   : 0.0000   Min.   :-6.59375   Min.   :-13.31100   Min.   :-2.00000
##  1st Qu.: 0.0000   1st Qu.:-0.79317   1st Qu.:  0.00000   1st Qu.:-0.16687
##  Median : 0.0000   Median : 0.00000   Median :  0.00000   Median : 0.00000
##  Mean   : 0.4698   Mean   :-0.00608   Mean   :  0.06625   Mean   : 0.00407
##  3rd Qu.: 0.2032   3rd Qu.: 0.72542   3rd Qu.:  0.00000   3rd Qu.: 0.23128
##  Max.   :13.8890   Max.   : 6.09709   Max.   : 12.85700   Max.   : 2.00000
##                    NA's   :35         NA's   :31          NA's   :244
##  af.bipolar_fd      meguid.bipolar_fd  env.logit_fd
##  Min.   :-16.8490   Min.   :-17.7820   Min.   :-6.85104
##  1st Qu.: -2.2105   1st Qu.: -2.6105   1st Qu.:-1.18905
##  Median :  0.0000   Median :  0.0000   Median : 0.00000
##  Mean   :  0.1665   Mean   :  0.1191   Mean   :-0.00977
##  3rd Qu.:  2.4015   3rd Qu.:  2.6225   3rd Qu.: 1.06624
##  Max.   : 14.9760   Max.   : 23.2450   Max.   : 6.26728
##  NA's   :31         NA's   :31         NA's   :35
```

Alright, so let us move on to the analysis part. First, I would want to know what vote shares of extreme right parties we are dealing with (over time).

```r
ds %>% ggplot(mapping = aes(y = er.v.c, x = lubridate::year(as.Date(ds$edate)))) +
  geom_line() +
  xlab("Year") +
  ylab("Share of radical right party \n with 0 at electoral threshold") +
  facet_wrap(~iso2c)
```



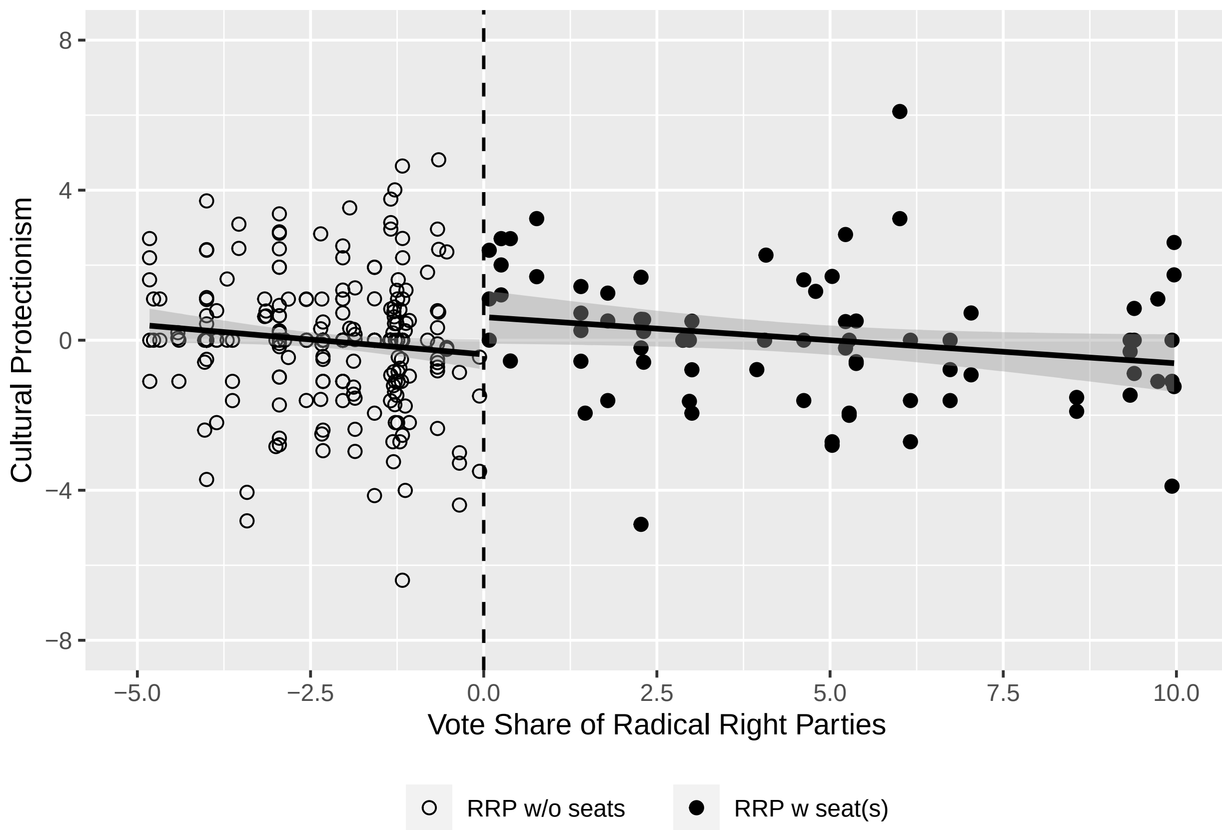
Is there something you would want to know about the data? Let us try to inspect that. Try and adapt the code below. geom_TYPE can be `geom_plot()`, `geom_line()`, `geom_area()`, etc. check https://ggplot2.tidyverse.org/reference/

