Preferences for Local Public Goods and the Gig Economy

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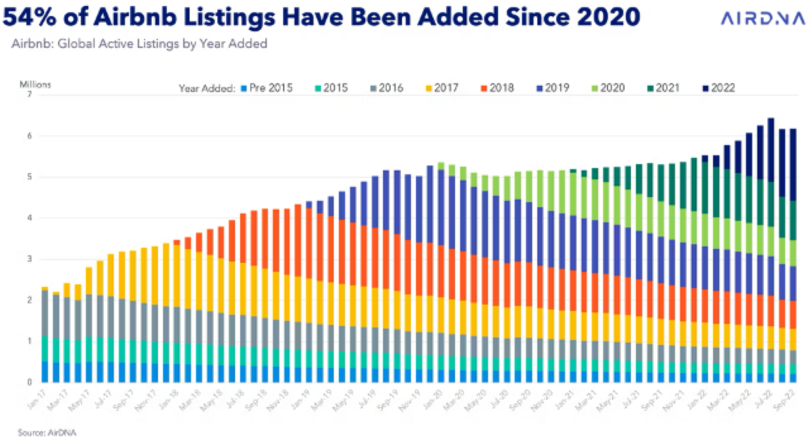
The gig or sharing economy (e.g. Uber, Lyft, Airbnb) has fundamentally changed the functioning of some markets and the design of public policies.



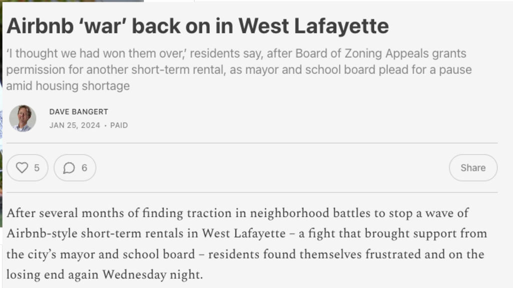
The sharing economy deals with markets regulated (and taxed) mostly by local governments. This has created a complex and heterogenous policy setting.

Tippecanoe County residents raise concerns for Airbnb's in neighborhoods

By: Vince Martorano Oct 25, 2023 Updated Oct 27, 2023 7

Neighbors across Tippecanoe County are concerned with having transient neighbors living in rental properties.

Source: https://www.basedinlafayette.com/p/airbnb-war-back-on-in-west-lafayette



Airbnb 'war' back on in West Lafayette

'I thought we had won them over,' residents say, after Board of Zoning Appeals grants permission for another short-term rental, as mayor and school board plead for a pause amid housing shortage

DAVE BANGERT
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After several months of finding traction in neighborhood battles to stop a wave of Airbnb-style short-term rentals in West Lafayette – a fight that brought support from the city's mayor and school board – residents found themselves frustrated and on the losing end again Wednesday night.

Source: https://www.wlfi.com/news/tippecanoe-county-residents-raise-concerns-for-airbnbs-in-neighborhoods/article_4943609e-73a7-11ee-9aea-0b5197acbd30.html

Introduction

- This paper examines the mechanisms through which preferences for local public goods influence the decision to participate in the gig economy.
- Examine how results from school bond referendums (which capture differences on constituent's preferences for local public education), determine the incentives to participate (enter/exit) the sharing-economy (in this case, Airbnb).
- Empirical analysis: results of school district bond referendums in Texas between 2014 and 2019.

Theoretical Considerations

Bond Referendums

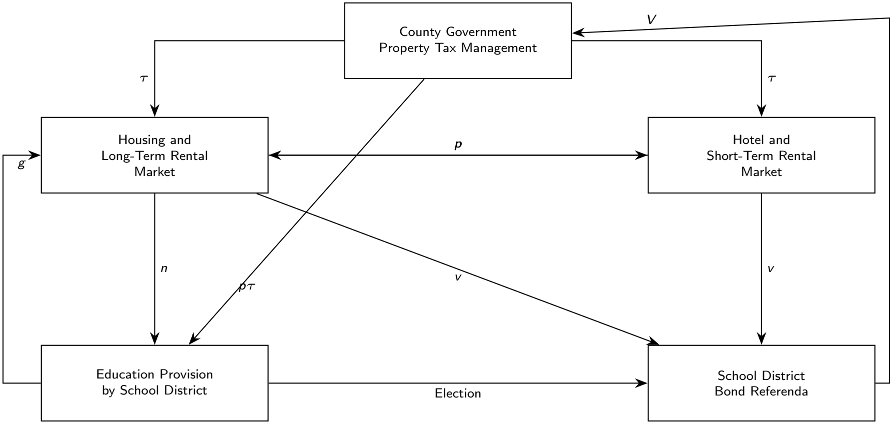
- School districts require voter approval to issue debt to finance capital improvements.
- Direction of the vote is shaped by the heterogeneity in the preferences for local government-provided goods.

