LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

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1. Introduction

1.1 Summary: Research Question and Design

Manacorda et al. (2011) investigate the causal effect of anti-poverty governmental cash and food card transfers on self-reported political support for the incumbent government. The anti-poverty program (PANES) was planned, designed and evaluated in cooperation between the newly elected center-left government of Uruguay and researchers of the University of the Republic in Uruguay, including an author of the study. Selection into PANES was made based on a predicted income score that consolidates several variables like a wealth index, insurance status, presence of children and more. Participants of PANES were surveyed at program start in 2005, 18 months afterwards and a third time after PANES ended in 2008. The surveys represent expressed political support, measured by a preference comparison of the incumbent government relative to the previous one.

1.2 Motivation of Regression Discontinuity Design

To analyze the causal effect of cash and food card transfers on political support, the authors chose a Regression Discontinuity Design (RDD). It is a quasi-experimental method that relies on a cutoff in a running variable to assign treatment and control. This approach uses quasi randomization of individuals around the cutoff, providing a counterfactual for untreated individuals. Replicating Manacorda et al. (2011), this report uses the predicted income score as the running variable. It sets a sharp and rule-based threshold for treatment allocation at the predicted score of 2. I centered the running variable around this cutoff to ease interpretation, therefore a positive (negative) income score is above (beneath) the cutoff which is now set at 0 due to the centering.

A preliminary visual inspection of the data (Figure 1) suggests a discontinuity at the policy cutoff. Values seem to be higher to the left of the cutoff and a jump at the cutoff is apparent. The treatment (PANES) was assigned to the left of the cutoff.

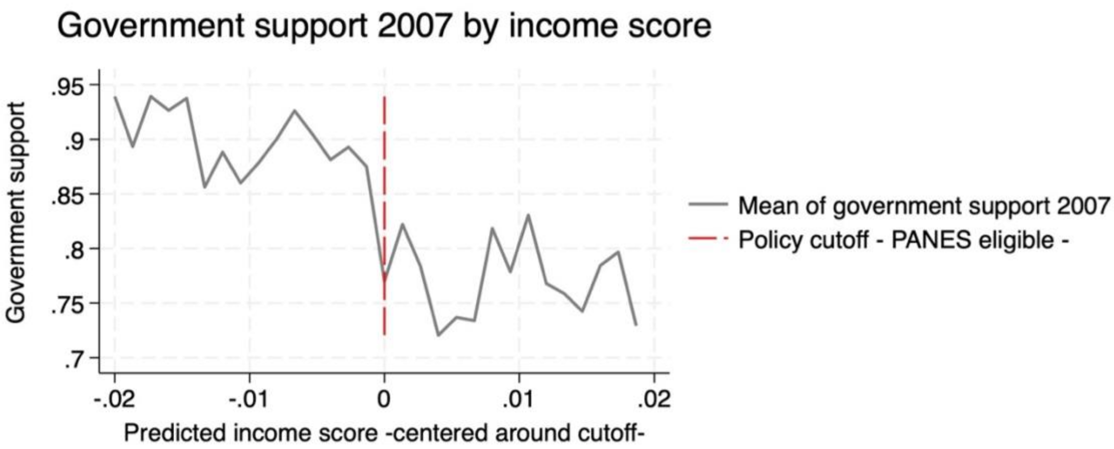

Figure 1: Graphical discontinuity check by plotted means of bins around the cutoff

2. Replication and Robustness Check

2.1 Replication

I am using a similar but not the same data set as Manacorda et al. (2011). While only having data points from ±0.02 around the cutoff, this report replicates the findings and assess its robustness but will not be able to analyze larger bandwidths due to data constraints. Thus, I will not discuss expanded bandwidths.

2.1.1 Histograms, Heaping and the McCrary Test

Verifying the RDD's continuity assumption and the absence of non-random heaping is vital to measure an unbiased treatment effect. Histograms in Figure 2 and Figure 3 display the frequency distribution of predicted income scores with a 0.0001 binning precision. Heaping seems to be observable even if not directly at the cutoff. I am not able to find rounding or evident heaping in the raw data while eye-balling it, however even if not directly at the cutoff, some heaping seems to be visible in the histograms. To address this, a donut-hole regression will be implemented as a robustness test in the following chapter. Nonetheless, as Barreca, Lindo, and Waddell (2016) suggest, even distant heaping can influence estimates, which requires more sophisticated robustness tests. The similarity observed between the histograms likely stems from the focused examination range, within a 0,04 range around the cutoff, a fraction of the full scale of predicted income scores. However, conceptually a discrete histogram, displaying discrete data, illustrates the frequency with each bar's height, while in a continuous histogram the area under the histogram corresponds to the proportion of data relative to the total data set. Please note that I also provide histograms with different widths (Figure 16 and 17) to examine heaping, and a smoothed representation using kernel density estimates (Figure 18) in the appendix.

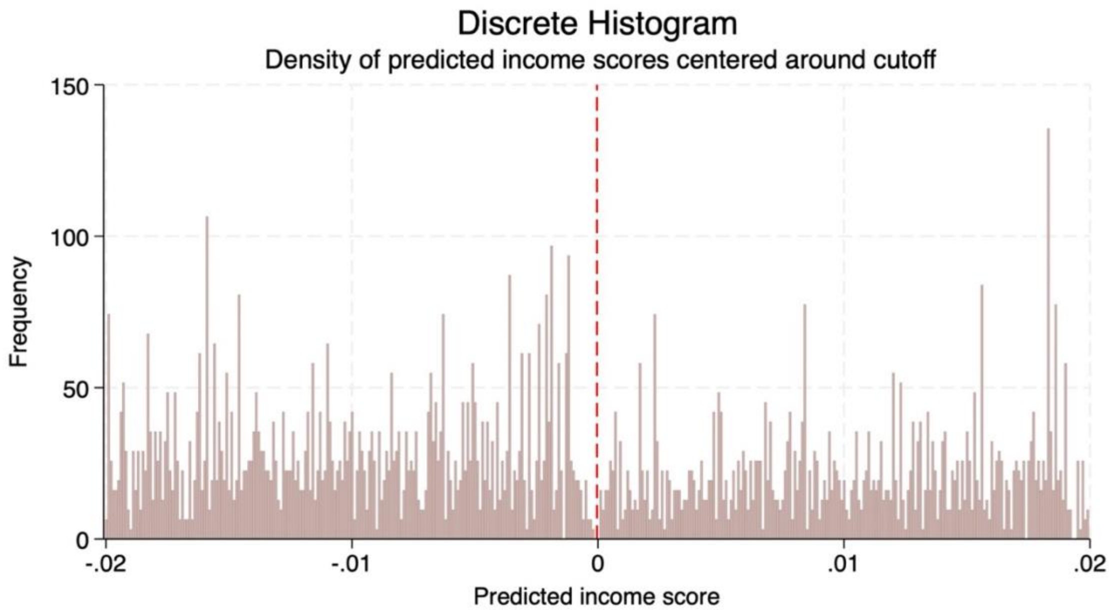

Figure 2: Discrete histogram of predicted income scores with a bar width of 0.0001

.04

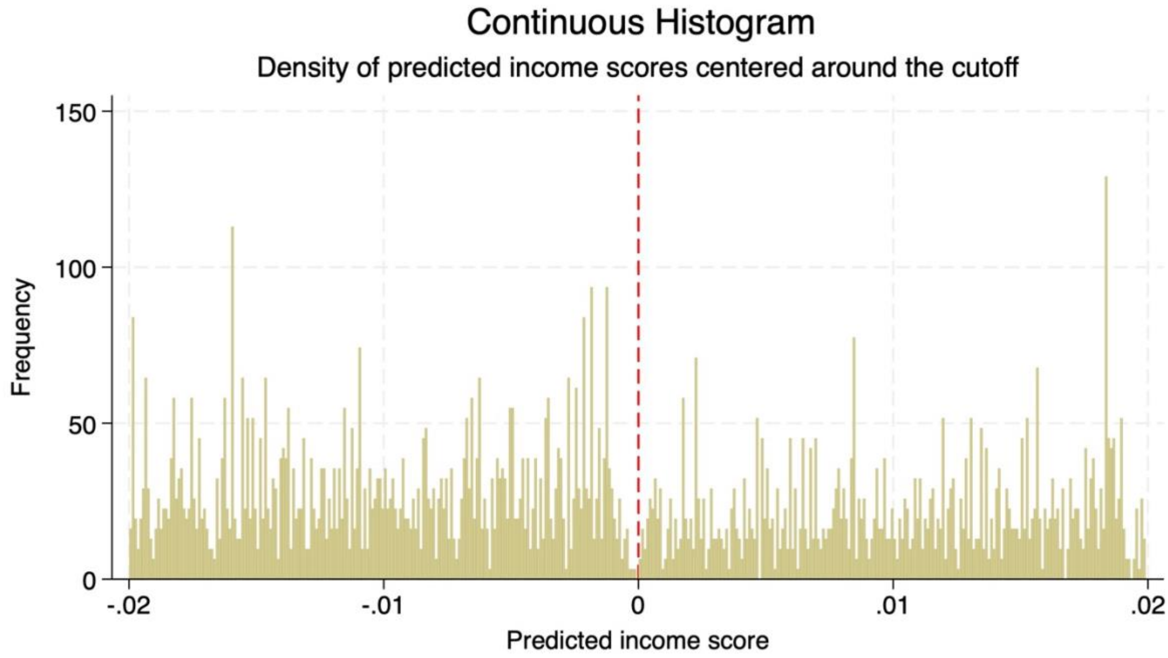

Figure 3: Continuous histogram of predicted income score with a bar width of 0.0001

The McCrary density test (McCrary, 2008) was used to further assess potential discontinuity around the cutoff. With a p-value of 0.4111 and overlapping confidence intervals (Figure 4), this suggests that the predicted income score was not precisely manipulated and reinforces the assumption of local randomization and continuity (Cunningham, 2021).

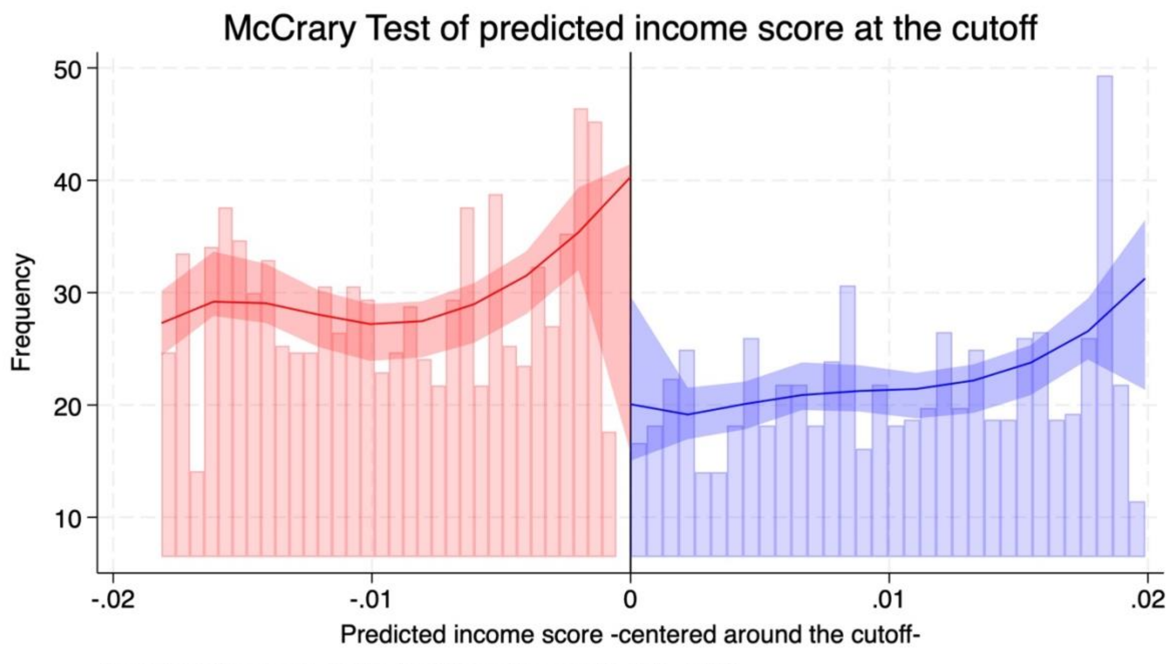

Figure 4: McCrary test for continuity of the running variable at the cutoff

2.1.2 Placebo Regressions on Covariates

To ensure the validity of the RDD, it's critical to test whether covariates remain stable across the treatment threshold. This step verifies that the assignment to treatment is as good as random concerning observed baseline characteristics. Placebo regressions on covariates such as gender, mean household size, respondent's age and education, and log income showed no significant jumps, apart from mean household size (Table 1). The significance of mean household size at the 5% level may challenge the randomization assumption. To mitigate this, mean household size will be accounted for in the regression models.

