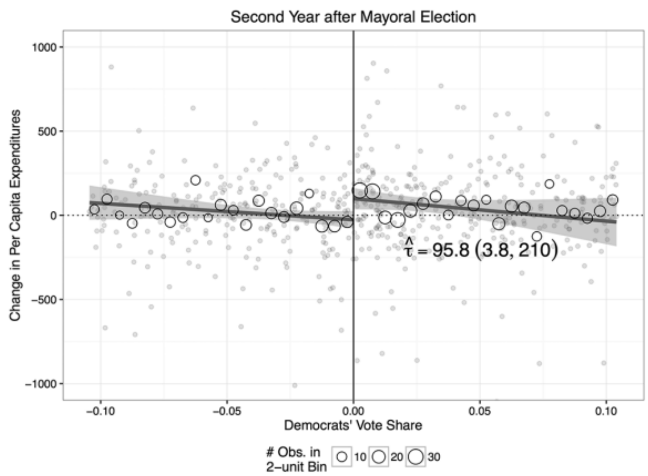
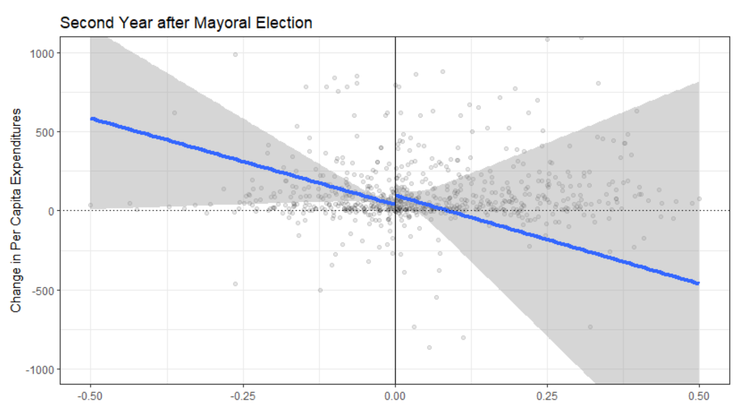
Replication Target

My goal for the replication exercise is Figure 2 from “Mayoral Partisanship and Municipal Fiscal Policy”, de Benedictis-Kessner & Warshaw (JOP 2016 p.1131). Their main result[1] shows that municipalities which elected Democrats in close elections had (slightly) higher public spending per capita than municipalities that just elected a Republican. They interpret the result as a demonstration that partisanship is an important feature of municipal politics in the United States.



Replication Result

Through the process of merging publicly available data to the authors’ original data collection, I am able to construct a subsample of the dataset they use in their main data. In particular I am unable to collect data for approximately 200 municipal elections occurring before 1967; am unable to replicate the merge between candidates and CF-scores for approximately 20 elections; and I am unable to merge to the public Census data for approximately 50. The below figure is my replication of the figure from the paper; I recover a point estimate of 26.912 (-50.9, 104.7) with their preferred uniform kernel and of 38.917 (-36.674, 114.508) with my preferred triangular kernel.



[1] The authors report their RD specification with tens of dependent variables. They do not adjust for multiple hypothesis testing. I have chosen the result they report first in Table 2, which is also the focus of the abstract.

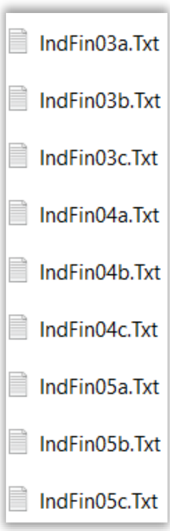
Original Data from Authors

The main challenge with studying municipal politics is the lack of data availability. The authors have impressively hand-collected electoral return data for thousands of local elections from 1957-2012 in cities with a population above 75,000. For these elections, they recover party affiliations for the winning candidate and the runner up[2]. They then subset their electoral data to those elections in which the candidates were a Democrat-Republican pair. The final sample reported in the paper is 981 contests. Since this data collection effort was original, I take their electoral results data as given and merge with the publicly available data that makes up the rest of the analysis.

