The Journal of Real Estate Finance and Economics
https://doi.org/10.1007/s11146-021-09870-0

Cutting Funding for Police Protection: The Consequences for the Size of Newly-Constructed Housing

David M. Brasington[1]

Accepted: 20 September 2021

Abstract

Households with children may Tiebout (1956) sort to safe cities. Cities that cut funding for police protection may become less attractive to households with children, spurring housing developers to build smaller houses with fewer rooms. Voting data on police tax levies using regression discontinuity suggests that newly-built houses have more rooms in cities that renew rather than fail their tax levies. The treatment effect peaks in the second year after the tax levy at 1.9 rooms, a sizeable difference over the mean of 6.6 rooms. House size tells a similar story: the difference between newly-built houses in communities that pass and fail public safety tax levies is 317.6 square feet (29.5 square meters), representing 15% of the mean house size in the sample. The results become evident 2 years after the tax levy and persist in the third year before petering out in the fourth year. The effect may stem from communities signaling a decreased commitment to public safety, rather than an increase in the crime rate itself, because cutting small tax levies has about the same effect on house size as cutting large tax levies.

Keywords Residential construction · House size · Tax levy voting · Police protection · Regression discontinuity · Tiebout sorting

JEL Codes H20 · H31 · H41 · R21 · R31

Introduction

The Tiebout (1956) model assumes that households sort to communities that most fit their preferences over taxes and public services. Public safety is an important service. Brasington (2017a) finds that public safety is the most commonly-cited reason that people choose their house.

David M. Brasington
david.brasington@uc.edu

[1] Economics Department, University of Cincinnati, Cincinnati, OH 45221-0371, USA

Published online: 30 September 2021

Housing developers may take into consideration the level of various public services in a community when deciding which types of houses to construct. For example, a community with attractive parks, schools, and public safety might inspire developers to build larger houses with more rooms to accommodate families. By the same token, if a community cuts funding to its police, people may perceive the community to be less committed to public safety. A decreased demand for large houses may prompt housing developers to build somewhat smaller houses with fewer rooms to cater to households with fewer children, like empty nesters. It is common in the U.S. for communities like cities, villages and townships vote on police funding.[1] These votes on funding are called tax levies, and they typically expire after a set number of years. For example, the Delhi Township trustees can pass an ordinance asking voters for an additional 0.2 percent property tax for police protection to last 5 years. If the tax levy passes by a simple majority vote of the population, the police get the additional funding. At the end of 5 years, the board of trustees will almost surely approach voters to renew the tax.

The current study uses regression discontinuity to compare cities in Ohio that renew and fail to renew tax levies for police services. It finds evidence that cities that cut police funding have newly-constructed houses with fewer rooms and smaller size than cities that renew their police tax levies. The effects are most evident 2 and 3 years after the tax levy, dissipating by the fourth year after the vote. Compared to cities that renew them, cities that fail their police tax levies have newly-built houses with 1.9 fewer rooms and 19% smaller size 2 years later. This effect persists to the third year after the tax levy fails, in which newly-constructed single family dwellings have 1.2 fewer rooms and 15% smaller size.

Literature Review

A search of the literature revealed no research in which the dependent variable is house size or the number of rooms in a house. However, the current study is related to different strands of well-developed literature. For example, there is a large literature on zoning regulations, including lot size zoning but sometimes also minimum house size zoning. Gyourko and Molloy (2015) includes a broad survey on the causes and effects of zoning regulations. There is also a growing literature on the small house movement. Boeckermann et al. (2019) examines people's reasons for moving into a small house, typically defined to be 200 square feet (about 18.5 square meters). Next, Turnbull et al. (2006) notes that house size

[1] For ease of exposition the paper will generally use the term "city" to refer to all types of local community government in Ohio: city, village, and township. These local community governments reside within counties, which also have police forces called sheriff's offices, but county-wide tax levies for sheriff's offices are excluded from the analysis. Details on how local voting on police funding occurs across the U.S. is available from www.balletpedia.org.

could influence house prices for a number of reasons. It finds the tax capitalization effect of house size is larger than the atypicality or conspicuous consumption effects. A large amount of the hedonic house price literature includes house size as a control variable. The elasticity of house price with respect to house size is 0.64 in Schultz and Schmitz (2009), 0.57 in Brasington and Haurin (2006), and 1.2 in Fik et al. (2003).

There are also several studies in the housing literature that use the regression discontinuity design as the estimation approach. Many of these examine the effect of government policy. Karamon et al. (2017) uses it to show that refinancing with the Home Affordable Refinance Program causes a 48 to 62% drop in the expected monthly default rate. Sun, et al. (2017) uses regression discontinuity to show that Beijing's attempt to cool its housing market with Home Purchase Restrictions caused a sizeable drop in resale prices and the price-to-rent ratio. Bhutta (2012) uses regression discontinuity to show that the Underserved Areas Goal of the Safety and Soundness Act has a small effect on GSE purchases and mortgage originations.

Methodology

Methodology: Independence of Observations

The ordinary least squares model assumes that observations are independent. Regression discontinuity studies that use voting data may violate this assumption. Specifically, since the insight of Cellini et al. (2010), researchers have had to contend with the possibility that failed tax levies are followed by successive levies until a levy is passed. Attempts to mitigate the non-independence problem include selecting the first tax levy or the largest tax levy.

The current study exploits the strategy of Brasington (2017b) to preserve the independence of observations by only considering votes whose timing is exogenous rather than endogenously chosen. When a new tax levy is proposed in Ohio, it is typically proposed for a fixed number of years, usually five. At the end of 5 years, the taxing authority usually comes back to the voters to renew or replace the tax levy.[2] A 5 year tax levy approved in 2003 has a renewal date that is exogenous to voters in 2008. If the vote to renew in 2008 fails, the taxing authority can come back to voters later, but the county board of elections classifies this as a new tax levy, not a renewal. The consequences of failing to renew a tax levy can be severe: the money from that particular tax levy stops flowing to the police department when the tax

[2] A replacement levy has the same tax rate as the levy set to expire. A renewal levy adjusts the tax rate to raise the same aggregate dollar amount of taxes as the levy set to expire. The current study refers to both of these types as renewal levies for ease of exposition. Renewal levies are about three times as common as replacement levies. The timing of replacement levies is exogenous in the same way that renewal levies are.

expires.[3] To be clear about the terminology, the tables show treatment effect estimates for renewing a tax levy; but a failure to renew a tax levy is the same as cutting funding, so throughout the paper both positive and negative ways of expressing the treatment effect are used.

