ALMA MATER STUDIORUM
UNIVERSITY OF BOLOGNA

The Effects of Participation in Cash Transfer Programs on Political Support for the Government

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1. Introduction

Can political support be bought? In no uncertain terms, this is an important question, especially given the recent trends in concentration of economic power: buying citizens' support is a simple way to transform economic power into political power. The easiest way to study this hypothetical is to observe how popular approval changes (transfer of political power) when there's cash transfer programs (transfer of economic power). We believe this to be the best strategy, because it is illegal in most countries to outright attempt to *buy* support, which makes direct data collection nigh-impossible.

Many such programs utilize an eligibility index based on factors like income, assigning benefits only to individuals below a clearly defined eligibility threshold or cutoff score. This sharp assignment rule based on a continuous variable provides an opportunity for causal inference through Regression Discontinuity Design (RDD). We argue that RDD is the best tool for this analysis, as it leverages this program structure to isolate the effect of participation near the cutoff, mitigating concerns about comparing potentially different groups far from the threshold. Our analysis will therefore use RDD to estimate the causal effect of cash transfer program participation on political support for the government among individuals close to the program's eligibility cutoff.

2. Data

The data we used in this paper is about PANES program (Plan de Atención Nacional a la Emergencia Social) of Uruguay, initiated by the newly elected left-wing government against the previous right-wing liberal government in 2005. The original version of the data was collected by Manacorda et al. [1] from the Uruguayan Ministry of Social Development. The version we used was made available for the purposes of the exercises in Huntington-Klein's textbook *The Effect* [2], and is slightly different than the one used by Manacorda et al. [1], as indicated in the textbook. We obtained the data from the Github repository NickCH-K/causaldata [3] by navigating to R/data/gov_transfers.rda.

The dataset contains 5 variables for 1948 observations. *Income_Centered* includes the predicted incomes of certain individuals near and centered at the cutoff score. The binary *Participation* takes a 0 for individuals not participating in the program, and 1 for those who do. *Support* takes 0 for participants who find the previous government better than the current one, 1 for those who find the current one better than the previous one, and 0.5 for those indifferent between the two, obtained by surveys. *Age* and *Education* indicate the average “ and years of education completed by the members of the household. A pairwise correlation plot of this dataset may be seen by consulting Figure 1. To conduct a logistic regression as explained in Section 3 and Section 4, we created the variable *Support_Binomial*, which took the value 1 for *Support*=1 and 0 otherwise. Some descriptive statistics for the dataset may be seen by consulting Table 3 in Section 6.

Additionally, we constructed two datasets (*half_bw* and *quart_bw*) to permit the use of different bandwidths in our analysis. As the original dataset had *Income_Centered* run between approximately -0.02