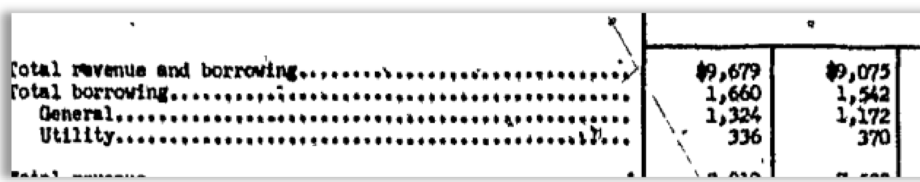
The author's original data is available on the Harvard Dataverse. Since the only data in their replication file is a final "regression-ready" build, I subset to a collection of variables that refer to specific election characteristics (vote shares, location identifiers, and candidate names). For variable selection, see *00_writedata.R*.

Publicly Available Data

For the headline result, we need data on expenditure and population for U.S. municipalities. The authors rely on the Historical Data Base of Individual Government Finances, collected yearly by the Census Bureau. They adjust for inflation (i.e. report in 2012 dollars). The other relevant data are CF-Scores from Adam Bonica's DIME (2014), which the authors use to identify partisan lean for candidates whose party affiliation is unknown.



The Historical Data Base of Individual Government Finances is available on the Census Bureau website. For years 1967-2012, the files are available as a huge collection of year-variable-partitioned text files. These are a little tricky to work with: the script *_govdata_read.sh* concatenates the relevant variables into a single comma delimited text file using *awk* at the command line. Unfortunately, for the years 1957-1966, the only publicly available version I was able to find is a set of scanned PDFs. For this reason, I was unable to collect that data given time constraints. DIME's CF-scores are available online, as are annual CPI figures.



Total revenue and borrowing	$9,679	$9,075
Total borrowing	1,660	1,542
General	1,324	1,172
Utility	336	370

Data Cleaning

The script *01_clean_eletoral.R* cleans the electoral data. The authors compile data from several sources; the replication files contain candidate names and party affiliations across several variables, some of which are missing. They also include "final" variables used in analysis. I attempt to reconstruct the final

[2] *"We coded candidates' partisanship based on any clear indicators that candidates leaned toward one of the two parties. These indicators included past or future partisan elected offices that a candidate held, mentions in historical newspaper articles of their partisanship, and campaign-donation-based data. For instance, we would code a candidate as a Democrat if he or she ran for state legislature as a Democrat prior to running for mayor."* (p. 1127)

variables, combining the non-missing electoral data. I eject data for which I am able to infer with certainty that one candidate was not a Democrat or Republican (156 races); I also eject data for which the authors have not directly recorded party affiliation and for which the candidate's name is missing such that stitching to DIME CF-Scores is impossible (14 races).

There are 13 race which have a candidate with non-missing name but missing party affiliation. In theory, one could find these candidates in the DIME recipient/contributor data and infer their party affiliation from there. With a rather crude name search algorithm[3], I was unable to find any of these candidates' names in DIME, so I drop these observations also.

The script *02_elections_to_census.R* merges the cleaned electoral results to the Census of Governments data. I subset to municipal local government data, apply a series of patches for slightly incorrect address strings in the authors' original data[4], and then merge to the census. I match observations in the elections data to instances of the government expenditure data where (a) the city of the election is contained in the name of the municipality in the census data and (b) the state FIPS codes align. I take the municipal expenditure and population in the year of the election and two years subsequently.

Importantly, I drop 171 observations due to lack of data before 1967. This is not something I can fix without applying some OCR algorithm to the PDFs containing the earlier data. I drop a further 21 observations for lack of congruence with any census records; a further 58 do not find a census record for both the year of election and two years afterwards[5]. The final sample for analysis includes 714 races, approximately 73% of the sample reported in the paper.