```
# ds %>% ggplot(mapping = aes(y= YAXISVARIABLE, x= XAXISVARIABLE)) + geom_TYPE
```

Figure 1: Mainstream party position change on cultural protectionism

Nice, so now we can directly proceed to replicating the main Fig. 1

```
p1 <- jump.plot( data = subset( ds , er.v.c_l <= 10 )
                 , force.var = 'er.v.c_l'
                 , yvar = 'multic.logit_fd'
                 , seat.identifier = 'er.in_l'
                 , polynomial = 1
)
p1
```



That went smoothly. Let us inspect what this `jump.plot()` function does.

```
# jump.plot() # hold Strg/Cntrl and click on the function.
# This should open another tab with the function code.
# Alternatively, we can also click on the fucntion in our Global Environment.
```

Table 2: Mainstream party position change on cultural protectionism

Abou-Chadi and Krause also provide estimates. In particular, they provide the Local Average Treatement Effect (LATE) coeficient, which is just above and below the threshold.

```
rd.multic <- rd.base( data = ds
                      , force.var = 'er.v.c_l'
                      , yvar = 'multic.logit_fd'
                      , seat.identifier = 'er.in_l'
                      , fixed.effects = 'iso2c'
                      , clust1 = 'party'
                      , clust2 = 'edate'
                      , polynomials = c( 1 , 2 , 3 , 4 )
                      , bws = NULL
)
rd.multic
```

```
##       LATE  St. Err.      p-value Bandwith       Approach Polynomial
## 1 3.072*** 0.6428928 3.178801e-06    3.315 Non-Parametric          1
```

```
## 2 4.388*** 1.1838742 2.648093e-04    3.315 Non-Parametric          2
## 3 3.777*** 0.8201074 5.709008e-06   global     Parametric          3
## 4 4.853*** 1.0028809 1.945080e-06   global     Parametric          4
##   N left of c N right of c
## 1         214          32
## 2         214          32
## 3         272         119
## 4         272         119
```

We can certainly check what the authors did within their `rd.base()` function. It is relatively advanced, but to cut a long story short: They built an indicator variable for the electoral threshold as we discussed in the lecture, call that indicator variable `above` and use that as an instrumental variable in 'AER::ivreg(), based on

```
formula = multic.logit_fd ~ er.in_l + poly(er.v.c_l, 20, raw = TRUE) +
    poly(force_above, 20, raw = TRUE) + as.factor(iso2c) | above +
    poly(er.v.c_l, 20, raw = TRUE) + poly(force_above, 20, raw = TRUE) +
    as.factor(iso2c)
```

This is an approach that is normally employed in so called fuzzy RDD designs. This confuses me a bit, not as such (it is standard for fuzzy RDD) but because in their paper they talk about using a sharp RDD approach. Anyway, here you find a somewhat simpler approach in **R**, if you want ***RDD*** code to play around for your own analysis: https://www.econometrics-with-r.org/13-4-quasi-experiments.html

Mainstream left and right wing party position change on cultural protectionism

After having established that there is a general LATE, Abou-Chad and Krause proceed by estimating the LATE for both left- and right-wing parties. That can be called estimating *heterogeneous treatment* effects, as the LATE may differ across groups within the treated.

Table 3: Mainstream left party position change on cultural protectionism