Methodology: Intuition behind Regression Discontinuity

A key concept to understanding regression discontinuity is that of the running variable. In the current study, the running variable is the proportion of votes in favor of renewing a tax levy on police protection. Regression discontinuity assumes that cities that have similar values of the running variable have similar values for observed covariates. This is critical near the 50% vote cutoff, because it means that cities are essentially randomized in whether they receive treatment or not, so that renewing police taxes—and not omitted variables—is responsible for any change in the size of newly-constructed houses.

Methodology: Assumptions of the Model

Because regression discontinuity assumes that cities that vote similarly are also similar in characteristics, it is necessary to collect data on these cities and compare their means, something that is done in the Data section below.

It is also necessary to guard against the possibility that some agent is able to precisely assign cities to a particular value of the running variable. Instead of a smooth distribution of votes near 50% there would be a discontinuity: a large number of communities with just over 50% in favor with a notably smaller number with just under 50%. One way to test for this possibility is by performing the density test of Cattaneo et al., (2018, 2019). The test fails to reject the null hypothesis of no discontinuity, with a p value of 0.46 for the test of the number of rooms outcome, and a p value of 0.99 for the house size outcome.

Methodology: Formal Model of Regression Discontinuity

The regression discontinuity design can be summarized in Eq. (1):

$$House\ Char_{ij} = \alpha + T_{ij}\beta + f\left(X_{ij}, W_{ij}\right) + \varepsilon_{ij} \tag{1}$$

[3] The city government can try to compensate for the losses with part of its so-called inside millage. Cities in Ohio have an automatic 10 mills (0.1%) of property tax that does not have to be voted into effect, called inside millage. The city has broad discretion over how to use this tax revenue, including health, poverty relief, roads, elections, parks, and pollution control. Any money beyond the 10 mills must be requested from the voters for a specified purpose. Inside millage is small compared to the average 157 mills (1.57%) of effective property tax in the state (smartasset, 2020). The median renewal police levy in the sample is for 2 mills, with a mean of 2.4.

In Eq. (1) *House Char* represents the outcome variables: the number of rooms and the square footage of newly-constructed houses in a city, which vary by city i and time period j. The α is an intercept. The T is a dummy variable for whether a city receives treatment (successfully renewing the police tax) or not, so that β is the treatment effect estimate, the focus of the paper. Next, X is the running variable, the share of votes in favor of renewing the tax. With simple majority voting, X must exceed 0.50 in order for the tax levy to renew.

Regression discontinuity uses all the observations in order to estimate the proper bandwidth around the cutoff to estimate the treatment effect. We use the estimator of Calonico et al., (2017, 2019), which finds the mean squared error-optimal $\widehat{T}$ in the presence of covariates W. The optimal bandwidth is about 0.10 in our samples, indicating that observations between about $X \in [0.45, 0.55]$ are used to estimate $\widehat{T}$.

We use three different kernel functions and five different bandwidth estimating options to investigate the robustness of the results. Estimates are also shown for local-linear and quadratic functional forms. We conclude our discussion of Eq. (1) by noting that ε is a Gaussian error term.

Data

The current study combines data from three sources: housing sales from CoreLogic, covariates from the U.S. Census Bureau, and voting data from the Ohio Secretary of State's office. In 2015 the Ohio Secretary of State's office sent the author a compact disc of voting data on Ohio local issues from 1995 to 2013. Years 2014 and 2015 were available on the Secretary of State's web site. A server crash destroyed digital records of pre-1995 votes, but paper copies were scanned into.pdfs with data on votes from 1991 through 1994. A team of paid and volunteer assistants entered the voting data into an Excel spreadsheet, including 2704 votes on police tax levies. The votes come from 283 cities, villages and townships during the sample timeframe. As explained in Sect. Methodology: Independence of Observations, to help preserve the independence of observations only the 1192 votes to renew existing police tax levies are kept in the sample. The running variable "Votes in Favor" comes from the voting data. Votes in Favor has a mean of 0.60, with a standard deviation of 0.11. Its minimum value is 0.07, with a maximum of 0.90. The median levy size is 2 mills, where 2 mills collects 2 dollars for every $1,000 in assessed property value. The mean is 2.4 mills, with a standard deviation of 1.1, a minimum of 0.2 and a maximum of 17.5 (Table 1).

The outcome variables are the number of rooms in, and the size of, newly-constructed houses. CoreLogic supplied a data set of the universe of over 4,000,000 houses that sold in Ohio from 1995 to early 2016. Nearly 3,000,000 were successfully matched to demographic variables from the U.S. Census, voting data, property value data, and school district data. Observations were dropped to keep only single-family dwellings that sold in arms-length transactions. Outliers in sale price were also dropped. The mean of the number of rooms in a house was kept for each

Table 1 Variable definitions

Variable name	Definition	Source
Number of rooms	Mean number of rooms in newly-constructed houses in the city, an outcome variable	CoreLogic
House size	Mean size of newly-constructed houses in the city in square feet, an outcome variable	CoreLogic
Votes in favor	Proportion of votes in favor of renewing a police tax levy in the city, the running variable	Secretary of State's Office
Covariates		
Black	Proportion residents in the city who self-identify as black/African-American	Census
Hispanic	Proportion of self-identified Hispanic residents of any race in the city	Census
Single parent household	Proportion of households in the city with own children under age 18 living in the household with no spouse present	Census
No kids	Proportion of households in the city without own children under age 18 living in the household	Census
Separated	Proportion of population in the city aged 15 and older married but separated	Census
Divorced	Proportion of population in the city aged 15 and older who are divorced	Census
Bachelors	Proportion of persons aged 25 years and older in the city with highest educational attainment a 4-year college diploma	Census
Graduate degree	Proportion of persons aged 25 years and older in the city with highest educational attainment a graduate degree like law school, medical school, master's degree or Ph.D	Census
Labor force participation	Proportion of the population 16 years and older in the city that participates in the labor force	Census

Notes about Sources: CoreLogic refers to a data set of housing sales the author leased from CoreLogic; sales span the years 1995 to 2015. Secretary of State's Office refers to.pdf files obtained from the Ohio Secretary of State's Office. Police renewal tax levies occurred between 1995 and 2015. Census refers to U.S. Census Bureau. Values from 1995 to 1999 are interpolated from 1990 to 2000 decennial censuses; values from 2001 to 2009 are interpolated from 2000 to 2010 decennial censuses; and values from 2010 to 2015 are yearly (5-year) estimates from the American Community Survey. The term 'city' means village, city, or township that the house resides in