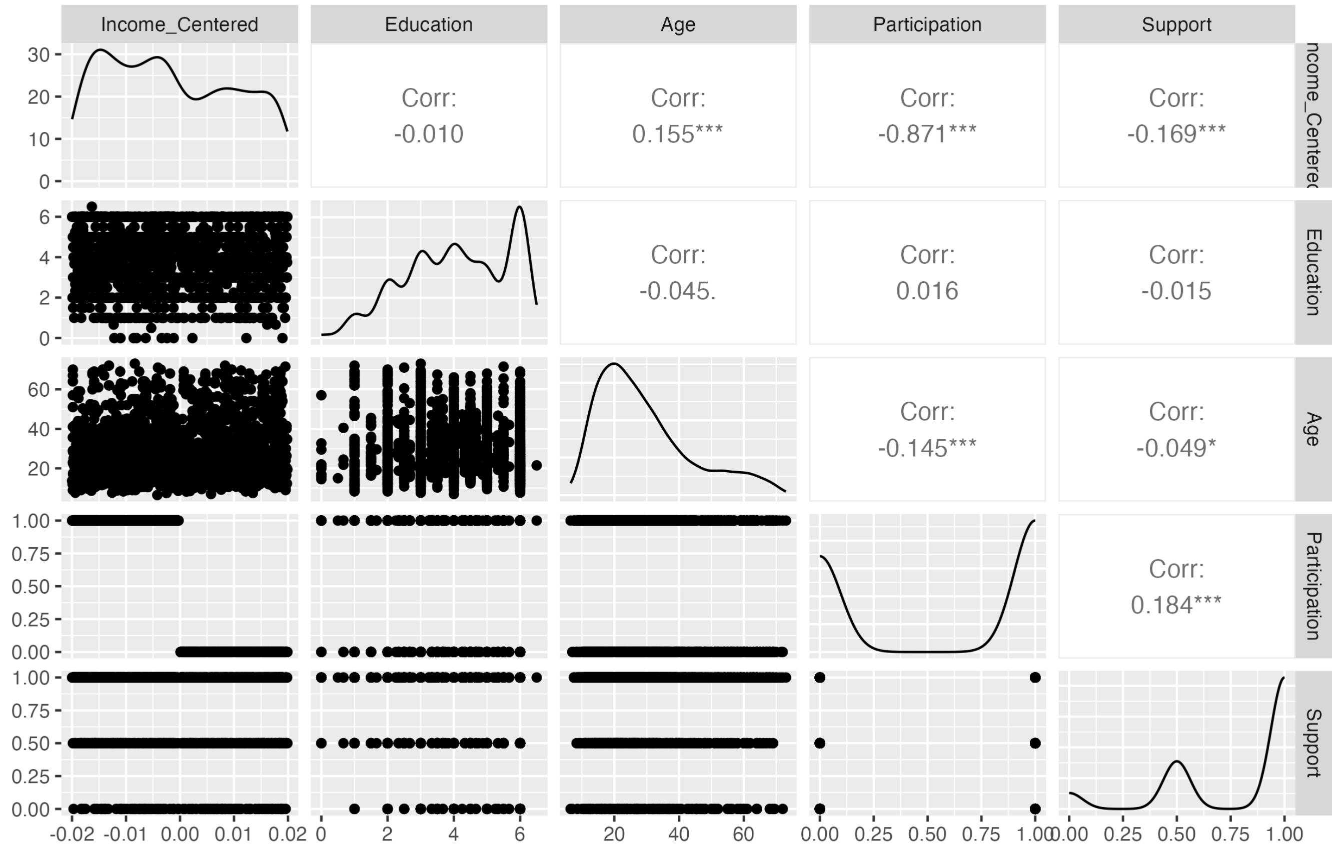

Figure 1: Pairwise correlation plot of the dataset prior to any modifications.

and 0.02, we obtained the half and quarter bandwidth datasets by filtering observations for which *Income_Centered* ran between −0.01 and 0.01 and −0.005 and 0.005 respectively. Some descriptive statistics may be seen by consulting Table 4 in Section 6 and Table 1 below.

3. Methods

We employed an RDD to evaluate the impact of the cash transfer programs on citizens' political support of the government where Program enrollment is determined by predicted income (*Income_Centered*).

Before estimating the treatment effect, we performed standard RDD validity checks. First, we assessed potential manipulation of the eligibility index around the cutoff using a density test (see Figure 4). The results indicated no significant discontinuity in the density, suggesting no evidence of manipulation. Second, we examined the relationship between the eligibility index (*Income_Centered*) and program enrollment (Participation) near the cutoff to assess compliance. We observed perfect compliance (see Figure 3), consistent with a sharp RDD framework, where treatment assignment is effectively determined by the eligibility index relative to the cutoff.

Under the sharp RDD assumptions, the treatment effect (the LATE, or Local Average Treatment Effect) is estimated by the discontinuity in the outcome (*Support*) at the cutoff. We estimated this effect using regression models (*lm* function). Our baseline

Income_Centered	**Education**	**Age**	**Participation**	**Support**	**Support_Binomial**
Min. :−0.0049910	Min. :0.000	Min. : 6.50	Min. :0.0000	Min. :0.0000	Min. :0.0000
1st Qu.:−0.0030440	1st Qu.:3.000	1st Qu.:19.00	1st Qu.:0.0000	1st Qu.:0.5000	1st Qu.:0.0000
Median :−0.0013000	Median :4.000	Median :25.58	Median :1.0000	Median :1.0000	Median :1.0000
Mean :−0.0005979	Mean :4.171	Mean :29.18	Mean :0.5974	Mean :0.8084	Mean :0.6818
3rd Qu.: 0.0019182	3rd Qu.:6.000	3rd Qu.:36.00	3rd Qu.:1.0000	3rd Qu.:1.0000	3rd Qu.:1.0000
Max. : 0.0049710	Max. :6.000	Max. :71.00	Max. :1.0000	Max. :1.0000	Max. :1.0000
NA	NA's :16	NA	NA	NA	NA

Table 1: Descriptive statistics for quarter bandwidth data.

model regressed *Support* on *Participation* and the centered eligibility index (*Income_Centered*). To account for potentially non-linear underlying relationships between income and support, we estimated quadratic and cubic specifications by adding polynomial terms ($\mathrm{I}(\mathrm{Income\_Centered}^2)$) and ($\mathrm{I}(\mathrm{Income\_Centered}^3)$) to the models. Furthermore, we estimated slope interaction specifications, allowing the relationship between *Income_Centered* and *Support* to differ for participants and non-participants by including an interaction term ($\mathrm{Participation} * \mathrm{Income\_Centered}$). We also included specifications controlling for *Age*)within the slope interaction framework. Finally, for key specifications, we estimated logistic models (*glm* function with *family* = *binomial*) using the binary *Support_Binomial* variable described in Section 2.

Recognizing that RDD estimates represent a local effect and can be sensitive to the chosen bandwidth, we performed the analysis across three bandwidths defined in Section 2: the full dataset (*gov_transfers*), the half bandwidth (*half_bw*), and the quarter bandwidth (*quart_bw*). This allows assessment of the results' sensitivity to the observations included around the cutoff.

Model specifications deemed most significant, from the quarter bandwidth, are presented in Section 4, while results across all bandwidths and specifications are available in Section 6 (Table 5, Table 6, and Table 7). Analyses were conducted in R, code and packages used are in Section 6.

4. Results

Our analysis of different specifications across bandwidths yielded clear results. As mentioned, the most interesting specifications found were all within the quarter bandwidth, which was selected due to the sufficient amount of observations, specifically in the quadratic, slope, slope controlling for age, and logistic.