```
ds <- ds %>%
  dplyr::group_by( iso2c ) %>%
  dplyr::mutate( country.mean.rile.logit = mean( rile.logit , na.rm = TRUE )) %>%
  dplyr::ungroup( ) %>%
  dplyr::group_by( party ) %>%
  dplyr::mutate( mean.rile.logit = mean ( rile.logit , na.rm = TRUE )) %>%
  dplyr::ungroup( )
rd.ml <- rd.base( data = subset( ds , ( mean.rile.logit < country.mean.rile.logit ))
                  , force.var = 'er.v.c_l'
                  , yvar = 'multic.logit_fd'
                  , seat.identifier = 'er.in_l'
                  , fixed.effects = 'iso2c'
                  , clust1 = 'party'
                  , clust2 = 'edate'
                  , polynomials = c( 1 , 2 , 3 , 4 )
                  , bws = NULL
)
rd.ml
```

```
##       LATE  St. Err.      p-value Bandwith       Approach Polynomial
## 1 2.996*** 0.8683497 0.0008536307    2.999 Non-Parametric          1
## 2  2.157** 0.9278206 0.0223856418    2.999 Non-Parametric          2
```

```
## 3 3.685*** 1.0078671 0.0003512669   global     Parametric          3
## 4 4.067*** 1.2369685 0.0012531449   global     Parametric          4
##   N left of c N right of c
## 1          91           19
## 2          91           19
## 3         124           59
## 4         124           59
```

Table 4: Mainstream right party position change on cultural protectionism

```
rd.mr <- rd.base( data = subset( ds , ( mean.rile.logit > country.mean.rile.logit ))
                  , force.var = 'er.v.c_l'
                  , yvar = 'multic.logit_fd'
                  , seat.identifier = 'er.in_l'
                  , fixed.effects = 'iso2c'
                  , clust1 = 'party'
                  , clust2 = 'edate'
                  , polynomials = c( 1 , 2 , 3 , 4 )
                  , bws = NULL
)
rd.mr
```

```
##       LATE  St. Err.      p-value Bandwith       Approach Polynomial
## 1 3.435*** 0.7648786 1.736232e-05    3.515 Non-Parametric          1
## 2 7.951*** 1.8514596 3.792391e-05    3.515 Non-Parametric          2
## 3 4.164*** 0.8571944 2.575779e-06   global     Parametric          3
## 4 6.312*** 1.3448671 5.357578e-06   global     Parametric          4
##   N left of c N right of c
## 1         121           11
## 2         121           11
## 3         148           60
## 4         148           60
```

Interesting, so right wing parties respond stronger to the presence of radical right parties' presence in parliament.

Robustness Checks

To top up, Abou-Chadi and Krause, provide several robustness checks to show how stable their results are.

Varying bandwith around electoral threshold

Here is how they calculated the data plotted in Figure 2.

```
rd.sens.data <- rd.sens( data = ds
                         , force.var = 'er.v.c_l'
                         , yvar = 'multic.logit_fd'
                         , seat.identifier = 'er.in_l'
                         , fixed.effects = 'iso2c'
                         , clust1 = 'party'
                         , clust2 = 'edate'
                         , polynomials = c( 1 , 2 )
                         , bws = seq( 1.5 , 10 , .25 )
                         )
rd.sens.data
```

Only countries with legally binding thresholds.

Figure 3: Mainstream party position change on cultural protectionism, countries with legally fixed threshold