Voters on Bond Referendums

1. Vote for approving the referendum: benefits $>$ costs of the increase in the tax burden.
2. Two types of voters: residential households and Airbnb hosts.
3. Residential households:
   - Benefits $=$ Increased quality on education provision.
   - Costs $=$ Tax burden of the bond issue.
4. Airbnb hosts: Do not consume education, nor are necessarily eligible to vote in the referendum (absentee landlords), yet they have to pay the property tax.

Network of Adjacent Action Situations

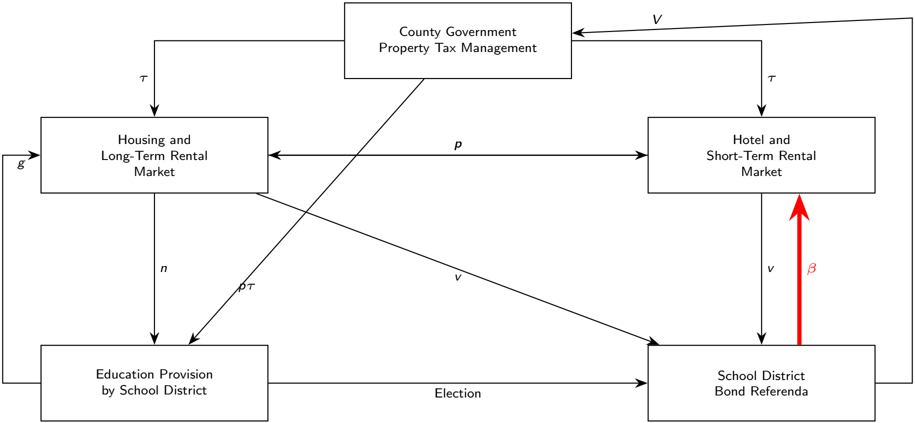
Figure: Network of Adjacent Action Situations - Participation in the Gig Economy and Support for School District Bond referendums



Note: τ denotes property tax rates, p denotes the vector of equilibrium prices of taxable residential and non-residential real estate, $p\tau$ refers to property tax revenues to fund education provision, n refers to the number of students attending the school district, g refers the quality-quantity of public education consumed by households, v denotes the vote made by homeowners eligible to participate in the election, V refers to the outcome of the bond referendum, and *Election* denotes school district's action to call for a bond referendum.

Research Question

Figure: Network of Adjacent Action Situations - Participation in the Gig Economy and Support for School District Bond referendums



Note: the thick red line shows the research hypothesis and β_1 is the parameter of interest. τ denotes property tax rates, p denotes the vector of equilibrium prices of taxable residential and non-residential real estate, $p\tau$ refers to property tax revenues to fund education provision, n refers to the number of students attending the school district, g refers the quality-quantity of public education consumed by households, v denotes the vote made by homeowners eligible to participate in the election, V refers to the outcome of the bond referendum, and *Election* denotes school district's action to call for a bond referendum.

Empirical Challenges

Empirical Question

- Bond approval decreases Airbnb supply: tax burden story.
- Bond approval increases Airbnb supply: property tax capitalization (benefit view).

Empirical Challenges: Reverse Causality

- A regression of the result on the bond referendums on Airbnb supply might be biased due to the endogeneity problems.
- Reverse causality: Airbnb supply could determine the direction of the vote via the composition of the constituents participating on the election.

Empirical Challenges

Potential Solution: Regression Discontinuity Design (RDD)

- Comparison around the cutoff: between school districts with narrow approvals/rejections on the referendum.
- Strength: within a small bandwidth around the cutoff, assignment to treatment (i.e. observing a bond approval) is as good as random. Quasi-experiment.

Limitations of the Static Regression Discontinuity

- Fails to account the dynamic nature of referendums. School districts hold elections sequentially, observing (potentially) different results each time. Some issues might get voted more than once (if rejected the first times).
- In policy evaluation terms: school districts observe multiple treatments and could switch between the treatment and control arms of the study (staggered adoption).