Replication

The script *03_replicate.R* attempts to directly replicate the point estimate and figure from the paper. First, I stitch in the CPI data and construct total municipality expenditure per capita measures for each election, at the time of the election and two years later, in 2012 dollars. The change in per capita expenditure over the two-year horizon is the outcome variable. The forcing variable is the difference from 50% in the Democratic share of the two-party vote.

I implement the RDD specification using the *rdrobust* package. The package generates semiparametric effect estimates by fitting local linear regressions either side of the cut-off with an efficiency-maximised bandwidth and weighting kernel of the researcher's choice, generating bias-aware confidence intervals (see Calonico et al. 2014, Calonico et al. 2017). The original authors' specification uses a uniform kernel; I prefer the triangular kernel due to its better ex-ante properties, lowering the weight on units further from the cutoff (Imbens & Wager, 2017). The author's replication code uses a deprecated version of the same package.

The table below presents the results. I find point estimates approximately a third the magnitude of the point estimates reported in the paper. Since I dropped approximately 30% of the sample, it should be

[3] I have only done fuzzy string matches in Stata before, and it seems the apparatus to achieve this in R is a little wonky. Given the relatively few observations of interest, this shouldn't impact results too much.
[4] For example, "ROCHESTR" is corrected to "ROCHESTER". See *./data/string_patches.csv* in my replication directory.
[5] Clearly, the authors successfully merged these records. I may have been a little over-judicious in removing identifiers that looked too close to government identifiers in the replication data; leaning on that side of things seemed in the spirit of the assignment.

expected that the point estimate would differ; it is notable that the main data I removed was from 1967 or earlier. It seems that older elections are driving a large portion of the result in the paper[6].

Specification	Estimate	P-Value	95% CI	Eff. N
Replication Results				
Triangle Kernel	38.917	0.313	[-36.674, 114.508]	153
Uniform Kernel	26.912	0.678	[-50.920, 104.745]	145
Author Results				
Uniform Kernel	95.78	.04	[3.8, 210]	-

Finally, I replicate the headline figure. I fit local polynomials either side of cut-off and weight observations in line with the uniform kernel, for congruence with the paper's results. The figure is available in my replication file, on the project's GitHub repo, and at the top of this report. Despite the plotted local linear regressions having much wider confidence intervals distant from cut-off relative to the figure in the paper, it is worth noting that *at* cut-off my RDD results have slightly narrower CIs than reported in the paper.

References

Benedictis-Kessner, Justin de, and Christopher Warshaw. "Mayoral Partisanship and Municipal Fiscal Policy." The Journal of Politics 78, no. 4 (October 2016): 1124–38. https://doi.org/10.1086/686308.

Bonica, Adam. "Mapping the Ideological Marketplace." American Journal of Political Science 58, no. 2 (2014): 367–86. https://doi.org/10.1111/ajps.12062.

Calonico, Sebastian, Matias D. Cattaneo, Max H. Farrell, and Rocío Titiunik. "Rdrobust: Software for Regression-Discontinuity Designs." The Stata Journal 17, no. 2 (June 1, 2017): 372–404. https://doi.org/10.1177/1536867X1701700208.

Calonico, Sebastian, Matias D. Cattaneo, and Rocio Titiunik. "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs." Econometrica 82, no. 6 (2014): 2295–2326. https://doi.org/10.3982/ECTA11757.

Imbens, Guido, and Stefan Wager. "Optimized Regression Discontinuity Designs." arXiv, June 7, 2018. https://doi.org/10.48550/arXiv.1705.01677.

Marshall, John. "Can Close Election Regression Discontinuity Designs Identify Effects of Winning Politician Characteristics?" American Journal of Political Science n/a, no. n/a. Accessed April 30, 2023. https://doi.org/10.1111/ajps.12741.

[6] To be honest, my main takeaway from this exercise is that this paper has quite fragile results. Combined with general concerns about the interpretability of close election designs (Marshall, 2022) and the lack of multiple-hypothesis adjustments, I am hesitant to claim we know very much at all about partisan influences on local fiscal policy.