Figure 2 offers a graphical comparison of our four best-performing models, while more specific results, confidence intervals, and significance can be found in Table 2.

The main results point towards the logistic model as being the best performing one, while the quadratic specification is the worst performing out of the four. This hints additionally the importance of the interaction term to gauge the correlation between *Participation* and *Income_Centered*.

Additional, but less conclusive, specifications were analyzed, these specifications can be consulted in Table 7. Notably, while *Participation* isn't statistically significant in the quarter bandwidth, it is very significant in the full bandwidth and less, but still significant in the half bandwidth.

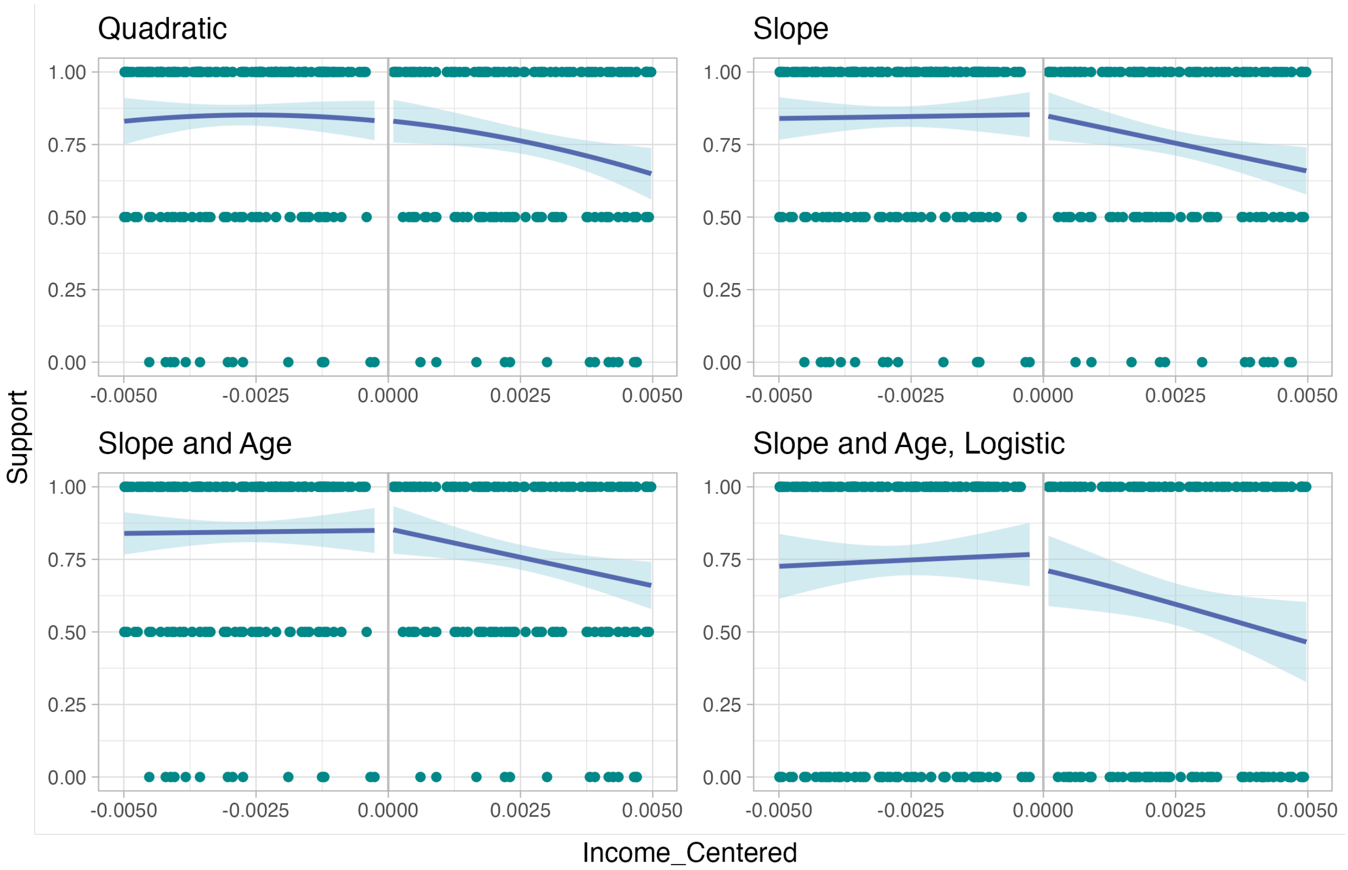

Figure 2: Graphic comparison of the significant specifications

	Quadratic	Slope	Slope and Age	Slope and Age, Logistic
(Intercept)	0.832***	0.851***	0.920***	1.328***
	(0.038)	(0.043)	(0.053)	(0.383)
Participation	−0.004	0.002	−0.005	0.285
	(0.061)	(0.061)	(0.061)	(0.457)
Income_Centered	−18.649+	−38.629**	−39.269**	−212.316*
	(10.258)	(14.593)	(14.532)	(101.999)
I(Income_Centered^2)	−3640.699*			
	(1847.998)			
Participation ∗ Income_Centered		41.374*	41.405*	257.726+
		(20.487)	(20.398)	(151.154)
Age			−0.002*	−0.014*
			(0.001)	(0.007)
Num.Obs.	462	462	462	462
R2	0.037	0.038	0.048	
R2 Adj.	0.031	0.031	0.040	
AIC	199.0	198.8	195.7	566.5
BIC	219.7	219.5	220.5	587.2
Log.Lik.	−94.490	−94.391	−91.868	−278.269
RMSE	0.30	0.30	0.30	0.45
p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001				

Table 2: Results of the most significant specifications

4.1. Interpretation

According to the findings presented in Table 2 we can derive the following interpretations for the first three models:

The *Intercept*, due to the centering, can be interpreted as the (mean) *Support* for the current government without intervention, which ranges from 0.832 in the quadratic model to 0.920 in the slope and age interaction model, so on average people were already more supporting of the government.