Stacked RDD: Intuitive Description

First Layer (Cross-Sectional): Standard RDD

$$y_i = \theta result_i + \beta vote_i + e_i$$

Second Layer (time-varying outcome RD): add panel dimension of the outcome variable . Estimate t independent models.

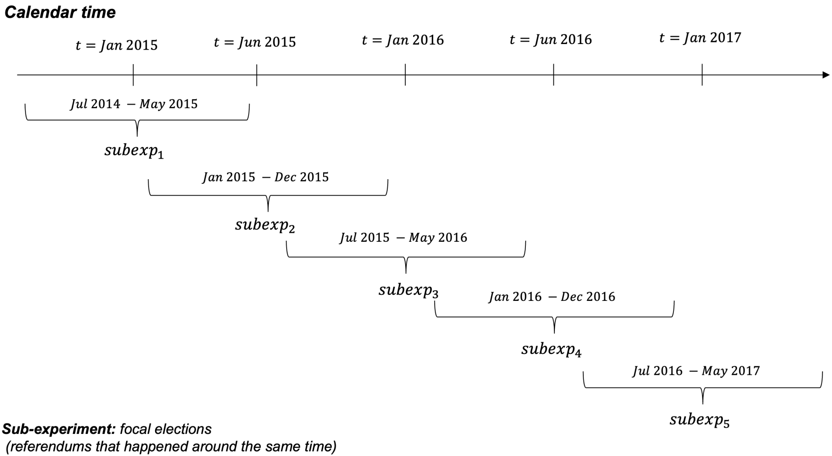
$$\begin{aligned} y_{i,t-1} &= \theta_{t-1} result_i + \beta_{t-1} vote_i + e_{i,t-1} \\ y_{i,t} &= \theta_t result_i + \beta_t vote_i + e_{i,t} \\ y_{i,t+1} &= \theta_{t+1} result_i + \beta_{t+1} vote_i + e_{i,t+1} \end{aligned}$$

- Coefficients θ_t mimic an event study.
- Define this fixed cross-sections with time-varying outcomes a sub-experiment (focal election).

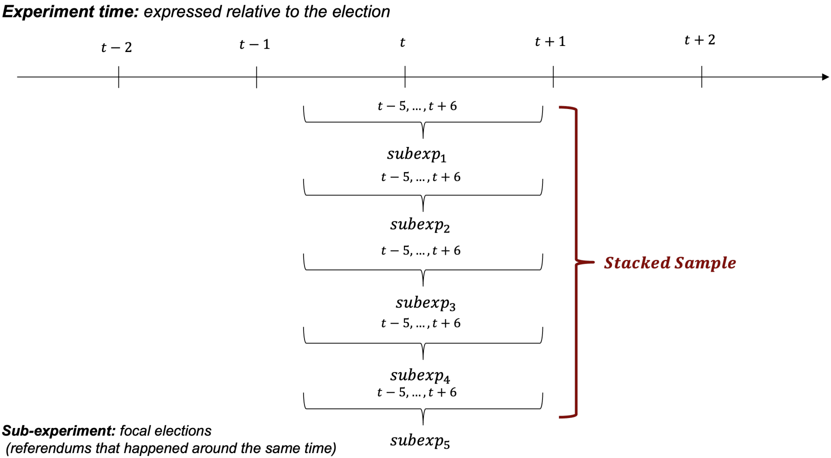
Third Layer (stacked RDD): each sub-experiment g is a focal election. Stack them. Estimate t independent models.

$$y_{itg} = \sum_{s \in t} \left(\theta_s result_{ig} + \beta_s vote_{ig} \right) + b_t + c_g + e_{itg}$$

Stacked Models (1)



Stacked Models (2)



Empirical Models: Event Study Stacked DID and Stacked RDD

Stacked DID (Event Study)

$$y_{itg} = \sum_{s \in t} \Big(\theta_s result_{ig} \times I(s = t) \Big) + \gamma X_{itg} + a_{ig} + b_t + c_g + e_{itg}$$

Stacked RDD a-la Cellini et al. (2010) (Event Study)

Cellini et al. (2010) proposed a version of the stacked time-varying RD. Their Intent-to-Treat (ITT) estimator uses time-to-event interactions with the treatment and polynomial of the running variable.

$$y_{itg} = \sum_{s \in t} \Big(\theta_s result_{ig} \times I(s = t) + \sum_p (\beta_s^p vote_{ig}^p \times I(s = t)) \Big) + \gamma X_{itg} + a_{ig} + b_t + c_g + e_{itg}$$