TABLE 1 - Placebo regression with baseline characteristics

Dependent variable	Coefficient (standard error)	Observations
1. Respondent is female	-0.025 (0.038)	2231
2. Mean household size	-0.273** (0.122)	3098
3. Household average age	-1.194 (1.29)	2232
4. Respondent age	-0.92 (1.242)	2231
5. Respondent years of education	0.228 (0.227)	2206
6. Respondent voted in 2004 elections	0.0310 (0.024)	2200
7. Log per capita income	-0.061 (0.055)	2150

Notes: The table reports results from OLS regression with robust standard errors of several pretreatment (2005) baseline characteristics on the running variable predicted income score.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Figure 5 illustrates the significant jump in mean household size at the cutoff, suggesting a potential systematic difference between the treatment and control groups. Being treated is associated with a 27.3% decrease in mean household size. This discrepancy could stem from the income score prediction formula.

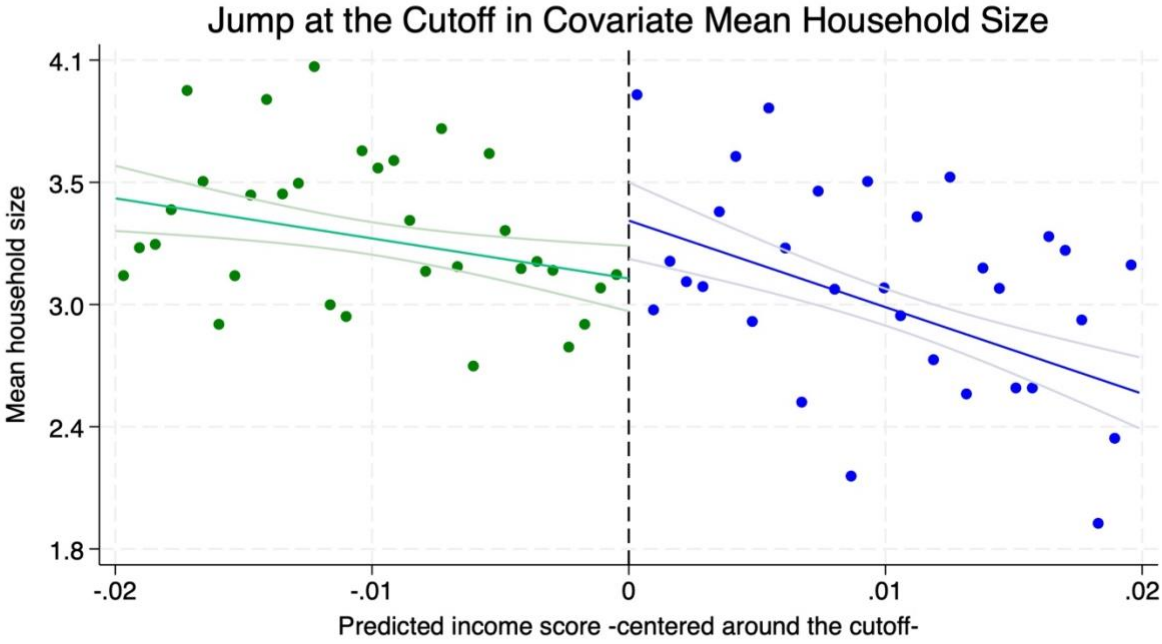

Figure 5: Significant jump at cutoff in covariate mean household size ($p < 0.05$)

2.1.3 Main Results

Table 2's analysis indicates a consistent positive effect of the treatment on government support in 2007 and 2008, with the impact being statistically significant across all specifications. The coefficients range from 9% to 13%. Tighter standard errors in models without controlling for mean household size suggest a better fit. While the positive sign of the coefficients reflects an increase in government support in line with the treatment, this effect is localized to individuals near the cutoff only due to the RDD design. Thus, the treatment effect is specific to a subset of the population and does not generalize across different income levels. Column 1 includes OLS estimates, Column 2 a second order polynomial of the running variable and Columns 3 and 4 include a control for mean household size in the respective linear and polynomial model. Additionally, we can observe a slightly smaller, however, still persistent and significant effect in 2008, suggesting that the effect of cash transfers might persist over time.

TABLE 2 - Main Results

Dependent variable	Coefficient (standard error) (1)	(2)	(3)	(4)	Observations
1. Government support 2007	0.1096***	0.1302***	0.1093***	0.1298***	2089
	(0.026)	(0.039)	(0.026)	(0.039)	
2. Government support 2008	0.0998**	0.0928**	0.1009**	0.0958**	1948
	(0.029)	(0.043)	(0.030)	(0.043)	

Notes: The table reports estimate of the effect of having a predicted income score incumbent government in 2007 (during PANES program) and in 2008 (post PANES). Column 1 includes ordinary least squares estimate, column 2 a second order polynomial of the running variable predicted income score. Columns 3 and 4 include the control for mean household size in the respective linear and polynomial model, in that order.
Standard errors are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Figure 6 displays the linear model's highly significant jump at the cutoff, visualizing a local average treatment effect of 10.96%, while also illustrating the linear fit. Complementing this, Figure 7 illustrates the treatment effects across various bandwidths, providing a first robustness check. Despite the changes in bandwidth, the treatment effect consistently ranges around 10%, reinforcing the reliability of our findings. Please note that I attached a visualization using second order polynomial in the appendix (Figure 19).

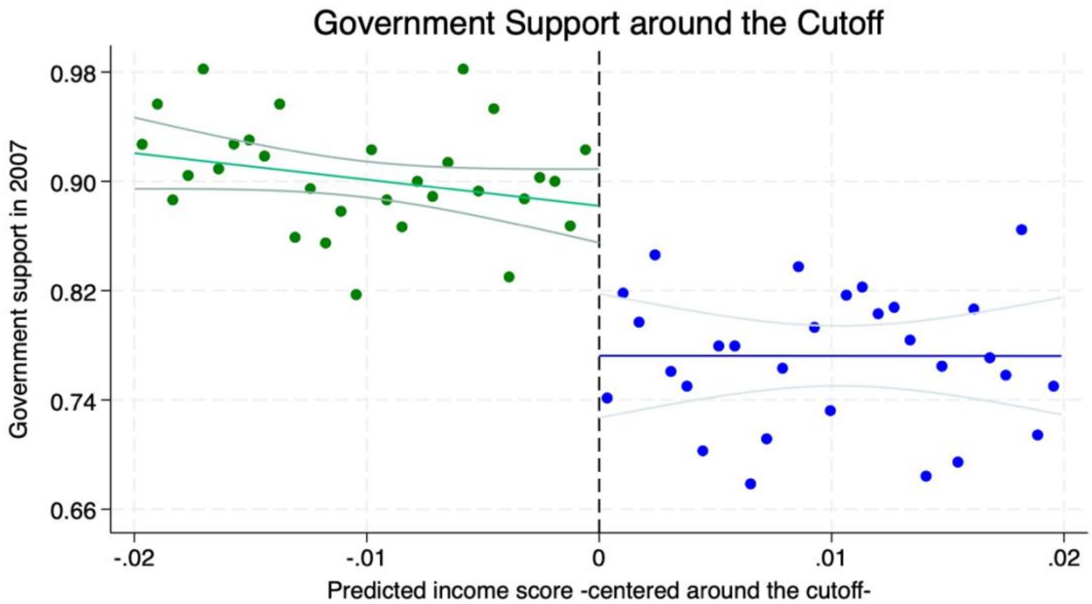

Figure 6: Visualisation of treatment effect using linear fit model

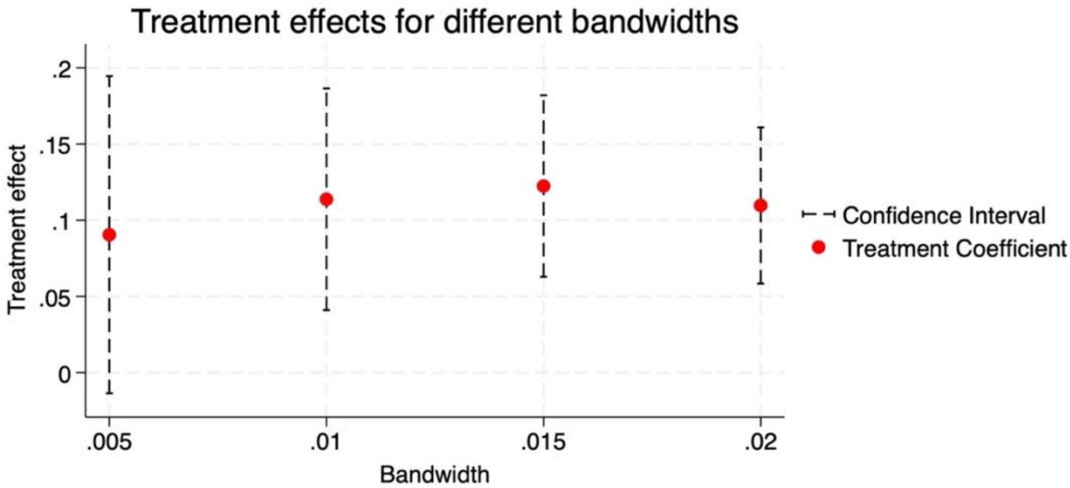

Figure 7: Treatment effects for different bandwidth calculated using OLS regression with robust standard errors and no controls

2.1.4 Main Results of Confidence in the President and in MIDES and Interest in Politics

Apart from self-reported political support for the government, I investigated the effect of being PANES eligible on the confidence in the current president, in the Ministry of Social Development (MIDES) and on interests in politics using linear and second order polynomial regressions. I chose confidence in the current president as it is interesting to see how PANES affects the confidence in the competencies of the current president as a single person. Additionally, analyzing the effect on MIDES display that after having received cash transfers from the current government and receiving visits from MIDES personnel, the confidence in those institutions seems to have increased significantly. Improving confidence through cash transfers is a critical insight into political behavior. Not only did the confidence increase for the Ministry that executed the program by around 13-15%, but also the confidence in the president as an individual by around 8-12%. Moreover, interest in politics could be an important indicator of actual voting behavior. It shows a positive significant coefficient in the linear model with a magnitude of 5%. If participants are more interested in politics after receiving the transfers, they might also be more willing to vote and express his/her interests.

TABLE 3 - Confidence in president, MIDES and Interest in Politics

Dependent variable	Coefficient (standard error) (1)	(2)	Observations
1. Confidence in the current president	0.0821**	0.1201**	1937
	(0.035)	(0.055)	
2. Confidence in the Ministry of Social Development	0.1515***	0.1336**	1805
	(0.036)	(0.055)	
3. Interest in politics	0.0564**	0.0191	2045
	(0.028)	(0.044)	

Notes: The table reports estimate of the effect of being PANES eligible on the confidence in the current president and in the Ministry of Social Development as well as on interests in politics using a linear (1) and a squared (2) model.
Standard errors are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Please note that I attached an additional robustness check through donut hole regression with those three dependent variables in the appendix (Table 8).