Table 2 Variable means (standard deviation)

	Global sample			Effective sample	
	Full sample	Passed levies	Failed levies	Passed levies	Failed levies
Outcome variables					
Number of rooms	6.6 (1.1)	6.7 (1.1)	6.4 (1.1)	6.5 (1.1)	6.4 (1.2)
House size	2119.0 (654.1)	2157.2 (670.1)	1951.9 (551.3)	1917.9 (593.1)	1944.9 (538.5)
Covariates					
Black	0.032 (0.11)	0.032 (0.11)	0.028 (0.080)	0.018 (0.043)	0.032 (0.084)
Hispanic	0.013 (0.016)	0.013 (0.016)	0.013 (0.014)	0.010 (0.012)	0.012 (0.013)
Single parent household	0.10 (0.06)	0.10 (0.06)	0.11 (0.06)	0.11 (0.05)	0.12 (0.07)
No kids	0.62 (0.07)	0.62 (0.07)	0.61 (0.09)	0.62 (0.06)	0.61 (0.10)
Separated	0.014 (0.010)	0.014 (0.011)	0.013 (0.008)	0.014 (0.007)	0.014 (0.008)
Divorced	0.11 (0.03)	0.11 (0.04)	0.11 (0.03)	0.11 (0.03)	0.12 (0.04)
Bachelors	0.12 (0.08)	0.13 (0.09)	0.10 (0.06)	0.11 (0.07)	0.10 (0.07)
Graduate degree	0.07 (0.06)	0.07 (0.06)	0.05 (0.04)	0.05 (0.05)	0.05 (0.04)
Labor force participation	0.64 (0.07)	0.63 (0.07)	0.65 (0.07)	0.63 (0.07)	0.64 (0.07)
Number of observations	1192	996	196	178	103

Sample means shown at the time of the police tax levy vote except for the outcome variables, for which the outcomes are the number of rooms and size of newly-constructed houses 2 years after the tax levy vote. Global sample is full set of observations; effective sample is observations for which running variable Votes in Favor is between 0.45 and 0.55, a typical effective bandwidth. Number of observations shown for covariates; see additional tables for number of observations for outcome variables

newly-constructed house for each city in each year, as was the mean size of a house in square feet. Using individual house-level data for number of rooms and size of house would have kept a larger number of observations than aggregating up to the city level, but doing so would overweight the fastest-growing cities and underweight slower-growing cities.

The voting data spans 25 years, during which time the average city experiences just over four votes on police funding renewal. The U.S. Census Bureau shows it takes only a month for a developer to start building after obtaining permits (U.S. Census, 2020a), and about six months to construct a house (U.S. Census, 2020b). During this timeframe it would be costly for a developer to adjust its strategy, but the empirical results will show that changes in house characteristics appear with a 2 or 3 year lag after voting.

A number of characteristics of a city are collected from the U.S. Census Bureau and matched to the housing and voting data. These characteristics include information about racial and ethnic composition, the presence of children, single-parent households, marital status, educational attainment, and labor force participation rates. Because the census was collected in 1990, 2000, 2010, and yearly from 2011 through 2015, many of the values rely on linear interpolation. Covariate similarity is important for the validity of regression discontinuity, so Table 2 shows the means of the covariates for the full sample of cities, the sample of cities that successfully renew their police tax levies, and the sample of cities that fails them. The 1192 observations used in the estimator of Calonico and et al., (2017, 2019) yields an optimal effective bandwidth of about 0.05 on either side of the cutoff. This means that 103 failed tax levies are compared to about 178 passed tax levies to come up with the treatment effect estimates.

Another common way to test the assumption of covariate balance is to use the covariates as dependent variables in the regression function of Eq. (1). When this is done, no treatment effect estimate $\tilde{\tau}$ achieves statistical significance, indicating that the first derivative of the regression functions for treatment and control are equal at the cutoff.[4] Figure 3 shows graphs of the covariates as a function of the running variable using the rdplot command of Calonico et al. (2015).

Results

Results—Number of Rooms

Tables 3, 4, 5 and 6 show treatment effect estimates of renewing a police tax levy on the number of rooms in newly-constructed houses. Figure 1 is a graphical illustration for years that suggest statistical significance, although it is important to point out that figures can only show the raw correlation between treatment and outcome, without controlling for the covariates or the running variable.

Table 3 suggests no effect 1 year after a tax levy, but 1 year may be too soon for changes in demand for house characteristics to become apparent. Table 4 suggests that renewing police funding causes newly-constructed houses to have more rooms than in cities that fail to renew police tax levies. Despite the relatively low number of observations, the results are statistically significant at the 5% level as often as not, particularly for the set of results that allows for nonlinearity in the treatment effect estimate. The median treatment effect is 1.9 rooms.

[4] *p* values for treatment effect estimates are as follows: Black 0.170, Hispanic 0.312, Single Parent Household 0.371, No Kids 0.084, Separated 0.883, Divorced 0.403, Bachelors 0.716, Graduate Degree 0.267, and Labor Force Participation 0.786.

Table 3 Difference in number of rooms in newly-constructed houses in cities that pass vs. fail police tax levies, 1 year after vote

	Bandwidth selection procedure				
	(1)	(2)	(3)	(4)	(5)
Linear estimates					
Uniform	− 0.05 (0.88)	− 0.35 (0.21)	− 0.046 (0.90)	− 0.046 (0.90)	− 0.053 (0.88)
Triangular	− 0.15 (0.67)	− 0.20 (0.53)	− 0.20 (0.53)	− 0.15 (0.67)	− 0.19 (0.56)
Epanechnikov	0.055 (0.89)	− 0.19 (0.54)	− 0.071 (0.84)	0.055 (0.89)	-- 0.066 (0.85)
Nonlinear Estimates					
Uniform	0.0042 (0.99)	− 0.36 (0.34)	− 0.078 (0.86)	0.0042 (0.99)	− 0.13 (0.78)
Triangular	0.21 (0.76)	− 0.081 (0.87)	0.031 (0.95)	0.21 (0.76)	0.0033 (0.99)
Epanechnikov	− 0.00023 (1.00)	− 0.12 (0.81)	0.24 (0.66)	− 0.00023 (1.00)	0.14 (0.81)