Model Characteristics

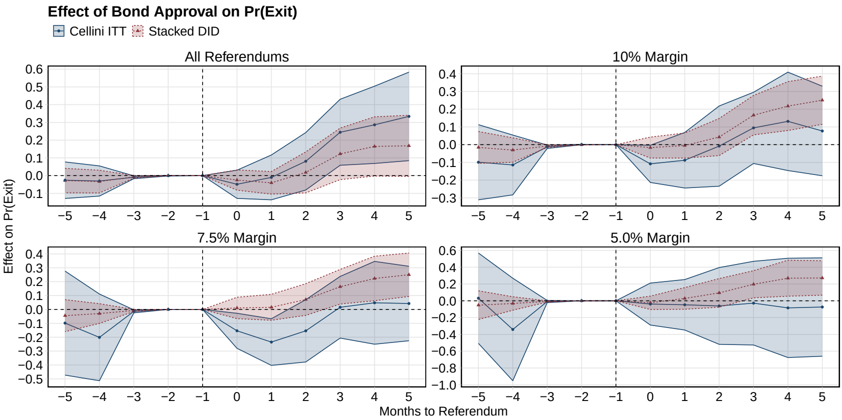
- **Sample:** Strongly balanced panel of Airbnb units i by month t.

- **Dependent Variable:** dummy equal to one if the Airbnb unit was **not listed** on the Airbnb website on month t. Linear probability model on $Pr(Exit)$.

- **Sample restriction:** only units that were listed on the website for 12 consecutive months before each focal election date. Rationale: exclude units that could be supplying seasonally. Helps to satisfy pre-trends.

- **Control variables:** percentage female, percentage black, median age, median household income, property tax rate, school enrollment per capita,housing units per capita, bond amount per student enrolled (proposed at the election).

- **Treatment-Control groups:** narrow approval-rejections (10%, 7.5% , 5% margins).



Notes: Each panel shows the estimates of coefficients θ_t on the treatment variable. Each panel corresponds to estimates using different bandwidths around the approval cutoff. Month before the election is dropped as reference category. Shaded areas show 95% confidence intervals built with clustered standard errors at the school district level.

Results Interpretation

- **Interpretation:** probability model on the probability of exiting the market. Analysis of the inelastic side of the market supply curve.

- Significant increase in $Pr(Exit)$ on the third month following the election.

- **Point Estimate Stacked DID (5% Margin):** increase of 19.7 percentage points on $Pr(Exit)$ due to the election.

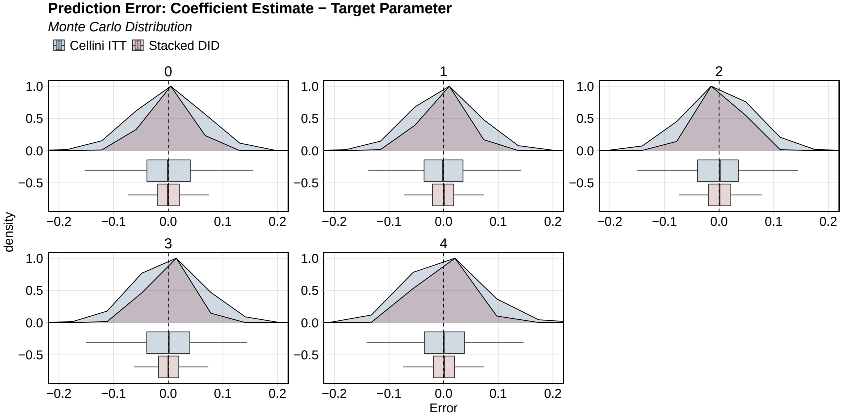
- **Context:** $Pr(Exit|Post = 0, Treat = 0) = 39.1\%$. Implied effect suggest $Pr(Exit)$ after the election is 1.50x larger.

- **Comparison:** Stacked RDD model suggests similar trends, but with noisier estimates.

- **Main Takeaway:** ITT Estimator at Cellini et al. (2010) is an stacked event study controlling for a polynomial on the vote variable.

Robustness Check: Estimator Reliability

Monte Carlo simulations (reps = 1000) show that this stacked DID model leads to more reliable estimates, with a less parameterized model. This could be explained by the collinearity between the running and the treatment variable on the RD model.