2.2 Robustness Check

2.2.1 Donut hole Regression

Donut hole regressions are employed to address potential manipulation around the cutoff, where outliers could influence the estimated treatment effect. By omitting data points closest to the cutoff, these models test the sensitivity of the results to such potential manipulations.

Table 4 employs a donut of ±0.005 and displays slightly increased coefficients for government support in the linear models and a large increase in the squared models, while preserving their significance even when decreasing statistical power through excluding data points near the cutoff. This implies that the treatment's influence remains stable even after excluding data points closest to the cutoff. The increased coefficients suggest that data points closely around the cutoff diminish the treatment effect.

TABLE 4 - Donut hole Regression

Dependent variable	Coefficient (standard error) (1)	(2)	(3)	(4)	Observations
1. Government support 2007	0.1157**	0.3216**	0.1156**	0.3225**	1600
	(0.045)	(0.131)	(0.045)	(0.131)	
2. Government support 2008	0.1379**	0.4480***	0.1377**	0.4488***	1486
	(0.055)	(0.158)	(0.055)	(0.158)	

Note: Results replicate Table 2 extended using a donut of ± 0.005. Data points in ± 0.005 around the cutoff are excluded. Columns 1 and 2 provide linear and second order polynomial models and Columns 3 and 4 the respective models extended by a control for household size.
Standard errors are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Figure 8 offers a graphical representation of the treatment effect of 11.57% on government support in 2007, utilizing a linear regression model adjusted with a donut of ±0.005. The treatment effect of 32.16% with the second order polynomial regression is displayed in Figure 9. The excluded data around ±0.005 strengthens the positive quadratic trend left to the cutoff, and the negative quadratic trend right to the cutoff. Therefore, significantly increasing the treatment effect, however not necessarily fitting the data best which is also observable in the relatively large standard errors.

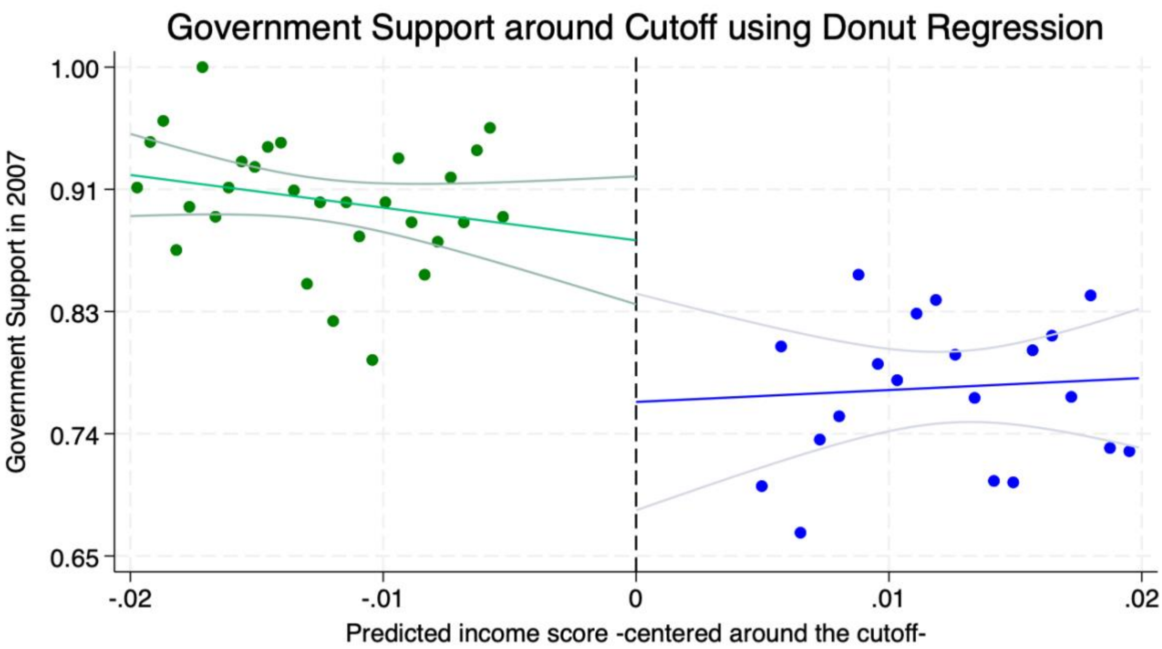

Figure 8: Visualisation of treatment effect using linear regression with a donut of ±0.005

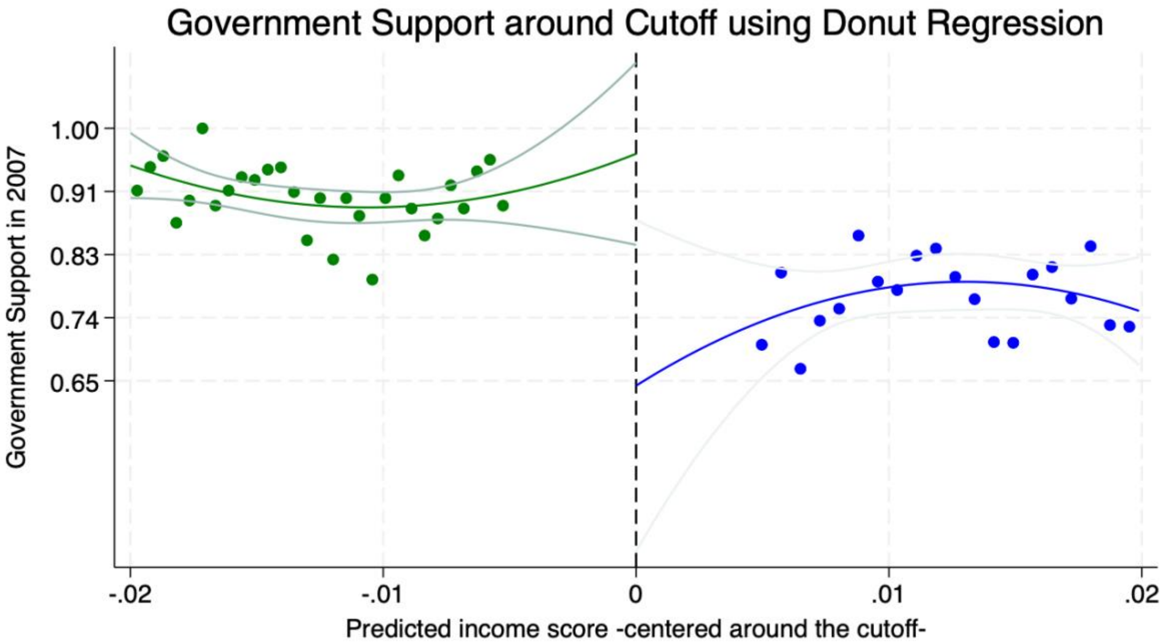

Figure 9: Visualisation of treatment effect using second order polynomial regression with a donut of ±0.005

Table 5's adjusted and smaller donut, with a range of ±0.002, further amplifies the positive and significant coefficients for both years. The coefficients of the squared model are again in a more similar range as compared to the main results in Table 2. This donut might be better suited, with lower standard errors indicating a better fit. The treatment effect ranges from 11-16% in 2007 with again an increase in the 2008 results. Please note that I also display a graphical linear and squared representation with the adjusted donut of ± 0.002 in the appendix (Figure 20 and Figure 21).

TABLE 5 - Adjusted Donut

	Coefficient (standard error)				
Dependent variable	(1)	(2)	(3)	(4)	Observations
1. Government support 2007	0.1160***	0.1658***	0.1160***	0.1659***	1914
	(.032)	(0.062)	(0.004)	(0.062)	
2. Government support 2008	0.1363***	0.2070***	0.1367***	0.2096***	1781
	(0.055)	(0.068)	(0.0373)	(0.068)	

Note: Results replicate Table 2 extended by the use of a donut of ± 0.002. Data points in the area of ± 0.002 around the cutoff are excluded. Columns 1 and 2 provide linear and second order polynomial models and Columns 3 and 4 the respective models extended by a control for household size.
Standard errors are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

While Table 2 provides a baseline, Tables 4 and 5 show increased coefficients when excluding data near the cutoff. This consistent amplification across donut regressions implies that initial estimates might be slightly conservative, yet the treatment's positive effect remains robust and significant in a range of 10-16%.

2.2.2 Local Polynomials

After a donut hole analysis, local polynomial regressions serve to further evaluate the initial treatment effect. It includes a bias correction, different bandwidths optimized by MSERD and MSETWO, and the use of a Epanechnikov kernel that weights observations closer to the cutoff stronger. I am using a second order local polynomial in Table 6 as lower polynomial orders seem to be more effective in RDD (Gelman and Imbes, 2018).

TABLE 6 - Local Polynomials with symmetric and asymmetric bandwidths

	Coefficient (standard error)		
Dependent variable	(1)	(2)	(3)
1. Government support 2007	0.1770**	0.1697**	0.1255***
	(.087)	(0.085)	(0.040)
2. Government support 2008	-0.0587	-0.0927	0.0614
	(0.077)	(0.091)	(0.044)

Note: Column 1 is using a symmetric bandwidth based on MSERD, Column 2 is using asymmetrical bandwidth based on MSETWO and Column 3 is using the whole bandwidth of 0.002. An Epanechnikov kernel is used to weight observations closer to the cutoff stronger.
Standard errors are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Narrower bandwidths like those determined by MSERD (± 0.005) suggest a 17.7%** treatment effect, while an asymmetric MSETWO bandwidth (-0.005/+0.006) indicates a similar effect. The full bandwidth analysis tempers the effect to 12.5%***, emphasizing the sensitivity of the treatment effect to the data's proximity to the cutoff. In contrast, 2008 presents mixed results, with no significant effect observed. The lack of consistency warrants caution in interpreting the 2008 results.

Figure 10 illustrates the treatment effects calculated using local polynomials of the second order. The graph shows the estimated coefficients for different bandwidths at 0.005, 0.01, 0.015, and 0.02. Despite varying bandwidths, the treatment effects display remarkable consistency, which validates the robustness of our main findings and supports the conclusion that the treatment has a significant and stable local average effect of around 10% or higher.