Participation, as anticipated, is not statistically significant.

Income_Centered in the the models have a consistent negative relationship with support, −18.64 in quadratic and −38.62 and −39.26 in the *Slope* and *Slope and Age* models respectively. The selection of the quarter bandwidth additionally supports *Income_Centered* as a valuable predictor, as while significance for *Participation* decreased with the bandwidths, it increased for *Income_Centered*.

The interaction term added in the slope regressions shows the correlation between *Income_Centered* and *Participation*, indicating their relationship.

The *Age* estimates prove to be significant, with an effect of marginally decreasing support (-0.002) as it increases.

Our logistic regression model's interpretation, is as follows:

The intercept can be interpreted as the odds ratio of people (without intervention) of showing support for the government, while *Participation* is still not significant.

Income_Centered and the *Income_Centered ∗ Participation* interaction give two very large estimates, essentially accounting for one another, due to the values of *Income_Centered* ranging from −0.2 to 0.2, but we still are able to evince a negative relationship between *Income_Centered* levels and support.

The estimate for *Age* keeps its negative relationship with Support for the government.

5. Conclusions

In conclusion, using regression discontinuity design we were able to observe, on average, no significant pattern between families that received cash transfers and support for the current government across different models, specifically in the quarter bandwidth.

Thus our results are in contrast with those in Manacorda et al. [1], probably due to the differences in bandwidth selection and clustering of the observations done in their work.

Another consideration we can make is the power of money in election cycles proper. Even knowing that cash transfers from the government *don't* bring support, we can pose the hypothesis that cash transfers from private entities *do*. This is possible because the reasons the effect might not be present in the government's case, such as distortionary taxation or the Ricardian equivalence, don't apply to private sector donations.

Potential limitations, and opportunities for future work, that may be present in our study lie mainly between the lackluster number of observations and methods that account for this shortage. Additionally, household ideology data wasn't recorded in the original dataset, but RDD would require it to vary smoothly around the cutoff in absence of treatment, which may have introduced bias in the estimates.

6. Appendix

Below, you may consult the tables with relevant data, graphs, and the R code used. You may find the GİthubI repositoryory containing all the files regarding our computational analysis by clicking here.

Income_Centered	Education	Age	Participation	Support	Support_Binomial
Min. :−0.019991	Min. :0.000	Min. : 6.50	Min. :0.0000	Min. :0.0000	Min. :0.000
1st Qu.:−0.011714	1st Qu.:3.000	1st Qu.:18.38	1st Qu.:0.0000	1st Qu.:0.5000	1st Qu.:0.000
Median :−0.002795	Median :4.000	Median :25.67	Median :1.0000	Median :1.0000	Median :1.000
Mean :−0.001580	Mean :4.071	Mean :29.12	Mean :0.5785	Mean :0.7962	Mean :0.674
3rd Qu.: 0.008447	3rd Qu.:5.500	3rd Qu.:36.00	3rd Qu.:1.0000	3rd Qu.:1.0000	3rd Qu.:1.000
Max. : 0.019892	Max. :6.500	Max. :73.00	Max. :1.0000	Max. :1.0000	Max. :1.000
NA	NA's :51	NA	NA	NA	NA

Table 3: Descriptive statistics for full bandwidth data.

Income_Centered	Education	Age	Participation	Support	Support_Binomial
Min. :−0.0099980	Min. :0.000	Min. : 6.50	Min. :0.0000	Min. :0.0000	Min. :0.000
1st Qu.:−0.0053990	1st Qu.:3.000	1st Qu.:19.00	1st Qu.:0.0000	1st Qu.:0.5000	1st Qu.:0.000
Median :−0.0017010	Median :4.000	Median :25.75	Median :1.0000	Median :1.0000	Median :1.000
Mean :−0.0006164	Mean :4.028	Mean :29.41	Mean :0.5731	Mean :0.7882	Mean :0.667
3rd Qu.: 0.0046920	3rd Qu.:5.333	3rd Qu.:36.50	3rd Qu.:1.0000	3rd Qu.:1.0000	3rd Qu.:1.000
Max. : 0.0099930	Max. :6.000	Max. :73.00	Max. :1.0000	Max. :1.0000	Max. :1.000
NA	NA's :28	NA	NA	NA	NA

Table 4: Descriptive statistics for half bandwidth data.