Notes: Each panel shows the empirical distribution of the prediction errors of the Monte Carlo experiments for both estimators. Prediction error is computed as the raw difference of the estimated coefficient and the assumed parameter (known at each Monte Carlo experiment). The data generating process for the outcome variable assumed the same fixed-effects structure included on the estimator. Each panel corresponds to the coefficient $t + a$ after the election, where $a = 0, .., 4$.

Conclusions

- Individuals supplying housing on rental markets might have different preferences towards the goods and services provided by the governments operating at their location.
- This paper examines the quasi-experimental setting created by referendums to analyze the effects of changes in tax burden on the incentives to participate in the gig-economy.
- Empirical results from Texas suggest that increases in property tax burden (i.e. measured by school bond elections) lead to an increase the in the probability of exiting the gig-economy.
- The empirical analysis in this paper shows a bridge between two relevant methodologies on the policy evaluation literature.

Contact

Thanks for your attention!

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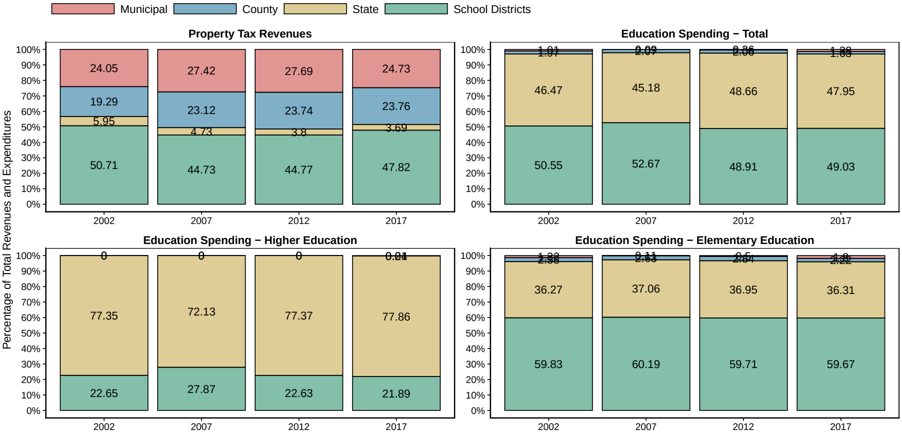
Appendix

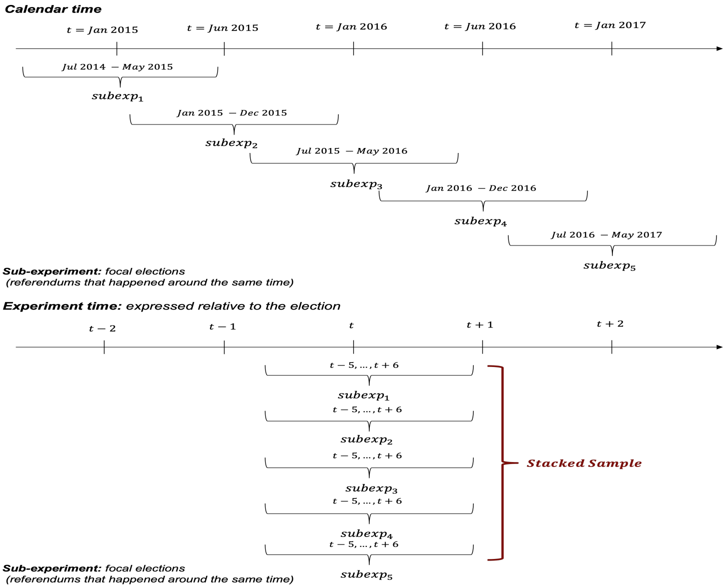
Property Tax Collection and Education Provision

Figure: Distribution of Property Tax Revenues and Education Spending by Level of Government



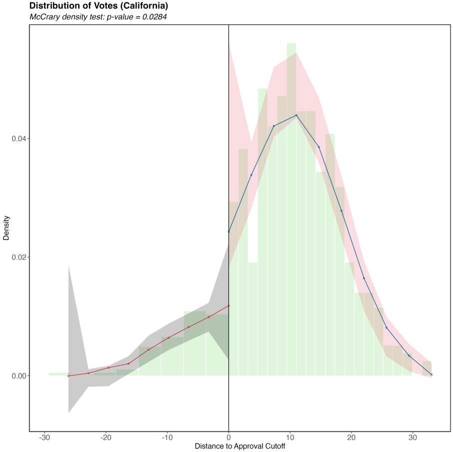
Note: This data shows the distribution of property tax revenues and education spending by level of government (state, county, municipal and school districts. For this classification, municipal governments include cities, townships, and special districts), according to the data from the Census of Local Government Finances collected by Pierson et al. (2015).