Regression discontinuity treatment effect estimates shown with p value in parentheses below using a variety of different options. Number of observations = 547. Bandwidth selection procedures are bias-corrected, coverage error-rate optimal bandwidths based on the rdrobust command in Stata, as detailed in Calonico, et al. (2017) and Calonico, et al. (2014). (1) is a robust bias-corrected bandwidth selection procedure that uses a common bandwidth on both sides of the cutoff; (2) allows two distinct bandwidths on either side of the cutoff; (3) selects the bandwidth for the sum of the estimates; (4) selects the minimum of (1) and (3); and (5) selects the median of (1), (2), and (3) for each side of the cutoff separately. The linear estimates use local linear regression for the point estimates of the treatment effect and a local quadratic regression for the bias correction, which are the defaults for the rdrobust command. The nonlinear estimates allow quadratic and cubic regression for the point estimates and bias correction. Uniform, triangular, and Epanechnikov are different kernel functions to construct the local-polynomial estimators. The covariates listed in Table 1 are included in all regressions. The default variance–covariance matrix estimator is used, which mandates that at least 3 nearest neighbors are used in the calculations

The results are further supported by Table 5, in which 29 out of 30 estimates are statistically significant. The results suggest that 3 years after the vote newly-constructed houses typically have 1.2 more rooms in cities that renew police funding compared to cities that fail to renew police funding. The nature of regression discontinuity suggests that this is a causal relationship rather than just an association. Table 6 shows that the strength of the relationship seems to fade or disappear in the fourth year after the tax levy. Only the linear estimates with uniform kernel density are robust; and the magnitude of the treatment effect is also smaller at 0.66 rooms. Only two of the other 25 estimates achieve statistical significance.

Falsification Testing – Number of Rooms

Table 11 of the appendix shows the treatment effect estimates of renewing a police tax levy on the number of rooms in newly-built housing 1 year before the

Table 4 Difference in number of rooms in newly-constructed houses in cities that pass vs. fail police tax levies, 2 years after vote

	Bandwidth selection procedure				
	(1)	(2)	(3)	(4)	(5)
Linear estimates					
Uniform	0.31	0.042	– 0.30	0.31	– 0.18
	(0.38)	(0.90)	(0.20)	(0.38)	(0.57)
Triangular	0.21	0.10	0.69*	0.69*	0.21
	(0.47)	(0.75)	(0.043)	(0.043)	(0.51)
Epanechnikov	0.44	– 0.14	– 0.05	0.44	– 0.01
	(0.19)	(0.59)	(0.87)	(0.19)	(0.97)
Nonlinear estimates					
Uniform	1.90*	0.18	1.80*	1.80*	1.90*
	(0.002)	(0.66)	(0.005)	(0.005)	(0.002)
Triangular	2.14*	0.62	2.21*	2.21*	2.14*
	(0.001)	(0.12)	(0.000)	(0.000)	(0.001)
Epanechnikov	2.38*	1.10*	0.22	2.38*	0.96*
	(0.000)	(0.012)	(0.56)	(0.000)	(0.023)

Regression discontinuity treatment effect estimates shown with *p*-value in parentheses below using a variety of different options

*Statistically significant at the 5% level. Number of observations = 564. Bandwidth selection procedures are bias-corrected, coverage error-rate optimal bandwidths based on the rdrobust command in Stata, as detailed in Calonico, et al. (2017) and Calonico, et al. (2014). (1) is a robust bias-corrected bandwidth selection procedure that uses a common bandwidth on both sides of the cutoff; (2) allows two distinct bandwidths on either side of the cutoff; (3) selects the bandwidth for the sum of the estimates; (4) selects the minimum of (1) and (3); and (5) selects the median of (1), (2), and (3) for each side of the cutoff separately. The linear estimates use local linear regression for the point estimates of the treatment effect and a local quadratic regression for the bias correction, which are the defaults for the rdrobust command. The nonlinear estimates allow quadratic and cubic regression for the point estimates and bias correction. Uniform, triangular, and Epanechnikov are different kernel functions to construct the local-polynomial estimators. The covariates listed in Table 1 are included in all regressions. The default variance–covariance matrix estimator is used, which mandates that at least 3 nearest neighbors are used in the calculations

tax levy. A tax levy in 1999 should have no effect on outcomes in 1998, and this is what the table suggests.

The current study deals with voting on local taxes. A tax levy in Ohio passes if over 50% of votes support the tax. Another type of falsification test is to change the 50% cutoff for passing to a false level. If the results are still statistically significant, it might suggest that the outcome data is subject to random jumps, and that a significant finding at 50% might just be due to random chance. The mean police renewal tax levy receives 60% favorable votes. When the cutoff for passing a tax levy is falsely changed to 60%, the statistically

Table 5 Difference in number of rooms in newly-constructed houses in cities that pass vs. fail police tax levies, 3 years after vote

	Bandwidth selection procedure				
	(1)	(2)	(3)	(4)	(5)
Linear estimates					
Uniform	0.97* (0.000)	0.86* (0.000)	1.26* (0.000)	1.25* (0.000)	0.98* (0.000)
Triangular	1.01* (0.000)	0.51* (0.001)	1.07* (0.000)	1.07* (0.000)	1.01* (0.000)
Epanechnikov	1.02* (0.000)	0.44* (0.006)	1.05* (0.000)	1.05* (0.000)	1.02* (0.000)
Nonlinear estimates					
Uniform	1.87* (0.000)	0.42 (0.060)	1.23* (0.000)	1.87* (0.000)	1.19* (0.000)
Triangular	1.51* (0.000)	1.29* (0.000)	1.50* (0.000)	1.52* (0.000)	1.50* (0.000)
Epanechnikov	1.52* (0.000)	0.59* (0.002)	1.44* (0.000)	1.52* (0.000)	1.44* (0.000)

Regression discontinuity treatment effect estimates shown with *p* value in parentheses below using a variety of different options

*Statistically significant at the 5% level. Number of observations = 523. Bandwidth selection procedures are bias-corrected, coverage error-rate optimal bandwidths based on the rdrobust command in Stata, as detailed in Calonico, et al. (2017) and Calonico, et al. (2014). (1) is a robust bias-corrected bandwidth selection procedure that uses a common bandwidth on both sides of the cutoff; (2) allows two distinct bandwidths on either side of the cutoff; (3) selects the bandwidth for the sum of the estimates; (4) selects the minimum of (1) and (3); and (5) selects the median of (1), (2), and (3) for each side of the cutoff separately. The linear estimates use local linear regression for the point estimates of the treatment effect and a local quadratic regression for the bias correction, which are the defaults for the rdrobust command. The nonlinear estimates allow quadratic and cubic regression for the point estimates and bias correction. Uniform, triangular, and Epanechnikov are different kernel functions to construct the local-polynomial estimators. The covariates listed in Table 1 are included in all regressions. The default variance–covariance matrix estimator is used, which mandates that at least 3 nearest neighbors are used in the calculations

significant results for years 2, 3 and 4 after the vote disappear. Only one of the 90 treatment effect estimates is statistically significant, and that one is negative, not positive. The pattern of results also suggests that something other than random chance is happening. It makes perfect sense for any change in residential construction design to not take place immediately after a vote, but that effects might appear with a lag before dissipating. In contrast, it would be curious if results were seen immediately after a vote, disappeared for a couple of years, and then reappeared.