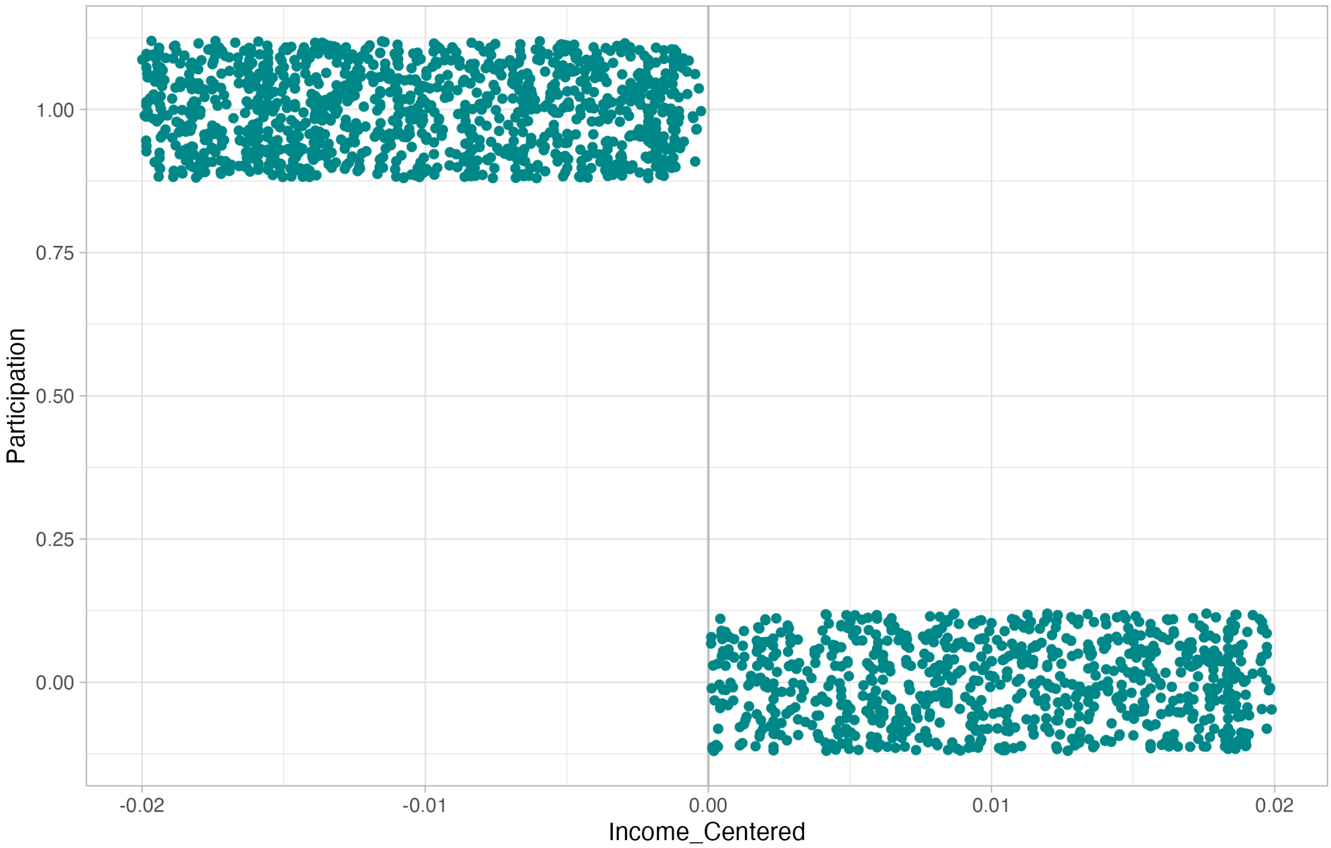

Figure 3: Participation in the program based on the eligibility determined by the cutoff score.