```
c.list <- c( 'AT' , 'BG' , 'CZ' , 'DE' , 'EE' , 'GR' , 'LV' , 'NL' , 'PL' , 'RO' , 'SE' , 'SI')
ds %>%
  filter( iso2c %in% c.list ) %>%
  filter( !( iso2c == 'AT' & edate < '1994-01-01' )) %>%
  filter( !( iso2c == 'GR' & edate < '1993-01-01' )) %>%
  filter( !( iso2c == 'SI' & edate < '2000-01-01' )) -> ds.fixed
p3 <- jump.plot( data = subset( ds.fixed , er.v.c_l <= 10 )
                 , force.var = 'er.v.c_l'
                 , yvar = 'multic.logit_fd'
                 , seat.identifier = 'er.in_l'
                 , polynomial = 3
)
p3
```

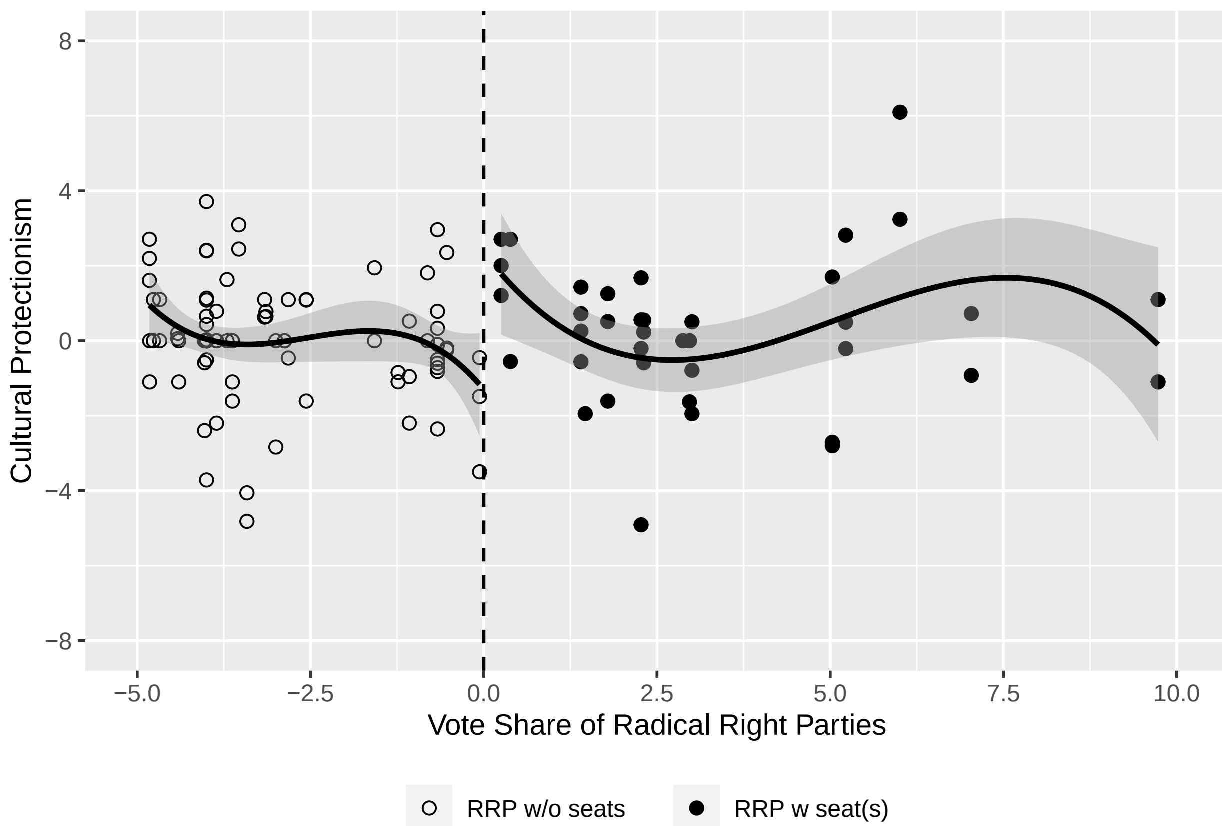


Table 5: Mainstream party position change on cultural protectionism, countries with legally fixed threshold

```
rd.fixed <- rd.base( data = ds.fixed
                     , force.var = 'er.v.c_l'
                     , yvar = 'multic.logit_fd'
                     , seat.identifier = 'er.in_l'
                     , fixed.effects = 'iso2c'
                     , clust1 = 'party'
                     , clust2 = 'edate'
                     , polynomials = c( 1 , 2 , 3 , 4 )
```

```
                      , bws = NULL
)
rd.fixed
```

```
##       LATE  St. Err.      p-value Bandwith       Approach Polynomial
## 1 2.666*** 0.6568163 1.404817e-04    3.790 Non-Parametric          1
## 2 3.602*** 0.8143358 4.168852e-05    3.790 Non-Parametric          2
## 3 4.186*** 0.4649292 1.809254e-15   global     Parametric          3
## 4 3.487*** 0.7040694 2.182586e-06   global     Parametric          4
##   N left of c N right of c
## 1          47           27
## 2          47           27
## 3          95           59
## 4          95           59
```

Seems, overall, and beside their advanced R-programming, Abou-Chadi and Krause provide relatively reliable results that main party positions change when a radical right party is present in parliament.