Table 6 Difference in number of rooms in newly-constructed houses in cities that pass vs. fail police tax levies, 4 years after vote

	Bandwidth selection procedure				
	(1)	(2)	(3)	(4)	(5)
Linear estimates					
Uniform	0.71* (0.005)	0.58* (0.013)	0.66* (0.010)	0.66* (0.009)	0.61* (0.016)
Triangular	0.37 (0.082)	0.10 (0.61)	− 0.02 (0.91)	0.37 (0.082)	0.11 (0.057)
Epanechnikov	0.55* (0.017)	0.16 (0.446)	-0.026 (0.90)	0.55* (0.017)	0.21 (0.34)
Nonlinear estimates					
Uniform	0.36 (0.28)	0.44 (0.17)	0.48 (0.16)	0.48 (0.16)	0.35 (0.29)
Triangular	0.37 (0.23)	0.39 (0.16)	0.35 (0.27)	0.35 (0.27)	0.37 (0.23)
Epanechnikov	0.49 (0.086)	0.18 (0.50)	0.28 (0.40)	0.28 (0.40)	0.42 (0.12)

Regression discontinuity treatment effect estimates shown with *p*-value in parentheses below using a variety of different options

*Statistically significant at the 5% level. Number of observations = 528. Bandwidth selection procedures are bias-corrected, coverage error-rate optimal bandwidths based on the rdrobust command in Stata, as detailed in Calonico, et al. (2017) and Calonico, et al. (2014). (1) is a robust bias-corrected bandwidth selection procedure that uses a common bandwidth on both sides of the cutoff; (2) allows two distinct bandwidths on either side of the cutoff; (3) selects the bandwidth for the sum of the estimates; (4) selects the minimum of (1) and (3); and (5) selects the median of (1), (2), and (3) for each side of the cutoff separately. The linear estimates use local linear regression for the point estimates of the treatment effect and a local quadratic regression for the bias correction, which are the defaults for the rdrobust command. The nonlinear estimates allow quadratic and cubic regression for the point estimates and bias correction. Uniform, triangular, and Epanechnikov are different kernel functions to construct the local-polynomial estimators. The covariates listed in Table 1 are included in all regressions. The default variance–covariance matrix estimator is used, which mandates that at least 3 nearest neighbors are used in the calculations

Results—House Size

Cities that renew police tax levies build houses with a larger number of rooms than cities that fail the tax levies. The larger number of rooms could signify a larger house size, or it could signify a constant house size with a larger number of smaller rooms.

Table 7 shows the treatment effect of renewing police tax levies on the size of newly-constructed houses 1 year after the tax levy. The null hypothesis cannot be rejected at the 5% level that houses built in cities that renew and fail police tax levies are the same size. These results are consistent with the results of Table 3, which showed no effect on number of rooms 1 year after a tax levy vote.

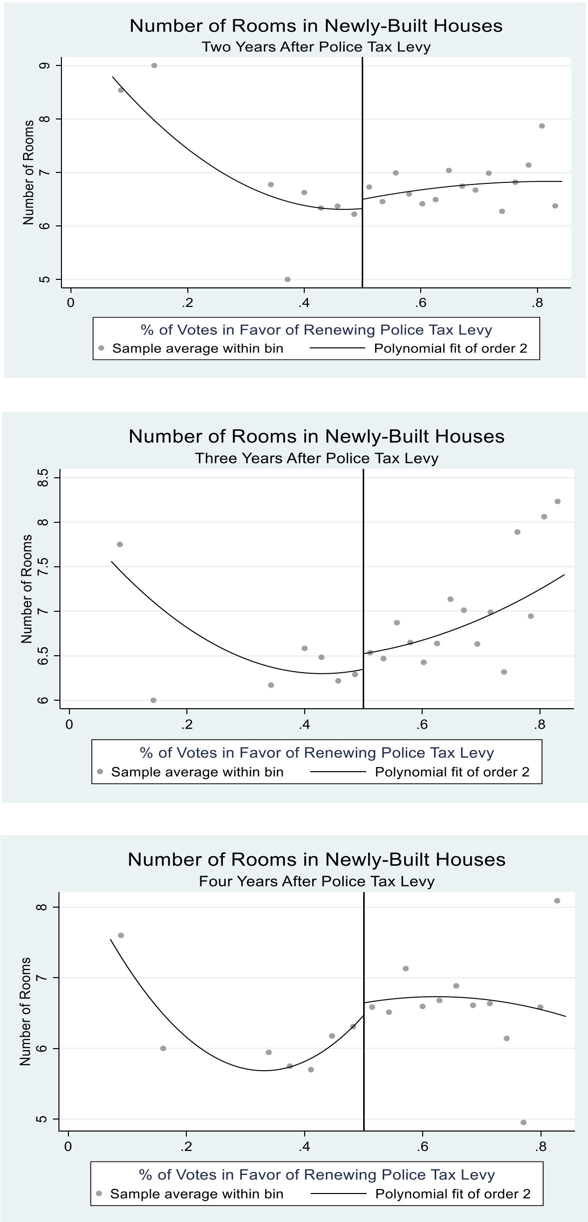


Fig. 1 Effect of Renewing Police Tax Levies on Number of Rooms in Newly-Built Houses

Table 8 looks 2 years after the vote. There are more statistically significant results than for year $t+1$; however, the evidence for increased house size in year $t+2$ is weaker than that for the number of rooms. Seven out of 30 estimates are statistically significant at the 5% level. If the results are taken at face value, it would suggest that renewing a police tax levy causes a 405.5 square feet (37.7 square meters) increased size of newly-constructed houses compared to cities