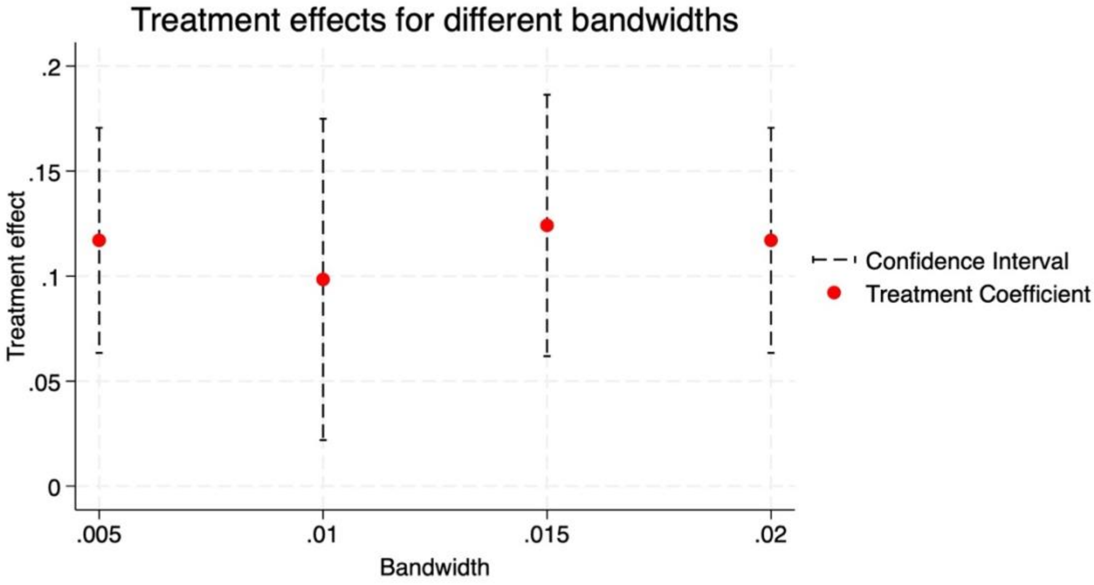

Figure 10: Treatment effects for different bandwidths calculated using nonparametric regression model

TABLE 7 - Local Polynomials with symmetric and asymmetric bandwidths and Donut

	Coefficient (standard error)		
Dependent variable	(1)	(2)	(3)
1. Government support 2007	0.05642 (0.1818)	0.1125 (0.139)	0.1658*** (0.0598)
2. Government support 2008	0.0250 (0.178)	0.032 (0.191)	0.2070*** (0.069)

Note: I chose to use the narrower donut of ± 0.002. Column 1 is using a symmetric bandwidth based on MSERD, Column 2 is using asymmetrical bandwidth based on MSETWO and Column 3 is using the whole bandwidth of 0.002. I am choosing a uniform kernel with a donut, as the data points close to the cutoff are excluded and a stronger weighting closer to cutoff is therefore not suitable.
Standard errors are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Introducing a donut (Table 7) to exclude data close to the cutoff increases the results again. I am now using a uniform kernel, which weights all data points the same, as we exclude data close to the cutoff. The treatment effect reduces to 5.64% with MSERD's narrow bandwidth of ± 0.008, suggesting again that near-cutoff data may diminish the effect size. The asymmetric bandwidth of MSETWO (-0.009/+0.008) reveals a 11.25% effect, while only the full range maintains a significant effect of 16.58%***. Reducing the bandwidth to ± 0.008 will lead to reduced statistical power. In combination with the excluded data from the donut, it is not unusual that the coefficients are not significant anymore.

Synthesizing these outcomes with the main findings (Table 2) suggests that while our conservative treatment effect estimate stands around 10%, broader bandwidths and the exclusion of data near the cutoff through donut hole regressions point to a potentially larger impact.

2.3 Graphical Presentations

For the final graphical illustration of the treatment effect, I present both linear and quadratic models through cmogram and rdplot visualizations. The cmograms includes confidence intervals, offering a clearer picture of uncertainty and enhancing the visual representation of the data's variance. Conversely, rdplots focus on the jump at the cutoff. Thus, more directly visualizing the RDD's focal discontinuity. An additional difference is that rdplot does not assume a constant standard deviation on each side of the cutoff. The asymmetric bandwidth of -0.005/+0.006, guided by the MSETWO algorithm, offers the advantage of a targeted analysis. It allows for the inclusion of more data where the treatment effect's variability might be greater, as to the right side of the cutoff. This selection can improve the robustness of the treatment effect estimation, especially in cases where the potential outcomes are not symmetrically distributed around the cutoff.

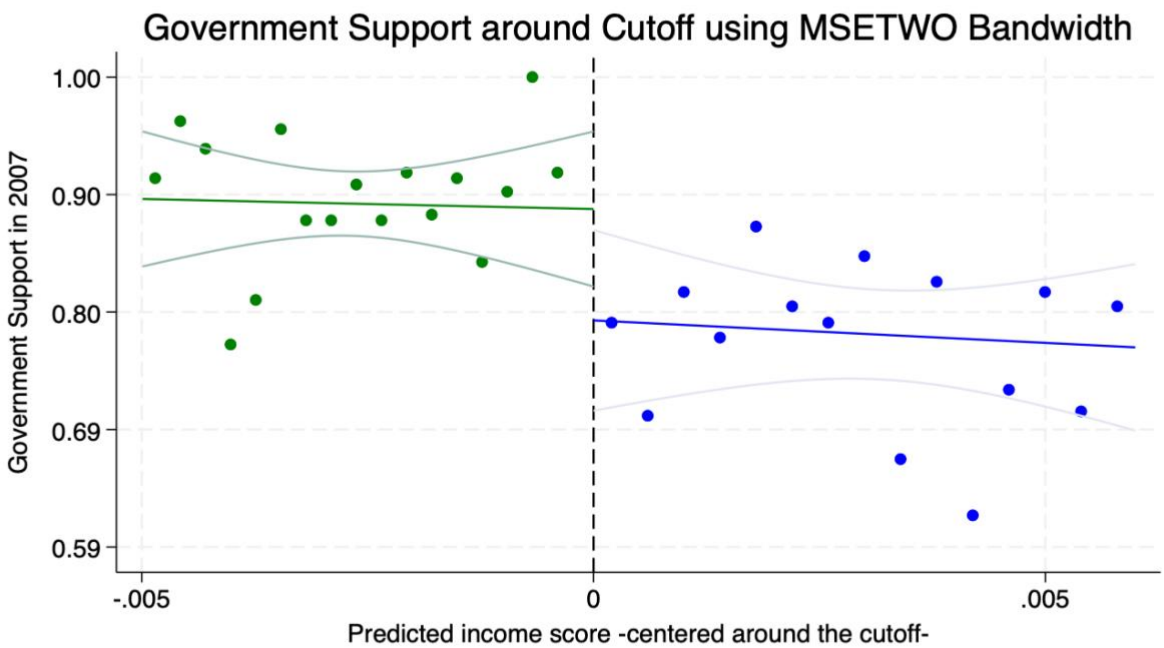

Figure 11: Visualisation of treatment effect using linear regression model and a bandwidth of -0.005/+0.006

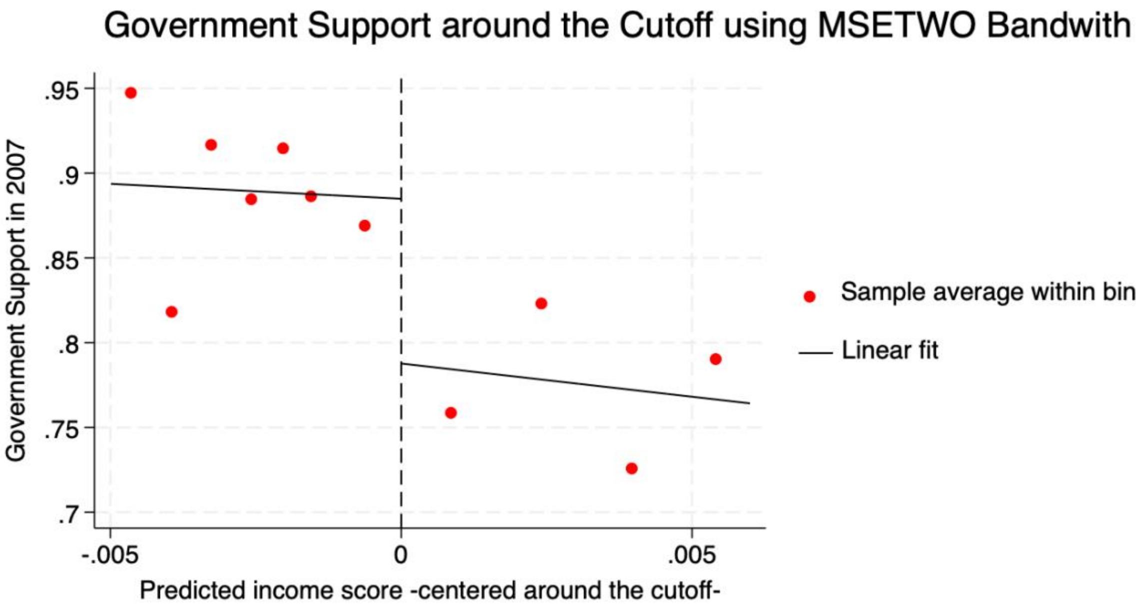

Figure 12: Visualisation of treatment effect using a linear fit and a bandwidth of -0.005/+0.006

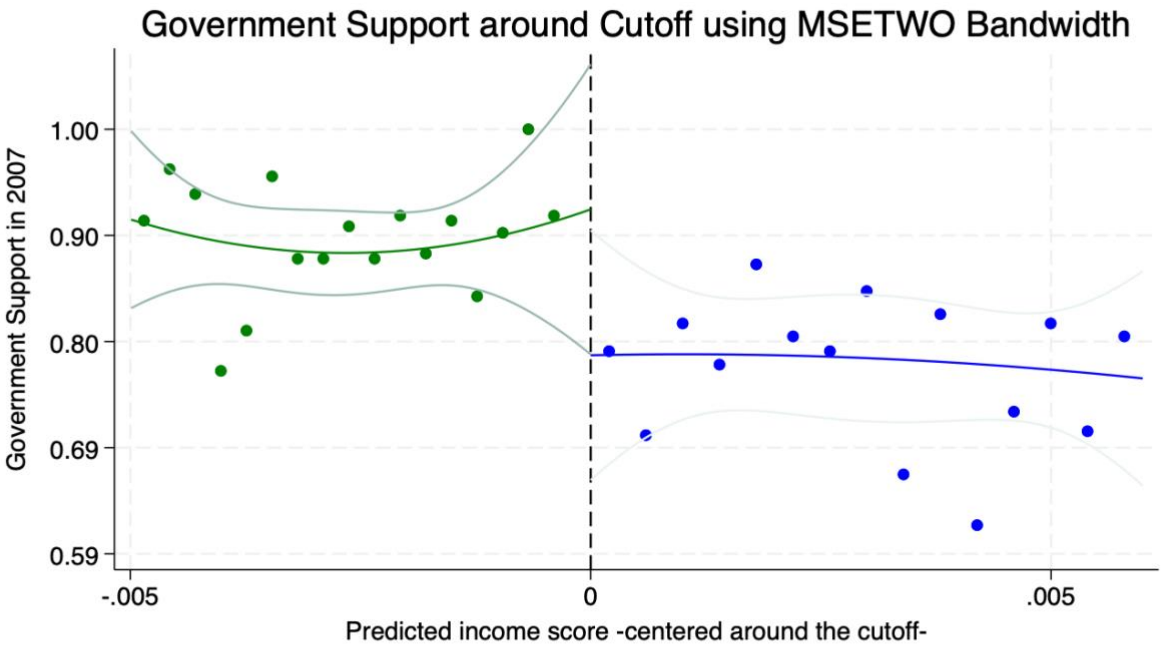

Figure 13: Visualisation of treatment effect using a quadratic model and a bandwidth of -0.005/+0.006

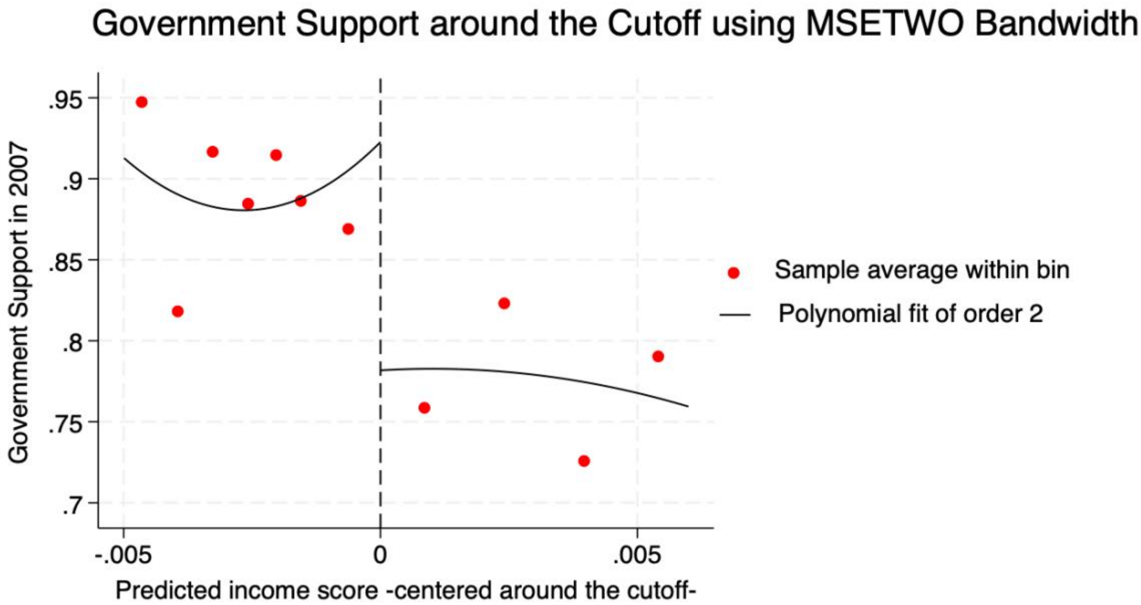

Figure 14: Visualisation of treatment effect using second order polynomial model and a bandwidth of -0.005/+0.006

3. Critique

3.1 Methodological Limitations

The study's external validity is constrained by several factors. Firstly, its focus on a specific demographic segment around the poverty threshold in Uruguay limits the applicability of the local average treatment effect (LATE) to the broader population. Moreover, the attempt to generalize the findings from Uruguay, with its distinct socioeconomic characteristics seems to overlook the variability in how different socioeconomic backgrounds might interact with citizens' responses to such programs. This is especially relevant when comparing Uruguay's poor to those in more developed countries like England.