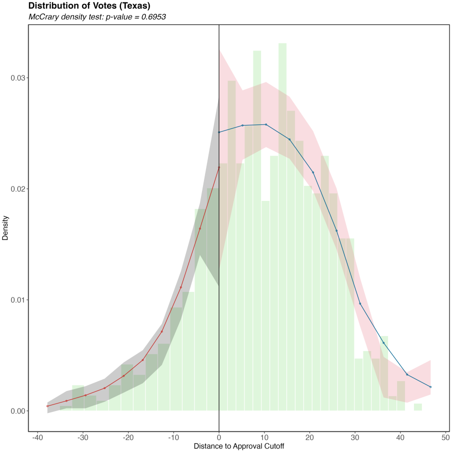
Stacked Models



Manipulation at the cutoff tests

Figure: Manipulation at the Cutoff Tests





Note: this panel shows the results for the McCrary test. The histogram shows the distribution of the running variable.

Covariate Balance and Data Description

Table: Covariate Comparison before the Election - Referendums with a 7.5% Margin

	Fail (N=46)		Pass (N=106)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	Std. Error
Airbnb Not Listed	0.356	0.451	0.075	0.261	-0.281***	0.071
% Female	0.500	0.025	0.502	0.032	0.002	0.005
% Black	0.066	0.051	0.038	0.036	-0.028**	0.008
Enrollment per Capita	0.265	0.041	0.252	0.053	-0.013+	0.008
Age (Median)	36.596	5.754	39.751	7.567	3.155**	1.122
Median Household Income	10.941	0.310	11.049	0.326	0.108+	0.056
Property Tax Rate	0.015	0.004	35.966	370.156	35.951	35.953
Debt Per Student	2.472	1.161	2.334	2.819	-0.138	0.323
Housing Units per Capita	232.215	49.415	245.469	58.349	13.254	9.231
	N	Pct.	N	Pct.		
2014	4	8.7	3	2.8		
2015	6	13.0	6	5.7		
2016	5	10.9	34	32.1		
2017	10	21.7	21	19.8		
2018	15	32.6	32	30.2		
2019	6	13.0	10	9.4		
California	7	15.2	46	43.4		
Texas	39	84.8	60	56.6		

Note: This table shows the balance table of the key socioeconomic variables used to explain bond referendum outcomes. Each observation corresponds to a bond referendum at the school district level. The last two columns at the left show the results of a t-test mean comparison. The panel at the bottom shows the composition of the sample across states and years, by the number of observations and percentage of the sample within the bandwidth for the analysis (7.5%). Airbnb not listed corresponds to the average of unit-months in the sample that reported to exit the market at some point during the analysis window.

Main Results: Regression Discontinuity

Table: RDD Results: Effect of Bond Referendums on Airbnb Supply

Model	Linear	Linear	Quadratic	Quadratic
Panel A: Parametric Estimator				
LATE	0.271	0.011	0.2453	-0.0325
	(0.5856)	(0.4418)	(0.5755)	(0.4328)
Mean Dep Var	2.5822	2.5822	2.5822	2.5822
Panel B: Non-Parametric Estimator				
LATE	0.2736	0.2929	0.5611	0.6099
	(0.3482)	(0.3479)	(0.5804)	(0.5734)
Mean Dep Var	2.5822	2.5706	2.5588	2.5582
Controls	No	Yes	No	Yes

Notes: This table shows the point estimates for the LATE. Standard errors reported in parantheses. LATE from Panel A corresponds to the coefficient of the treatment variable (passing the bond) on the sample of observations within the maximum optimal bandwidth calculated in Panel B (i.e. for the non-parametric approach, the decision of the optimal bandwidth depends on the model specification). This explains why there are differences in the mean of dependent variable on each model.

References

Cellini, Stephanie Riegg, Fernando Ferreira, and Jesse Rothstein, "The Value of School Facility Investments: Evidence from a Dynamic Regression Discontinuity Design," *Quarterly Journal of Economics*, February 2010, *125* (1), 215–261.

Pierson, Kawika, Michael L. Hand, and Fred Thompson, "The Government Finance Database: A Common Resource for Quantitative Research in Public Financial Analysis," *PLOS ONE*, June 2015, *10* (6), e0130119.