Table 7 Difference in house size in newly-constructed houses in cities that pass vs. fail police tax levies, 1 year after vote

	Bandwidth selection procedure				
	(1)	(2)	(3)	(4)	(5)
Linear estimates					
Uniform	122.0	– 47.1	46.5	101.5	67.1
	(0.22)	(0.62)	(0.64)	(0.30)	(0.50)
Triangular	137.2	34.4	38.1	137.2	55.6
	(0.20)	(0.73)	(0.70)	(0.20)	(0.58)
Epanechnikov	124.0	59.7	– 20.6	124.0	55.7
	(0.24)	(0.55)	(0.83)	(0.24)	(0.58)
Nonlinear estimates					
Uniform	184.9	– 38.7	50.6	184.9	27.5
	(0.26)	(0.74)	(0.73)	(0.26)	(0.86)
Triangular	272.8	111.9	250.8	272.8	273.0
	(0.22)	(0.39)	(0.15)	(0.22)	(0.12)
Epanechnikov	263.2	134.6	116.6	263.2	171.0
	(0.22)	(0.32)	(0.40)	(0.22)	(0.23)

Regression discontinuity treatment effect estimates shown with *p*-value in parentheses below using a variety of different options

*Statistically significant at the 5% level. Number of observations = 616. Bandwidth selection procedures are bias-corrected, coverage error-rate optimal bandwidths based on the rdrobust command in Stata, as detailed in Calonico, et al. (2017) and Calonico, et al. (2014). (1) is a robust bias-corrected bandwidth selection procedure that uses a common bandwidth on both sides of the cutoff; (2) allows two distinct bandwidths on either side of the cutoff; (3) selects the bandwidth for the sum of the estimates; (4) selects the minimum of (1) and (3); and (5) selects the median of (1), (2), and (3) for each side of the cutoff separately. The linear estimates use local linear regression for the point estimates of the treatment effect and a local quadratic regression for the bias correction, which are the defaults for the rdrobust command. The nonlinear estimates allow quadratic and cubic regression for the point estimates and bias correction. Uniform, triangular, and Epanechnikov are different kernel functions to construct the local-polynomial estimators. The covariates listed in Table 1 are included in all regressions. The default variance–covariance matrix estimator is used, which mandates that at least 3 nearest neighbors are used in the calculations

whose tax levies fail. This 405.5 increase represents 19% of the average size of a house in the full sample of Table 2.

The argument for a significant finding is strongest for the regression results 3 years after a vote. Table 9 shows almost no statistical significance when a linear functional form is assumed, but the results that allow for nonlinearity are different, achieving statistical significance in 13 out of 15 cases. The median estimate is 317.6 square feet (29.5 square meters), representing 15% of the mean house size in the sample. Figure 2 shows graphical treatment for timeframes that suggest statistical significance.

As was the case for Table 6 with number of rooms, Table 10 shows no difference in the size of newly-constructed houses 4 years after a police tax levy. If there is an

Table 8 Difference in house size in newly-constructed houses in cities that pass vs. fail police tax levies, 2 years after vote

	Bandwidth selection procedure				
	(1)	(2)	(3)	(4)	(5)
Linear estimates					
Uniform	70.1 (0.60)	– 336.1* (0.002)	16.9 (0.89)	90.2 (0.50)	-– 13.9 (0.91)
Triangular	183.7 (0.077)	– 59.4 (0.58)	156.6 (0.13)	186.8 (0.072)	152.7 (0.14)
Epanechnikov	156.8 (0.15)	– 81.5 (0.47)	239.0* (0.044)	253.8* (0.033)	180.9 (0.104)
Nonlinear estimates					
Uniform	298.6 (0.053)	125.3 (0.37)	405.5* (0.014)	405.5* (0.014)	305.1* (0.048)
Triangular	194.6 (0.110)	– 7.3 (0.95)	217.4 (0.076)	215.6 (0.079)	196.6 (0.107)
Epanechnikov	417.7* (0.008)	99.6 (0.44)	83.4 (0.50)	417.7* (0.008)	98.3 (0.45)

Regression discontinuity treatment effect estimates shown with p value in parentheses below using a variety of different options

*Statistically significant at the 5% level. Number of observations = 633. Bandwidth selection procedures are bias-corrected, coverage error-rate optimal bandwidths based on the rdrobust command in Stata, as detailed in Calonico, et al. (2017) and Calonico, et al. (2014). (1) is a robust bias-corrected bandwidth selection procedure that uses a common bandwidth on both sides of the cutoff; (2) allows two distinct bandwidths on either side of the cutoff; (3) selects the bandwidth for the sum of the estimates; (4) selects the minimum of (1) and (3); and (5) selects the median of (1), (2), and (3) for each side of the cutoff separately. The linear estimates use local linear regression for the point estimates of the treatment effect and a local quadratic regression for the bias correction, which are the defaults for the rdrobust command. The nonlinear estimates allow quadratic and cubic regression for the point estimates and bias correction. Uniform, triangular, and Epanechnikov are different kernel functions to construct the local-polynomial estimators. The covariates listed in Table 1 are included in all regressions. The default variance–covariance matrix estimator is used, which mandates that at least 3 nearest neighbors are used in the calculations

effect on house size, it may show up statistically in year $t+2$, is most consistently evident in year $t+3$, and vanishes 4 years after the vote. The evidence so far suggests that the increased number of rooms is accompanied by an increased size of house, but how believable are the house size results?

Falsification Testing—House Size

Renewing a police tax levy in 1999 could not have a causal effect on the size of newly-constructed houses in 1998. If such an effect is found, it raises questions about the reliability of results for years after the tax levy vote.