Internal validity concerns arise from the fact that the cash transfers (and food cards) should be the only treatment around the cutoff in order to assess its causality. However, PLANES eligible participants had increased contact and interactions with personnel of the government as they have been visited and interviewed. Positive interactions and conversations with government personnel could also lead to increased self-reported support, independently of the financial aid provided by PANES. This is a potential threat to the causality of the estimated effect.

Additionally, the reliance on self-reported measures of government support rather than actual voting behavior introduces uncertainties due to potential social desirability biases, which may not truly reflect voting behavior.

Moreover, the methodological depth of the study could be enhanced by incorporating a more diverse set of baseline characteristics, such as personality traits, which could reveal differentiated responses to the PANES program. Additionally, the analysis does not disaggregate the effects of cash transfers from cash transfers combined with food cards. Participants might react differently to those two transfers.

Finally, the absence of a bandwidth analysis in the original study is a significant oversight, given its importance in RDD for determining the data range around the cutoff used to estimate the treatment effect.

3.2 Contextual Limitations

While the study presents valuable insights into the PANES program's impact on government support, its contextual limitations are notable. The findings are rooted in a specific political and economic situation in Uruguay, characterized by the recent election of a center-left government that implemented an extraordinary anti-poverty program. Such conditions create a unique environment that significantly influences the perception of government programs and therefore the self-reported political support.

The generalizability of these results to other settings is questionable, as a newly elected government and its first major social initiative may not be present elsewhere. In countries where political institutions are more established or where there is no significant shift in policies towards low-income populations, the observed effects may be smaller. The novelty and media portrayal of PANES as a groundbreaking anti-poverty program could have led to an overreaction in self-reported political support for PANES recipients. This would have led to an overestimation of the treatment effects.

3.3 Policy Implications

Drawing on the study's conclusions, policymakers should approach the findings with caution. The treatment effect observed is specifically associated with the poorest households within the Uruguayan context and may not extend to other socioeconomic groups.

Additionally, the reliance on self-reported support for government, rather than measured voting behavior, is a notable limitation in assessing the program's political impact. Given that low-income groups often have lower voter turnout (Kawai et al., 2021), these reports may not reflect actual electoral outcomes. For policymakers, this suggests that while the program is well-received, its perceived success may not directly influence voting behavior.

4. Extension

4.1 Regression Discontinuity Design Extension

In this report, I have undertaken a bandwidth analysis as a significant extension to Manacorda et al. (2011). Bandwidth selection is crucial, as it can significantly influences the estimated effect size. My analysis fills a gap left by the original study, providing a more robust understanding of the program's impact.

The results (Figure 7, 15, and 10) present the treatment effects over multiple bandwidths for 2007 based on the OLS model, second order polynomial regression, and the second order local polynomial using biased corrected regression with rdrobust, in that order. All effects are statistically significant, with p-values below 0.1; most are highly significant, except for one linear treatment effect with p = 0.088 at the bandwidth of 0.005 (Figure 6). The quadratic models demonstrate high significance consistently. The treatment effects range between 9-13%. The confidence intervals extend from a low of -0.013622 to a high of 0.1945199 in the OLS with a bandwidth of 0.005 (Figure 6). This is the lowest bound for the coefficient in all models. These results support an average local treatment effect hovering around 10% as a conservative measurement.

Concluding from these robustness checks, we can assert that eligibility for the PANES Program in Uruguay from 2005 to 2007 is associated with an increase in around 10% in self-reported support for the incumbent government. This effect, drawn from a quasi-randomized design near the cutoff, is consistent across different bandwidths and is conservative compared to donut hole analysis results. However, it is based on self-reported support from relatively poor respondents during a culturally significant period of a newly elected government, limiting the external validity of these findings.

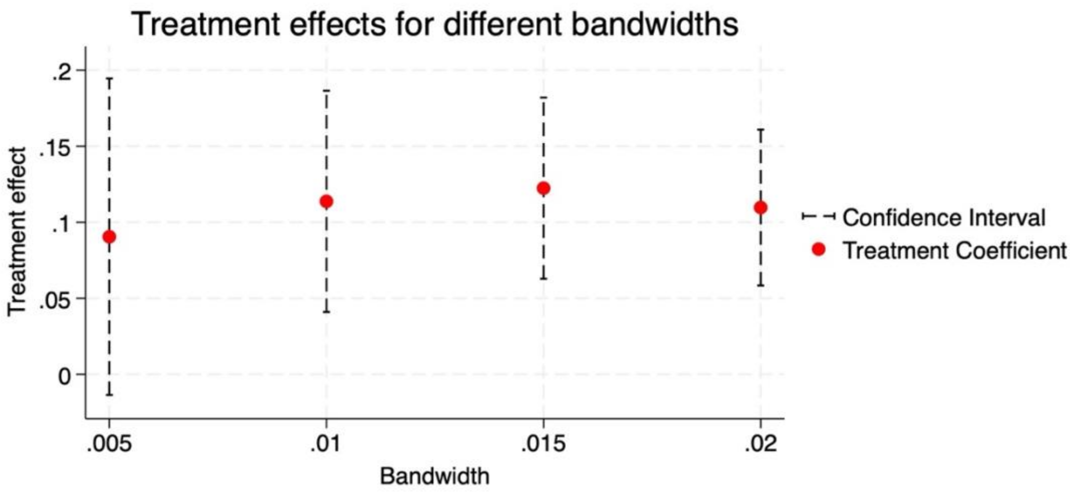

Figure 7: Treatment effects for different bandwidth calculated using OLS regression with robust standard errors and no controls

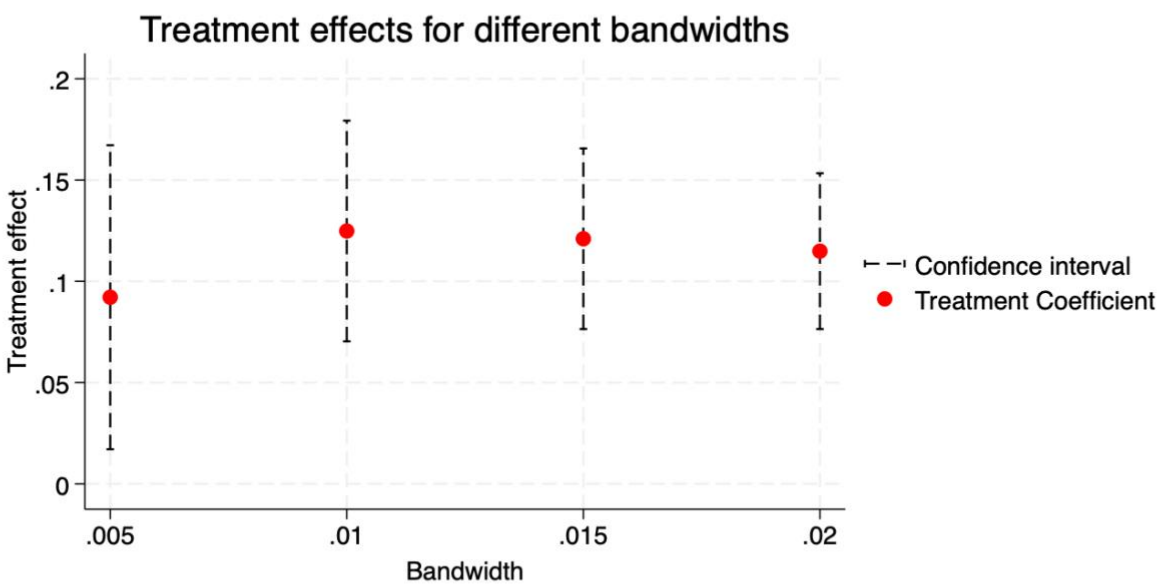

Figure 15: Treatment effects for different bandwidths calculated using second order polynomial regression model

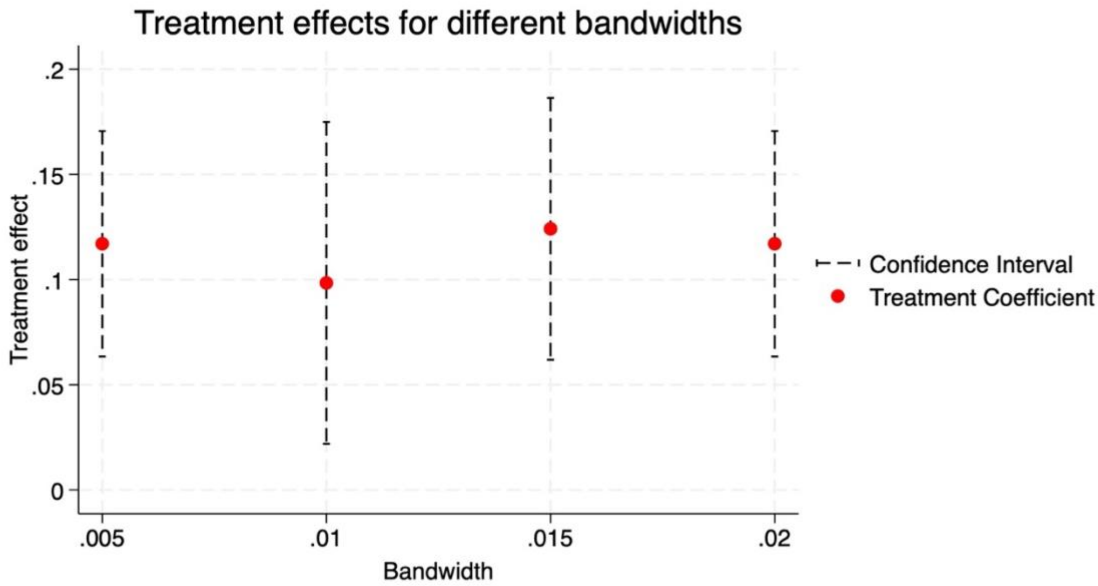

Figure 10: Treatment effects for different bandwidths calculated using nonparametric regression model

4.2 Alternative quasi-experimental Method

To enhance the methodological framework and address critiques, alternative quasi-experimental approaches are proposed. The authors' utilization of Difference-in-Differences (DiD) as a robustness check, which reportedly yields results similar to the original RDD is an opportunity for further investigation. Manacorda et al. (2011) use regional variations within Uruguay that present slightly different eligibility thresholds for the program. Another opportunity would be to extend the analysis beyond Uruguay and compare Uruguay to a similar country like Costa Rica, assuming the implementation of a comparable policy and a similar trend in both countries. Also, data before and after the program is needed. If applied, this could diminish the confounding effect of a new government's popularity and offer a more generalized understanding of the policy's efficacy.