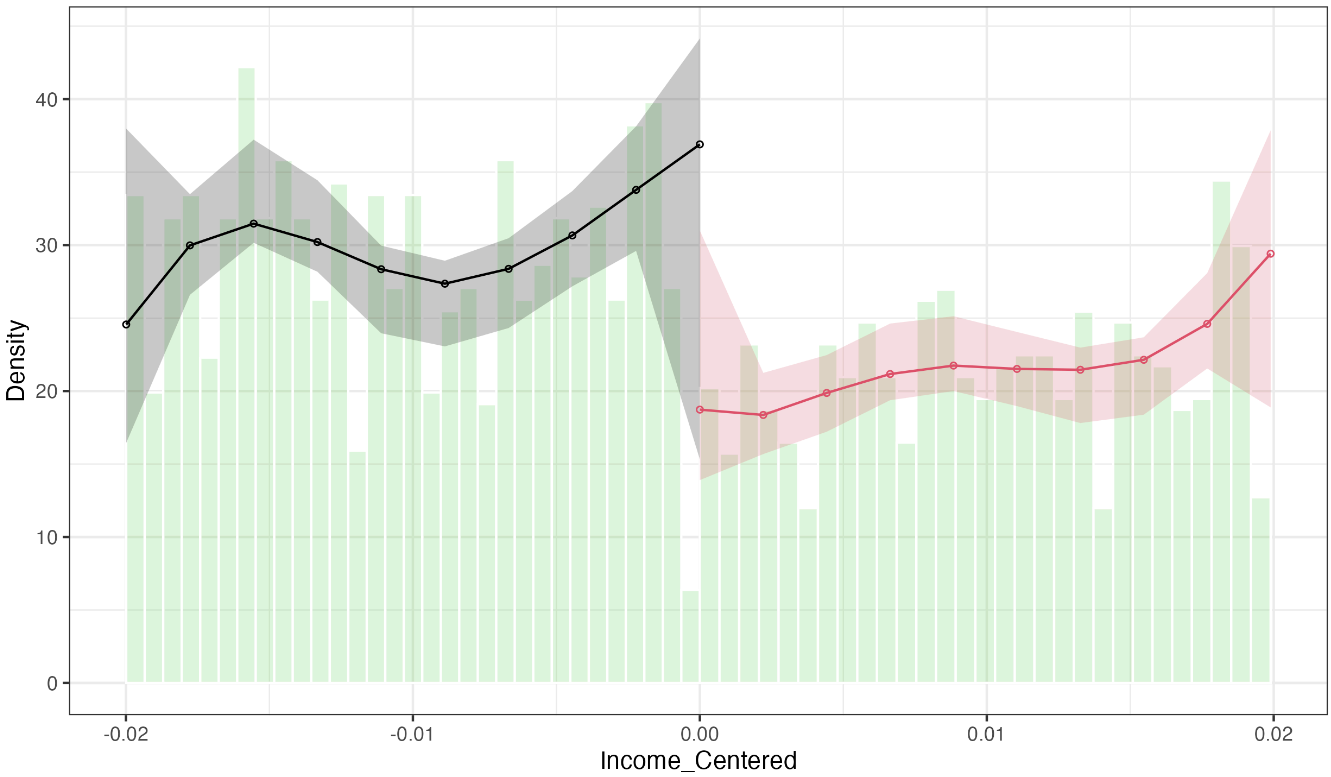

Figure 4: RDD density plot.

	Linear	Quadratic	Cubic	Slope	Slope and Age	Slope and Age, Logistic
(Intercept)	0.738***	0.727***	0.722***	0.730***	0.744***	0.322+
	(0.017)	(0.020)	(0.024)	(0.023)	(0.027)	(0.178)
Participation	0.097***	0.102***	0.113**	0.100***	0.099***	0.689***
	(0.029)	(0.030)	(0.040)	(0.030)	(0.030)	(0.201)
Income_Centered	−1.016	−0.810	0.417	−0.179	−0.110	−0.804
	(1.242)	(1.257)	(3.208)	(1.916)	(1.918)	(12.388)
I(Income_Centered^2)		63.156	62.537			
		(60.216)	(60.247)			
I(Income_Centered^3)			−3361.018			
			(8082.753)			
Participation ∗ Income_Centered				−1.442	−1.440	−8.648
				(2.516)	(2.516)	(17.247)
Age					−0.000	−0.001
					(0.000)	(0.003)
Num.Obs.	1948	1948	1948	1948	1948	1948
R2	0.034	0.035	0.035	0.034	0.035	
R2 Adj.	0.033	0.033	0.033	0.033	0.033	
AIC	1006.1	1007.0	1008.8	1007.7	1008.8	2402.6
BIC	1028.4	1034.8	1042.2	1035.6	1042.2	2430.5
Log.Lik.	−499.026	−498.475	−498.389	−498.862	−498.382	−1196.290

RMSE	0.31	0.31	0.31	0.31	0.31	0.46
- $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$						

Table 5: Results of regressions on full bandwidth data.

	Linear	**Quadratic**	**Cubic**	**Slope**	**Slope and Age**	**Slope and Age, Logistic**
(Intercept)	0.738***	0.753***	0.792***	0.773***	0.813***	0.610*
	(0.025)	(0.029)	(0.035)	(0.033)	(0.039)	(0.254)
Participation	0.083+	0.078+	−0.005	0.077+	0.076+	0.669*
	(0.044)	(0.044)	(0.061)	(0.044)	(0.044)	(0.297)
Income_Centered	−3.754	−4.074	−21.648*	−10.338+	−9.897+	−31.076
	(3.774)	(3.787)	(9.709)	(5.538)	(5.536)	(34.972)
I(Income_Centered^2)		−361.376	−332.251			
		(359.208)	(358.964)			
I(Income_Centered^3)			189824.200*			
			(96591.583)			
Participation ∗ Income_Centered				12.272	12.139	37.167
				(7.561)	(7.552)	(50.813)
Age					−0.001+	−0.006
					(0.001)	(0.005)
Num.Obs.	937	937	937	937	937	937
R2	0.035	0.036	0.040	0.037	0.041	
R2 Adj.	0.033	0.033	0.036	0.034	0.037	
AIC	534.6	535.6	533.7	533.9	532.5	1165.6
BIC	553.9	559.8	562.7	558.1	561.5	1189.8
Log.Lik.	−263.289	−262.781	−260.844	−261.968	−260.238	−577.788
RMSE	0.32	0.32	0.32	0.32	0.32	0.46
- $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$						

Table 6: Results of regressions on half bandwidth data.