Table 12 of the appendix suggests that a tax levy in period t causes no change in the size of newly-constructed houses in period $t-1$. When the false cutoff of 60% is used, the results are similarly reassuring. For years $t+2$ and $t+3$ after the vote—the years that hold the most promise of finding that police tax levies cause larger houses—estimates

Table 9 Difference in house size in newly-constructed houses in cities that pass vs. fail police tax levies, 3 years after vote

	Bandwidth selection procedure				
	(1)	(2)	(3)	(4)	(5)
Linear estimates					
Uniform	58.4 (0.59)	− 24.2 (0.83)	− 107.0 (0.33)	58.4 (0.59)	− 80.3 (0.47)
Triangular	108.1 (0.29)	− 66.5 (0.47)	135.3 (0.19)	147.1 (0.15)	98.9 (0.33)
Epanechnikov	173.9 (0.102)	60.5 (0.56)	28.6 (0.79)	173.9 (0.102)	65.0 (0.53)
Nonlinear Estimates					
Uniform	314.4* (0.018)	157.3 (0.19)	317.6* (0.016)	314.4* (0.018)	300.1* (0.022)
Triangular	402.1* (0.001)	238.4* (0.036)	94.1 (0.39)	402.1* (0.001)	238.7* (0.035)
Epanechnikov	650.5* (0.000)	397.1* (0.002)	258.7* (0.029)	650.5* (0.000)	397.1* (0.002)

Regression discontinuity treatment effect estimates shown with *p*-value in parentheses below using a variety of different options

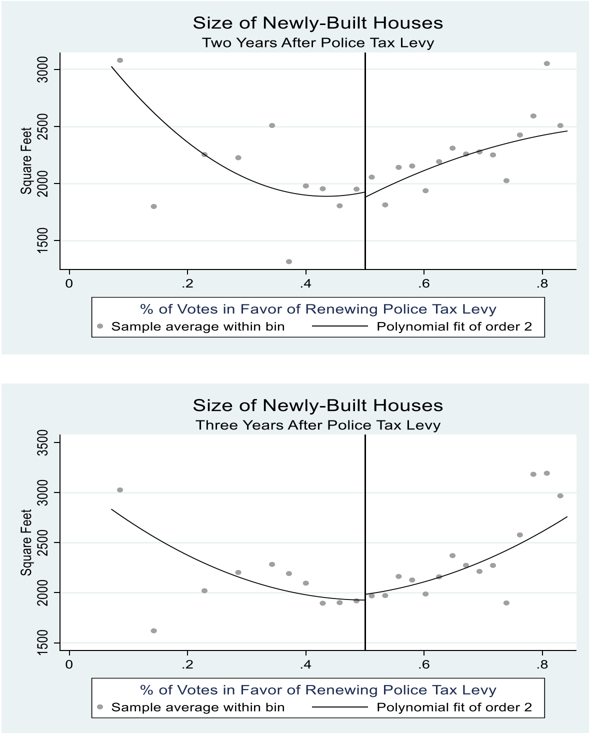
*Statistically significant at the 5% level. Number of observations = 594. Bandwidth selection procedures are bias-corrected, coverage error-rate optimal bandwidths based on the rdrobust command in Stata, as detailed in Calonico, et al. (2017) and Calonico, et al. (2014). (1) is a robust bias-corrected bandwidth selection procedure that uses a common bandwidth on both sides of the cutoff; (2) allows two distinct bandwidths on either side of the cutoff; (3) selects the bandwidth for the sum of the estimates; (4) selects the minimum of (1) and (3); and (5) selects the median of (1), (2), and (3) for each side of the cutoff separately. The linear estimates use local linear regression for the point estimates of the treatment effect and a local quadratic regression for the bias correction, which are the defaults for the rdrobust command. The nonlinear estimates allow quadratic and cubic regression for the point estimates and bias correction. Uniform, triangular, and Epanechnikov are different kernel functions to construct the local-polynomial estimators. The covariates listed in Table 1 are included in all regressions. The default variance–covariance matrix estimator is used, which mandates that at least 3 nearest neighbors are used in the calculations

are insignificant 57 out of 60 times using the false cutoff. The three cases that are statistically significant show negative, not positive treatment effects (Fig. 3).

Conclusion

The current study examines tax levy votes by cities, villages and townships in Ohio from 1995 to 2015. It looks specifically at votes to renew tax levies on police spending. A failure to renew the tax levy is the same as voting to cut police funding. Using the regression discontinuity design, it finds a difference between newly-built houses in cities that renew and fail to renew their police tax levies. Cities that renew have newly-built houses with more rooms than cities that fail their tax levies. The results become evident 2 years after the tax levy and persist in the third year before petering

Fig. 2 Effect of Renewing Police Tax Levies on House Size in Newly-Built Houses



out in the fourth year. The treatment effect estimate peaks in the second year after the tax levy at 1.9 rooms, a sizeable increase over the mean of 6.6 rooms.

Cities that renew their police tax levies may also build larger houses than cities that fail them. While no treatment effect is significant 1 year after the vote, there is some evidence of larger houses 2 years out and even stronger evidence 3 years out, with results petering out 4 years after the vote. The most consistent set of results is for houses built 3 years after the vote using regressions that allow for nonlinearity. Under these conditions, using a variety of kernels and bandwidth options, statistical significance is achieved in 13 out of 15 cases. The median estimate is 317.6 square feet (29.5 square meters), representing 15% of the mean house size in the sample. Overall it seems that larger houses are built with a larger number of rooms in cities that renew police funding rather than cutting it.

Housing developers could be reacting to a decreased demand for housing by people with children in communities that cut police funding.

We run a series of regressions to test this hypothesis. Still using police renewal tax levies, we change the outcome variables to median family income, the proportion of households with own children present, the proportion of city population that is between 0 and 5 years of age, and 5 to 17 years of age. We find no consistent pattern of treatment effect for median family income or ages 5 to 17. However, 3 years after a police levy vote, we find that cities that just successfully renew have 7 percentage points more children aged 0 to 5 than cities that barely vote against the tax. We also find that, 3 years after the vote, the percentage of households with children is 16

Table 10 Difference in house size in newly-constructed houses in cities that pass vs. fail police tax levies, 4 years after vote

	Bandwidth selection procedure				
	(1)	(2)	(3)	(4)	(5)
Linear estimates					
Uniform	23.0	– 261.7*	– 51.5	– 55.2	26.2
	(0.84)	(0.006)	(0.68)	(0.65)	(0.82)
Triangular	– 96.2	– 104.8	– 120.5	– 105.4	– 113.6
	(0.32)	(0.27)	(0.21)	(0.27)	(0.24)
Epanechnikov	– 128.3	– 62.6	– 109.7	– 95.3	– 112.0
	(0.20)	(0.55)	(0.28)	(0.35)	(0.27)
Nonlinear estimates					
Uniform	– 94.5	92.0	15.1	15.1	– 27.6
	(0.47)	(0.46)	(0.91)	(0.91)	(0.83)
Triangular	– 11.7	57.3	115.5	115.5	57.3
	(0.92)	(0.67)	(0.41)	(0.41)	(0.67)
Epanechnikov	– 11.0	– 31.0	17.1	17.1	– 9.6
	(0.93)	(0.79)	(0.89)	(0.89)	(0.94)