An alternative extension for further study is Instrumental Variables (IV). A time delayed rollout of PANES could be used as an instrument. This approach could help us understand the causal impact of the program by using the timing of the program's implementation as a proxy for the likelihood of receiving treatment. While RDD focuses on the treatment effect around a specific cutoff and DiD expands the scope across groups and times, IV can provide another estimate of causality by using the timing of treatment rollout. However, this method assumes that the timing of program implementation is random and not related to other factors that could affect political support.

5. References

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Cunningham, S. (2021). *Causal Inference: The Mixtape* (p. 352). Yale University Press. https://doi.org/10.2307/j.ctv1c29t27

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Kawai, K., Toyama, Y., & Watanabe, Y. (2021). Voter Turnout and Preference Aggregation. *American Economic Journal: Microeconomics*, *13*(4), 548–586. https://doi.org/10.1257/mic.20190063

Manacorda, M., Miguel, E., & Vigorito, A. (2011). Government Transfers and Political Support. *American Economic Journal: Applied Economics*, *3*(3), 1–28. https://doi.org/10.1257/app.3.3.1

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics*, *142*(2), 698–714. https://doi.org/10.1016/j.jeconom.2007.05.005

6. Appendix

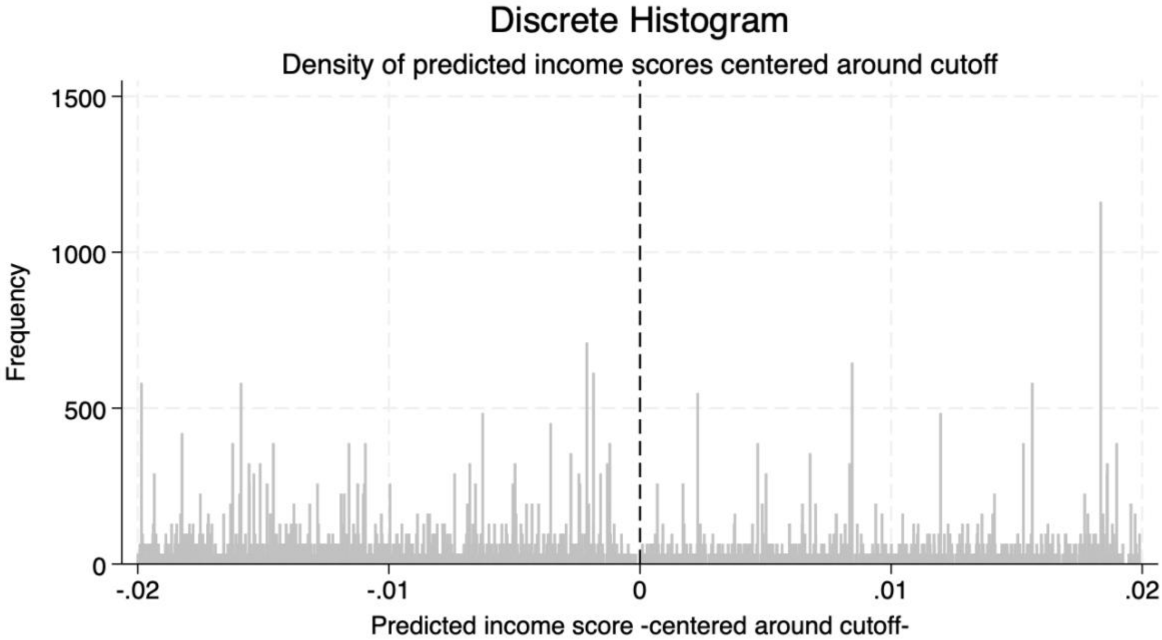

Figure 16: Discrete Histogram with changed width (0.00001)

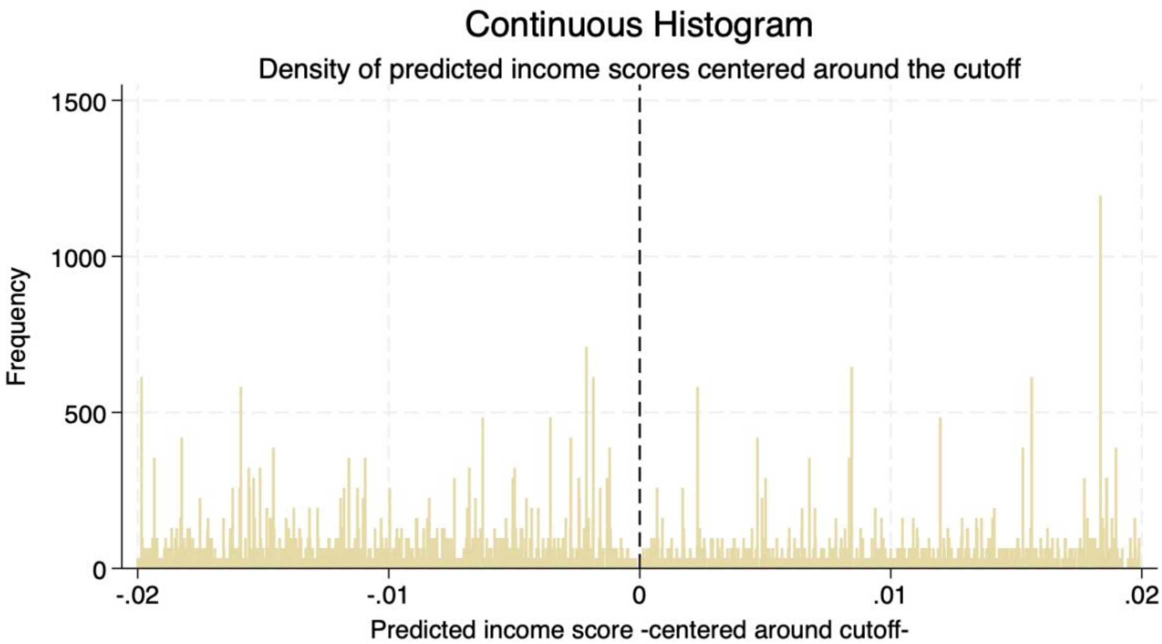

Figure 17: Continuous Histogram with changed width (0.00001)

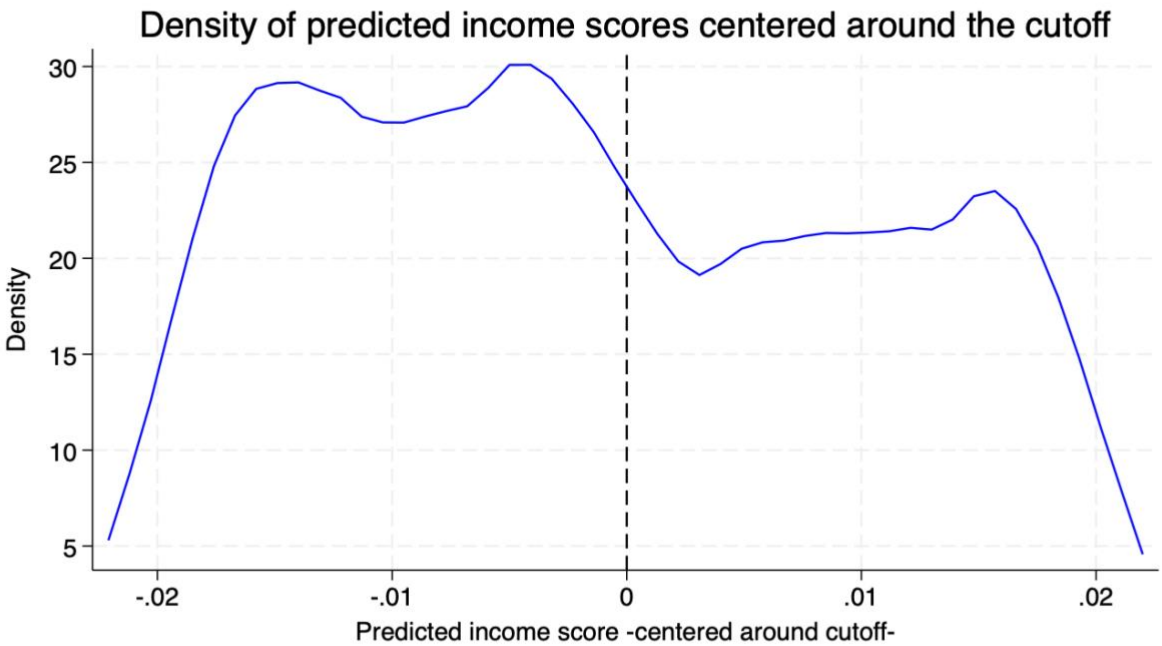

Figure 18: Kernel density estimate for a smoothed representation. Kernel = epanechnikov, Bandwidth = 0.0021

TABLE 8 - Confidence in president, MIDES and Interest in Politics with Donut

Dependent variable	Coefficient (standard error) (1)	(2)	Observations
1. Confidence in the current president	0.0631 (0.061)	0.2621 (0.176)	1471
2. Confidence in the Ministry of Social Development	0.1597** (0.063)	0.099 (0.186)	1372
3. Interest in politics	0.1050** (0.049)	0.0621 (0.146)	1557

Notes: The table reports estimate of the effect of being PANES eligible on the confidence in the current president and in the Ministry of Social Development as well as on interests in politics using a Donut of ± 0.005 and a linear (1) and squared (2) model. Standard errors are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