	Linear	**Cubic**
(Intercept)	0.738***	0.792***
	(0.025)	(0.035)
Participation	0.083+	−0.005
	(0.044)	(0.061)
Income_Centered	−3.754	−21.648*
	(3.774)	(9.709)
I(Income_Centered^2)		−332.251
		(358.964)
I(Income_Centered^3)		189824.200*
		(96591.583)
Num.Obs.	937	937

R2	0.035	0.040
R2 Adj.	0.033	0.036
AIC	534.6	533.7
BIC	553.9	562.7
Log.Lik.	−263.289	−260.844
RMSE	0.32	0.32
- p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001		

Table 7: Results of regressions on quarter bandwidth data not specified in the main body.

```
# The effects of participation in cash transfer programs on political support for the government
# Aydin, Salvi and Solidoro

# Loading the required libraries
library(tidyverse)
library(kableExtra)
library(GGally)
library(grid)
library(rddensity)
library(modelsummary)
library(ggpubr)

# Importing the data
load("data/gov_transfers.rda")

# Exploring the data
head(gov_transfers)

gov_transfers |>
  ggpairs()
ggsave("artifacts/ggpairs.png", width = 21, height = 14.8, unit = "cm")

# Checking the data
## Checking for fuzziness
gov_transfers |>
  group_by(Income_Centered < 0, Participation) |>
  count() |>
  kable("markdown") |>
  save_kable("artifacts/gov_transfers_fuzziness.md")

gov_transfers |>
  ggplot(aes(x = Income_Centered, y = Participation)) +
  geom_vline(xintercept = 0, color = "gray") +
  geom_point(color = "darkcyan", position = position_jitter(width = 0, height = 0.12)) +
  theme_light()
ggsave("artifacts/fuzziness.png", width = 21, height = 14.8, unit = "cm")

## Checking for manipulation
density <- gov_transfers$Income_Centered |>
  rddensity(c = 0)

density |>
  summary() |>
  capture.output() |>
  kable("markdown") |>
  save_kable("artifacts/gov_transfers_rd_density.md")

density |>
  rdplotdensity(X = gov_transfers$Income_Centered, type = "both", xlabel ="Income_Centered", ylabel =
"Density")
ggsave("artifacts/rd_density_plot.png", width = 21, height = 14.8, unit = "cm")
```

```r
# Creating a binomial Support variable and tibbles of different bandwiths
gov_transfers <- gov_transfers |>
  mutate(Support_Binomial = case_when(Support == 1 ~ 1, T ~ 0))

quart_bw <- gov_transfers |>
  filter(Income_Centered > -0.005 & Income_Centered < 0.005)

half_bw <- gov_transfers |>
  filter(-0.01 < Income_Centered & Income_Centered < 0.01)

## Exploring the edited data
gov_transfers |>
  summary() |>
  kable("markdown") |>
  save_kable("artifacts/gov_transfers.md")

quart_bw |>
  summary() |>
  kable("markdown") |>
  save_kable("artifacts/quart_bw.md")

half_bw |>
  summary() |>
  kable("markdown") |>
  save_kable("artifacts/half_bw.md")

# RDD calculation by different specifications and bandwiths
## Linear specifications
full_lm <- lm(Support ~ Participation + Income_Centered, data = gov_transfers)

half_lm <- lm(Support ~ Participation + Income_Centered, data = half_bw)

quart_lm <- lm(Support ~ Participation + Income_Centered, data = quart_bw)

## Quadratic specifications
full_q <- lm(Support ~ Participation + Income_Centered + I(Income_Centered^2), data = gov_transfers)

half_q <- lm(Support ~ Participation + Income_Centered + I(Income_Centered^2), data = half_bw)

quart_q <- lm(Support ~ Participation + Income_Centered + I(Income_Centered^2), data = quart_bw)

## Cubic specifications
full_c <- lm(Support ~ Participation + Income_Centered + I(Income_Centered^2) + I(Income_Centered^3),
data = gov_transfers)

half_c <- lm(Support ~ Participation + Income_Centered + I(Income_Centered^2) + I(Income_Centered^3),
data = half_bw)

quart_c <- lm(Support ~ Participation + Income_Centered + I(Income_Centered^2) + I(Income_Centered^3),
data = quart_bw)

## Slope interaction specifications
full_slope <- lm(Support ~ Participation + Income_Centered + Participation * Income_Centered, data =
gov_transfers)

half_slope <- lm(Support ~ Participation + Income_Centered + Participation * Income_Centered, data =
half_bw)

quart_slope <- lm(Support ~ Participation + Income_Centered + Participation * Income_Centered, data =
quart_bw)

## Interaction specifications controlling for age
```

```
full_age <- lm(Support ~ Participation + Income_Centered + Participation * Income_Centered + Age, data =
gov_transfers)

half_age <- lm(Support ~ Participation + Income_Centered + Participation * Income_Centered + Age, data =
half_bw)

quart_age <- lm(Support ~ Participation + Income_Centered + Participation * Income_Centered + Age, data
= quart_bw)

## Logit specifications with slope interactions controlling for age
full_lgt <- glm(Support_Binomial ~ Participation + Income_Centered + Participation * Income_Centered +