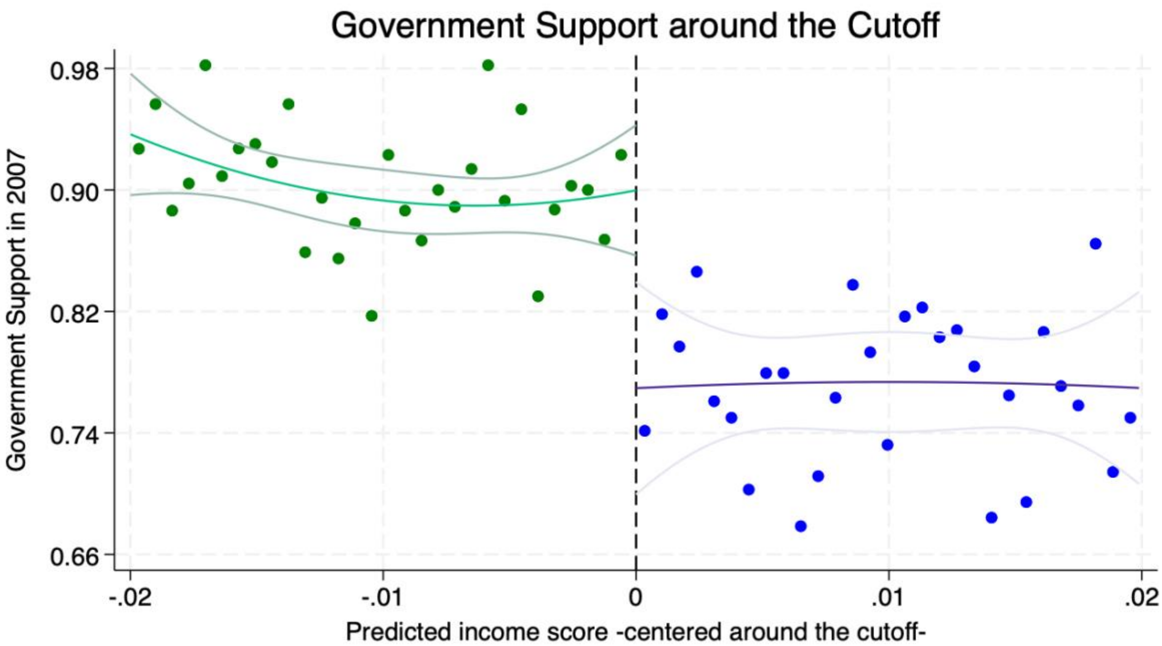

Figure 19: Visualisation of treatment effect using a quadratic model

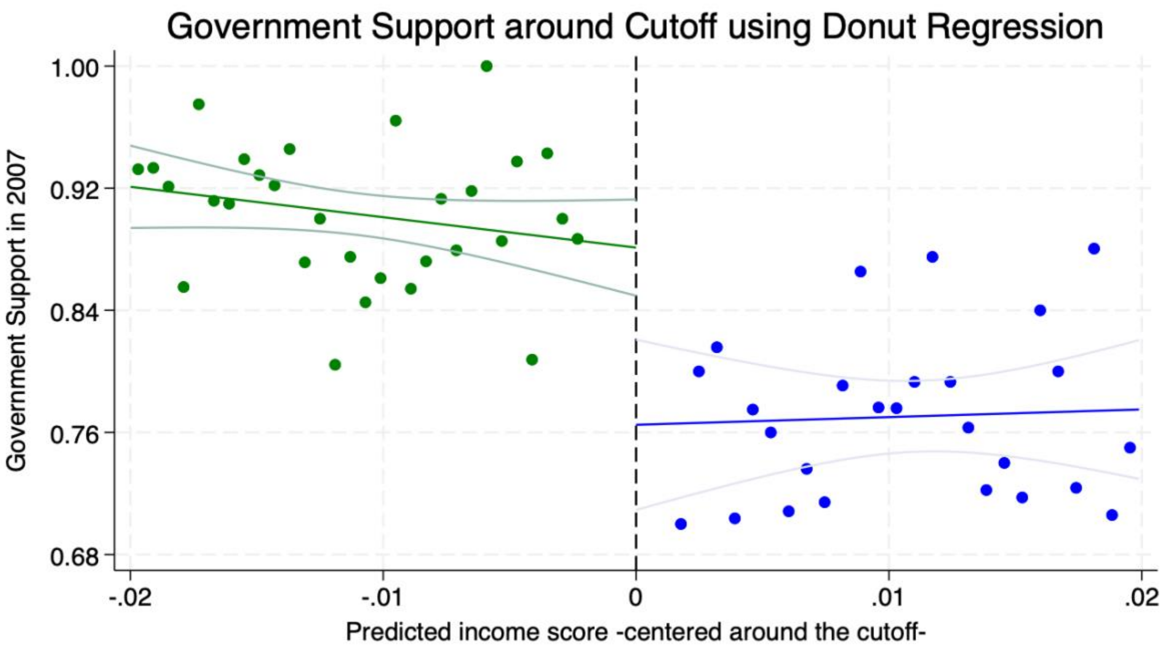

Figure 20: Visualisation of treatment effect using linear regression with an adjusted donut of ± 0.002

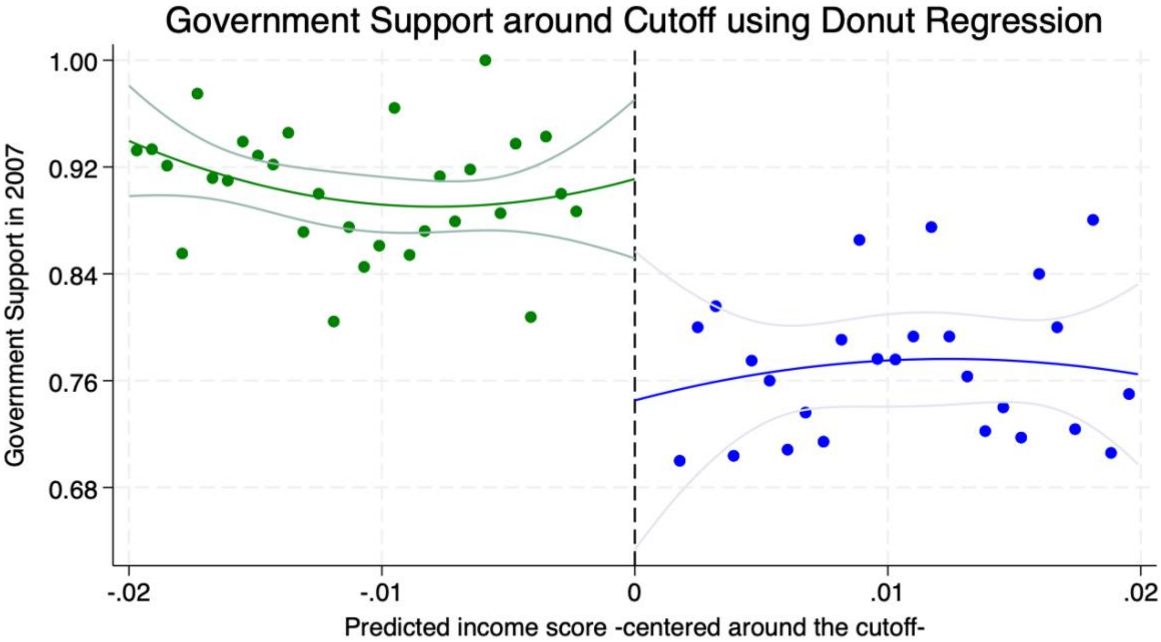

Figure 21: Visualisation of treatment effect using a quadratic fit with an adjusted donut ± 0.002

7. Do-File

```
************************************************************************
***********************
* name: 35612_PB47A
* description: summative assignment: replication and extension of manacorda et. al 2011
* last updated: January 24, 2023
************************************************************************
***********************

capture log close
clear
cd // change directory to your
capture log using ./assignment.log, replace

//Install packages
ssc install cmogram
ssc install rdrobust

******************************************** Create and rename variables
*Cutoff at 0.02
gen cutoff = 0.02

*Recenter running variable around the cutoff for better interpretation. If the running variable
is negative (positive), the data point is beneath (above) the cutoff.
gen rec_ind_reest = ind_reest - cutoff

*Generate second order polynomial of running variable
gen sq_rec_ind_reest = rec_ind_reest^2

*Generate treat, i.e. having income score below the cutoff and therefore receiving PANES
gen treat = 0
replace treat = 1 if rec_ind_reest < 0

*Rename for better understanding
rename rec_ind_reest predicted_income
rename treat panes_eligibility
rename sq_rec_ind_reest sq_predicted_income

******************************************** Descriptives
sum panes_eligibility, detail
sum predicted_income, detail
sum support_gov_2007, detail

******************************************** Histograms of running variable
*Discrete and continuous histograms look the same as we zoom in very strong and only have
data from +/- 0.02 of the cutoff, while the original predicted income score is on a larger scale.
If zooming in on a small range of a continuous variable and using a very fine bin width (like
```

0.0001), each bin might contain very few observations. This can make the histogram look like it's representing discrete data, as there will be many bins with low counts that resemble individual data points.

```
*Discrete
histogram predicted_income, discrete width(0.0001) ytitle(Frequency) xtitle(Predicted income score) xline(0) title(Discrete Histogram) subtitle(Density of predicted income scores recentered around cutoff) note(Discrete histogram)

*Changed width to inspect heapings
histogram predicted_income, discrete width(0.00001) ytitle(Frequency) xtitle(Predicted income score) xline(0) title(Discrete Histogram) subtitle(Density of predicted income scores recentered around cutoff) note(Discrete histogram)

*Continuous
histogram predicted_income, width(0.0001) ytitle(Frequency) xtitle(Predicted income score) xline(0) title(Continuous Histogram) subtitle(Density of predicted income scores recentered around the cutoff) note(Continuous histogram)

*Changed width to inspect heapings
histogram predicted_income, width(0.00001) ytitle(Frequency) xtitle(Predicted income score) xline(0) title(Continuous Histogram) subtitle(Density of predicted income scores recentered around the cutoff) note(Continuous histogram)

*Kernel density estimate for a smoothed representation
kdensity predicted_income, title(Density of predicted income scores centered around the cutoff) xline(0)

********************************************* Graphical Discontinuity check
*Create bins
local step = (.02)/15
egen bins = cut(predicted_income), at(-.02(`step').02)

* Means within bins
preserve
collapse (mean) support_gov_2007, by(bins)

* Twoway scatter
twoway (line support_gov_2007 bins) || (function y = 0, horiz range(support))

restore

********************************************* Bandwith?
*As we have no data points left from -0.02 and no data points right from 0.02, using the bandwith of -0.02/0.02 will result in the same results as of if not using it. I am therefore not including it in my code if I am reffering to a -0.02/0.02 bandwith
sum predicted_income

********************************************* MCcrary Test
```

*We see overlapping confidence intervals and a p-value of 0.4111. H0: continuity of the running variable predicted_income at the cutoff 0. Insignificant p-value suggests that we are not able to reject H0. It suggest continuity at the cutoff. This argues against heaping and manipulation.
rddensity predicted_income, c(0) plot

** Looking for jumps in covariates

*Placebo regression for potential covariates
reg female panes_eligibility##c.predicted_income, robust
reg bl_hhsize panes_eligibility##c.predicted_income, robust
reg ave_age panes_eligibility##c.predicted_income, robust
reg respondent_age panes_eligibility##c.predicted_income, robust
reg respondent_ed panes_eligibility##c.predicted_income, robust
reg voted panes_eligibility##c.predicted_income, robust
reg log_income panes_eligibility##c.predicted_income, robust

*Cmograms for significant jump (at p< 0.05% level)
cmogram bl_hhsize predicted_income, cut(0) scatter line(0) lfitci

** Main Model
*Linear without controls
reg support_gov_2007 panes_eligibility##c.predicted_income, robust
cmogram support_gov_2007 predicted_income, cut(0) scatter line(0) lfitci

*Linear with control for significant jumps in covariates
reg support_gov_2007 bl_hhsize panes_eligibility##c.predicted_income, robust

*Squared without controls
reg support_gov_2007 panes_eligibility##c.(predicted_income sq_predicted_income), robust
cmogram support_gov_2007 predicted_income, cut(0) scatter line(0) qfitci

*Squared with controls for significant jumps in covariates
reg support_gov_2007 bl_hhsize panes_eligibility##c.(sq_predicted_income predicted_income), robust

*Expanding the window does not change anything as we do not have data points past +/- 0.02. I decreased the bandwith stepwise

** Analysis of Post PANES 2008
*Linear without controls:
reg support_gov_2008 panes_eligibility##c.predicted_income, robust

*Linear with controls:
reg support_gov_2008 bl_hhsize panes_eligibility##c.predicted_income, robust

*Squared without controls:

```
reg support_gov_2008 panes_eligibility##c.(sq_predicted_income predicted_income), robust

*Squared with controls:
reg support_gov_2008 bl_hhsize panes_eligibility##c.(sq_predicted_income
predicted_income), robust


******************************************** Graph for different bandwiths

***With OLS
reg support_gov_2007 panes_eligibility##c.predicted_income if predicted_income > -0.02 &
predicted_income < 0.02 ,robust
reg support_gov_2007 panes_eligibility##c.predicted_income if predicted_income > -0.015
& predicted_income < 0.015 ,robust
reg support_gov_2007 panes_eligibility##c.predicted_income if predicted_income > -0.01 &
predicted_income < 0.01 ,robust
reg support_gov_2007 panes_eligibility##c.predicted_income if predicted_income > -0.005
& predicted_income < 0.005 ,robust

*Bandwith
gen bw = .
*Treatment effect
gen te = .
*Lower confidence interval bound
gen ci_lower  = .
*Upper confidence interval bound
gen ci_upper = .

replace bw = 0.005 in -4
replace te = 0.090449 in -4
replace ci_lower = -0.013622 in -4
replace ci_upper =  0.1945199 in -4

replace bw = 0.010 in -3
replace te = 0.1137275 in -3
replace ci_lower = 0.0409951 in -3
replace ci_upper = 0.1864599 in -3

replace bw = 0.015 in -2
replace te = 0.1223851 in -2
replace ci_lower = 0.062782 in -2
replace ci_upper = 0.1819882 in -2

replace bw = 0.020 in -1
replace te = 0.1096557 in -1
replace ci_lower = 0.0584138 in -1
replace ci_upper = 0.1608977 in -1
```

```
*Create scatter
twoway (rcap ci_lower ci_upper bw) (scatter te bw)

***With second order polynomial regression
reg support_gov_2007 panes_eligibility##c.sq_predicted_income if predicted_income > -
0.02 & predicted_income < 0.02 ,robust
reg support_gov_2007 panes_eligibility##c.sq_predicted_income if predicted_income > -
0.015 & predicted_income < 0.015 ,robust
reg support_gov_2007 panes_eligibility##c.sq_predicted_income if predicted_income > -
0.01 & predicted_income < 0.01 ,robust
reg support_gov_2007 panes_eligibility##c.sq_predicted_income if predicted_income > -
0.005 & predicted_income < 0.005 ,robust

*Bandwith
gen bw_sq = .
*Treatment effect
gen te_sq = .
*Lower confidence interval bound
gen ci_lower_sq  = .
*Upper confidence interval bound
gen ci_upper_sq = .

replace bw_sq = 0.005 in -4
replace te_sq = 0.0921225 in -4
replace ci_lower_sq = 0.0170727 in -4
replace ci_upper_sq = 0.1671724 in -4

replace bw_sq = 0.010 in -3
replace te_sq = 0.1248218 in -3
replace ci_lower_sq = 0.0703267 in -3
replace ci_upper_sq = 0.1793169 in -3

replace bw_sq = 0.015 in -2
replace te_sq = 0.1210069 in -2
replace ci_lower_sq = 0.0764068 in -2
replace ci_upper_sq = 0.1656071 in -2

replace bw_sq = 0.020 in -1
replace te_sq = 0.1148853 in -1
replace ci_lower_sq = 0.0764129 in -1
replace ci_upper_sq = 0.1533577 in -1

*Create scatter
twoway (rcap ci_lower_sq ci_upper_sq bw_sq) (scatter te_sq bw_sq)

********************************************** Choosing three other dependent
variables
```

```
* Being in treatment is associated with an increase of 8.215% in confidence_president
*Linear
reg confidence_president panes_eligibility##c.predicted_income, robust
*Squared
reg confidence_president panes_eligibility##c.(sq_predicted_income predicted_income),
robust


*Being in treatment is associated with an 15.15% increase of confidence_MIDES
*Linear
reg confidence_MIDES panes_eligibility##c.predicted_income, robust
*Squared
reg confidence_MIDES panes_eligibility##c.(sq_predicted_income predicted_income), robust

*Being in treatment is associated with an 23.68% increase of opinion about PANES (the
treatment)
*Linear
reg interest_politics panes_eligibility##c.predicted_income, robust
*Squared
reg interest_politics panes_eligibility##c.(sq_predicted_income predicted_income), robust


******************************************** Donut Hole regression main model
*Adjust for non-random heaping around the cutoff
gen     donut = 0
replace donut = 1 if predicted_income>-0.005 & predicted_income<0.005

***** 2007 Model
*Linear
reg support_gov_2007 panes_eligibility##c.predicted_income if donut==0, robust

*Linear with control for bl_hhsize
reg support_gov_2007 bl_hhsize panes_eligibility##c.predicted_income if donut==0, robust

*Squared
reg support_gov_2007 panes_eligibility##c.(sq_predicted_income predicted_income) if
donut==0, robust

*Squared with control:
reg support_gov_2007 bl_hhsize panes_eligibility##c.(sq_predicted_income
predicted_income) if donut==0, robust


** Decrease Donut:
gen donut2 = 0
replace donut2 = 1 if predicted_income>-0.002 & predicted_income<0.002

*Linear:
```

reg support_gov_2007 panes_eligibility##c.predicted_income if donut2==0, robust

*Linear with control
reg support_gov_2007 bl_hhsize panes_eligibility##c.predicted_income if donut2==0, robust

*Squared:
reg support_gov_2007 panes_eligibility##c.(sq_predicted_income predicted_income) if donut2==0, robust

*Squared with control
reg support_gov_2007 bl_hhsize panes_eligibility##c.(sq_predicted_income predicted_income) if donut2==0, robust

*Plot
*Linear:
cmogram support_gov_2007 predicted_income if donut == 0, cut(0) scatter line(0) lfitci
cmogram support_gov_2007 predicted_income if donut2 == 0, cut(0) scatter line(0) lfitci

*Squared:
cmogram support_gov_2007 predicted_income if donut == 0, cut(0) scatter line(0) qfitci
cmogram support_gov_2007 predicted_income if donut2 == 0, cut(0) scatter line(0) qfitci

***** 2008 Model
** With a Donut of ± 0.005
*Linear
reg support_gov_2008 panes_eligibility##c.predicted_income if donut==0, robust

*Linear with control for bl_hhsize
reg support_gov_2008 bl_hhsize panes_eligibility##c.predicted_income if donut==0, robust

*Squared
reg support_gov_2008 panes_eligibility##c.(sq_predicted_income predicted_income) if donut==0, robust

*Squared with control:
reg support_gov_2008 bl_hhsize panes_eligibility##c.(sq_predicted_income predicted_income) if donut==0, robust

** With a Donut of ± 0.002
*Linear:
reg support_gov_2008 panes_eligibility##c.predicted_income if donut2==0, robust

*Linear with control
reg support_gov_2008 bl_hhsize panes_eligibility##c.predicted_income if donut2==0, robust

*Squared:
reg support_gov_2008 panes_eligibility##c.(sq_predicted_income predicted_income) if donut2==0, robust

*Squared with control
reg support_gov_2008 bl_hhsize panes_eligibility##c.(sq_predicted_income predicted_income) if donut2==0, robust

** Donut Hole regression with three other dependent variables

*Linear:
reg confidence_president panes_eligibility##c.predicted_income if donut==0, robust
reg confidence_MIDES panes_eligibility##c.predicted_income if donut==0, robust
reg interest_politics panes_eligibility##c.predicted_income if donut==0, robust

*Squared:
reg confidence_president panes_eligibility##c.(sq_predicted_income predicted_income) if donut==0, robust
reg confidence_MIDES panes_eligibility##c.(sq_predicted_income predicted_income)e if donut==0, robust
reg interest_politics panes_eligibility##c.(sq_predicted_income predicted_income) if donut==0, robust

** Robustness check with rdrobust
*Local Polynomials
*Without Donut: Kernel epanechnikov: weighing observations closer to the cutoff stronger. Triangle would also work with weighing observations closer to cutoff even stronger. Calculates optimal bandwith based on mean standard error rd (mserd) as default

***************************** 2007 Model

**** Symmetric bandwidth:
rdrobust support_gov_2007 predicted_income, kernel(epanechnikov) masspoints(off) p(2) c(0)

***** Asymmetric
rdrobust support_gov_2007 predicted_income, kernel(epanechnikov) masspoints(off) p(2) c(0) bwselect(msetwo)

***** Forcing Rdrobust to keep +/- 0.02 bandwith
rdrobust support_gov_2007 predicted_income, h(0.02) kernel(epanechnikov) masspoints(off) p(2) c(0)

*With Donut: Kernel uniform as we removed observations around the cutoff with the donut

**** Symmetric bandwidth:

rdrobust support_gov_2007 predicted_income if donut2==0, kernel(uniform) masspoints(off) p(2) c(0)

***** Asymmetric
rdrobust support_gov_2007 predicted_income if donut2==0, kernel(uniform) masspoints(off) p(2) c(0) bwselect(msetwo)

***** Forcing Rdrobust to keep +/- 0.02 bandwith
rdrobust support_gov_2007 predicted_income if donut2==0, h(0.02) kernel(uniform) masspoints(off) p(2) c(0)

***************************** 2008 Model

**** Symmetric bandwidth:
rdrobust support_gov_2008 predicted_income, kernel(epanechnikov) masspoints(off) p(2) c(0)

***** Asymmetric
rdrobust support_gov_2008 predicted_income, kernel(epanechnikov) masspoints(off) p(2) c(0) bwselect(msetwo)

***** Forcing Rdrobust to keep +/- 0.02 bandwith
rdrobust support_gov_2008 predicted_income, h(0.02) kernel(epanechnikov) masspoints(off) p(2) c(0)

*With Donut: Kernel uniform as we removed observations around the cutoff with the donut

**** Symmetric bandwidth:
rdrobust support_gov_2008 predicted_income if donut2==0, kernel(uniform) masspoints(off) p(2) c(0)

***** Asymmetric
rdrobust support_gov_2008 predicted_income if donut2==0, kernel(uniform) masspoints(off) p(2) c(0) bwselect(msetwo)

***** Forcing Rdrobust to keep +/- 0.02 bandwith
rdrobust support_gov_2008 predicted_income if donut2==0, h(0.02) kernel(uniform) masspoints(off) p(2) c(0)

** Graph for different bandwiths

*With rdrobust. No Donut
rdrobust support_gov_2007 predicted_income, c(0) h(0.02)
rdrobust support_gov_2007 predicted_income, c(0) h(0.015)
rdrobust support_gov_2007 predicted_income, c(0) h(0.01)
rdrobust support_gov_2007 predicted_income, c(0) h(0.005)

```
gen bw_rdrobust = .
gen te_rdrobust = .
gen ci_lower_rdrobust = .
gen ci_upper_rdrobust = .

replace bw_rdrobust = 0.005 in 1
replace te_rdrobust = 0.11702 in 1
replace ci_lower_rdrobust = 0.170604 in 1
replace ci_upper_rdrobust = 0.06344 in 1

replace bw_rdrobust = 0.01 in 2
replace te_rdrobust = 0.0984 in 2
replace ci_lower_rdrobust = 0.174899 in 2
replace ci_upper_rdrobust = 0.021902 in 2

replace bw_rdrobust = 0.015 in 3
replace te_rdrobust = 0.12412 in 3
replace ci_lower_rdrobust = 0.186353 in 3
replace ci_upper_rdrobust = 0.061888 in 3

replace bw_rdrobust = 0.02 in 4
replace te_rdrobust = 0.11702 in 4
replace ci_lower_rdrobust = 0.170604 in 4
replace ci_upper_rdrobust = 0.06344 in 4

*Create scatter
twoway (rcap ci_lower_rdrobust ci_upper_rdrobust bw_rdrobust) (scatter te_rdrobust
bw_rdrobust)

********************************************* RDplot and cmogram

***** Original Window
*Linear
cmogram support_gov_2007 predicted_income, cut(0) scatter line(0) lfitci
rdplot support_gov_2007 predicted_income, binselect(qs) p(1) masspoints(off) c(0)
graph_options(title(Government Support around the Cutoff))

*Squared
cmogram support_gov_2007 predicted_income, cut(0) scatter line(0) qfitci
rdplot support_gov_2007 predicted_income, binselect(qs) p(2) masspoints(off) c(0)
graph_options(title(Government Support around the Cutoff))

****** Expanded Window does not change anything as we have no data points outside +/-
0.02

****** Asymmetric window
*** MSETWO calculates - 0.005     +0.006
```

```
rdrobust support_gov_2007 predicted_income, kernel(epanechnikov) masspoints(off) p(2)
c(0) bwselect(msetwo)

*Linear
cmogram support_gov_2007 predicted_income if predicted_income > - 0.005 &
predicted_income < 0.006, cut(0) scatter line(0) lfitci
rdplot support_gov_2007 predicted_income if predicted_income > - 0.005 &
predicted_income < 0.006, binselect(qs) p(1) massproints(off) c(0)
graph_options(title(Government Support around the Cutoff using MSETWO Bandwith))

*Squared
cmogram support_gov_2007 predicted_income if predicted_income > - 0.005 &
predicted_income < 0.006, cut(0) scatter line(0) qfitci
rdplot support_gov_2007 predicted_income if predicted_income > - 0.005 &
predicted_income < 0.006, binselect(qs) p(2) masspoints(off) c(0)
graph_options(title(Government Support around the Cutoff))
```