Age, family = binomial, data = gov_transfers)
exp(coef(full_lgt))

half_lgt <- glm(Support_Binomial ~ Participation + Income_Centered + Participation * Income_Centered +
Age, family = binomial, data = half_bw)
exp(coef(half_lgt))

quart_lgt <- glm(Support_Binomial ~ Participation + Income_Centered + Participation * Income_Centered +
Age, family = binomial, data = quart_bw)
exp(coef(quart_lgt))

# Specification comparisons
## Specifications in the paper's main body (selected from quarter bandwidth)
paper_comp <- msummary(
  list(
    "Quadratic" = quart_q,
    "Slope" = quart_slope,
    "Slope and Age" = quart_age,
    "Slope and Age, Logistic" = quart_lgt
  ),
  output = "artifacts/paper_comp.md", stars = T
)

## Specifications on full bandwidth
full_comp <- msummary(
  list(
    "Linear" = full_lm,
    "Quadratic" = full_q,
    "Cubic" = full_c,
    "Slope" = full_slope,
    "Slope and Age" = full_age,
    "Slope and Age, Logistic" = full_lgt
  ),
  output = "artifacts/full_comp.md", stars = T
)

## Specifications on half bandwidth
half_comp <- msummary(
  list(
    "Linear" = half_lm,
    "Quadratic" = half_q,
    "Cubic" = half_c,
    "Slope" = half_slope,
    "Slope and Age" = half_age,
    "Slope and Age, Logistic" = half_lgt
  ),
  output = "artifacts/half_comp.md", stars = T
)

## Other specifications on quarter bandwidth
quart_comp_other <- msummary(
  list(
```

```
    "Linear" = half_lm,
    "Cubic" = half_c
  ),
  output = "artifacts/quart_comp_other.md", stars = T
)

# Graphing the specifications in the paper's main body
## Quadratic specification
pred_q <- predict(quart_q, se.fit = T)
graph_q <- quart_bw |>
  ggplot(aes(x = Income_Centered, y = Support, group = Participation)) +
  geom_point(color = "darkcyan") +
  geom_vline(xintercept = 0, color = "gray") +
  geom_line(aes(y = pred_q$fit), color = "navy", size = 1) +
  geom_ribbon(aes(ymin = pred_q$fit - 1.96 * pred_q$se.fit, ymax = pred_q$fit + 1.96 * pred_q$se.fit),
fill = "lightblue", alpha = 0.5) +
  ggtitle("Quadratic") +
  theme_light() +
  lapply(list("xlab", "ylab"), rremove)

## Slope specification
pred_slope <- predict(quart_slope, se.fit = T)
graph_slope <- quart_bw |>
  ggplot(aes(x = Income_Centered, y = Support, group = Participation)) +
  geom_point(color = "darkcyan") +
  geom_vline(xintercept = 0, color = "gray") +
  geom_line(aes(y = pred_slope$fit), color = "navy", size = 1) +
  geom_ribbon(aes(ymin = pred_slope$fit - 1.96 * pred_slope$se.fit, ymax = pred_slope$fit + 1.96 *
pred_slope$se.fit), fill = "lightblue", alpha = 0.5) +
  ggtitle("Slope") +
  theme_light() +
  lapply(list("xlab", "ylab"), rremove)

## Slope and age specification
pred_age <- predict(quart_age, mutate(quart_bw, Age = mean(Age)), se.fit = T)
graph_age <- quart_bw |>
  ggplot(aes(x = Income_Centered, y = Support, group = Participation)) +
  geom_point(color = "darkcyan") +
  geom_vline(xintercept = 0, color = "gray") +
  geom_line(aes(y = pred_age$fit), color = "navy", size = 1) +
  geom_ribbon(aes(ymin = pred_age$fit - 1.96 * pred_age$se.fit, ymax = pred_age$fit + 1.96 *
pred_age$se.fit), fill = "lightblue", alpha = 0.5) +
  ggtitle("Slope and Age") +
  theme_light() +
  lapply(list("xlab", "ylab"), rremove)

## Logistic specification
pred_lgt <- predict(quart_lgt, mutate(quart_bw, Age = mean(Age)), type = "response", se.fit = T)
graph_lgt <- quart_bw |>
  ggplot(aes(x = Income_Centered, y = Support_Binomial, group = Participation)) +
  geom_point(color = "darkcyan") +
  geom_vline(xintercept = 0, color = "gray") +
  geom_line(aes(y = pred_lgt$fit), color = "navy", size = 1) +
  geom_ribbon(aes(ymin = pred_lgt$fit - 1.96 * pred_lgt$se.fit, ymax = pred_lgt$fit + 1.96 *
pred_lgt$se.fit), fill = "lightblue", alpha = 0.5) +
  ggtitle("Slope and Age, Logistic") +
  theme_light() +
  lapply(list("xlab", "ylab"), rremove)

## Merging the graphs
ggarrange(graph_q, graph_slope, graph_age, graph_lgt, ncol = 2, nrow = 2) |>
  annotate_figure(left = textGrob("Support", rot = 90, vjust = 0.5), bottom =
textGrob("Income_Centered"))
```

```r
ggsave("artifacts/plots.png", width = 21, height = 14.8, unit = "cm")
```

Bibliography

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[2] N. Huntington-Klein, *The Effect*. 2021. [Online]. Available: https://theeffectbook.net/

[3] "GitHub - NickCH-K/causaldata: Packages of Example Data for The Effect." [Online]. Available: https://github.com/NickCH-K/causaldata