Regression discontinuity treatment effect estimates shown with *p*-value in parentheses below using a variety of different options

*Statistically significant at the 5% level. Number of observations = 591. Bandwidth selection procedures are bias-corrected, coverage error-rate optimal bandwidths based on the rdrobust command in Stata, as detailed in Calonico, et al. (2017) and Calonico, et al. (2014). (1) is a robust bias-corrected bandwidth selection procedure that uses a common bandwidth on both sides of the cutoff; (2) allows two distinct bandwidths on either side of the cutoff; (3) selects the bandwidth for the sum of the estimates; (4) selects the minimum of (1) and (3); and (5) selects the median of (1), (2), and (3) for each side of the cutoff separately. The linear estimates use local linear regression for the point estimates of the treatment effect and a local quadratic regression for the bias correction, which are the defaults for the rdrobust command. The nonlinear estimates allow quadratic and cubic regression for the point estimates and bias correction. Uniform, triangular, and Epanechnikov are different kernel functions to construct the local-polynomial estimators. The covariates listed in Table 1 are included in all regressions. The default variance–covariance matrix estimator is used, which mandates that at least 3 nearest neighbors are used in the calculations

percentage points higher in cities that renew the tax. The results suggest residential sorting by households with children, and especially young children, in response to failing to renew police tax levies. The sorting may start immediately, but the effects are not statistically evident until 3 years later. As for the sequence of events, it seems logical that the decreased number of families with children comes first, and then housing developers respond to decreased demand for larger houses by building smaller houses.

We also run another experiment: splitting the sample between large and small tax levies, defined by being greater than or less than the median of 2 mills. We find only a 0.3-room stronger treatment effect for the large-tax sample, compared to a base of 1.9 rooms. If only the large-tax sample had shown an effect, or if it had shown a much bigger effect, it would suggest that an increase in the crime rate might be causing smaller houses, probably through the residential sorting channel just identified. Instead the results show an effect even for small tax levies. Cutting a small tax is less likely to lead to a change in the crime rate than cutting a large police tax levy, so if we find basically

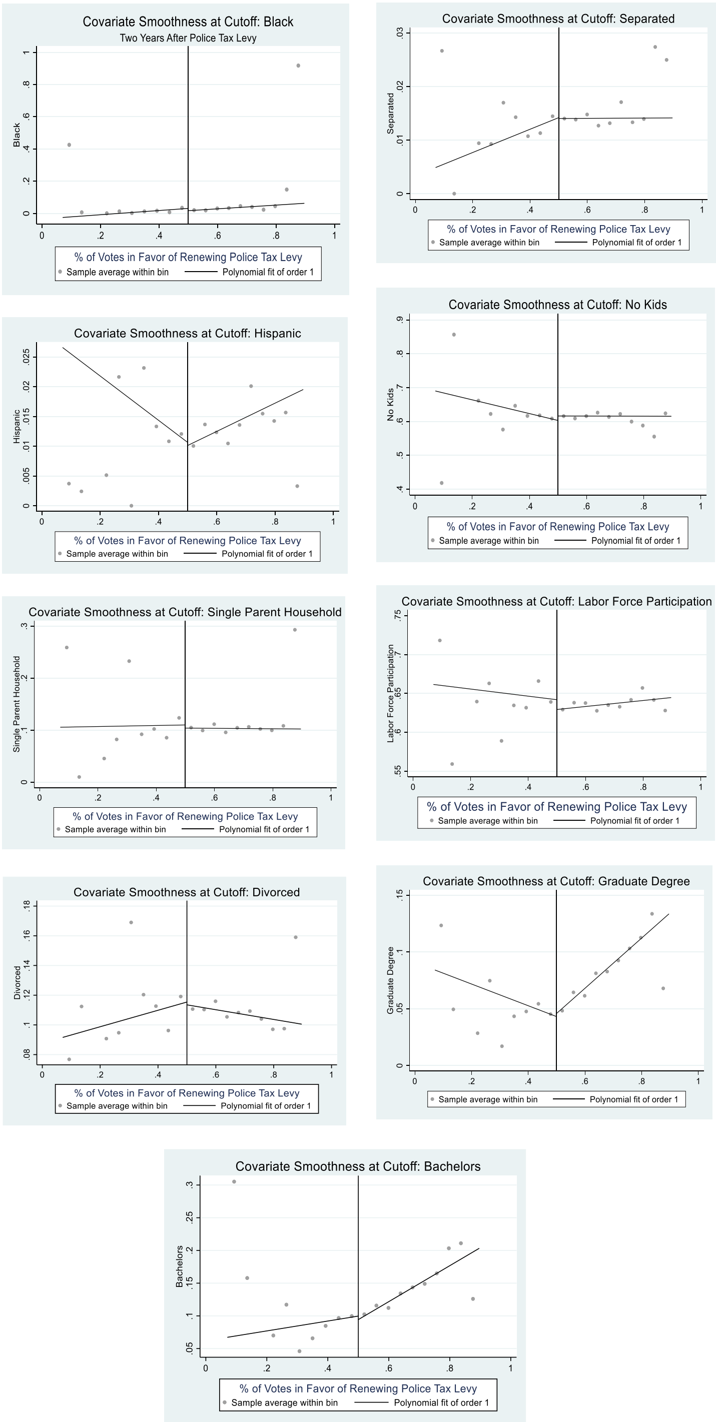


Fig. 3 Covariate Smoothness at the 0.50 Cutoff

the same effect, it suggests a signaling story. Failing to renew a police tax levy signals a reduced commitment to public safety, which causes marginal buyers with children to buy somewhere else, and may cause some existing families to move out.

It would be interesting to know if the decreased funding for police causes a drop in the number of new houses built, or if it simply changes the mix of housing built. If it causes a drop in the number of newly-constructed houses, this would suggest that some developers that had planned to build larger homes to cater to families put their plans on hold, while developers that had planned to build smaller houses continued with their plans. On the other hand, if cutting police funding does not cause a drop in the overall volume of new construction, it would suggest that some housing developers switch from building larger houses to building smaller houses.

Appendix

See Tables 11 and 12

Table 11 Difference in number of rooms in newly-constructed houses in cities that pass vs. fail police tax levies, 1 year before vote

	Bandwidth selection procedure				
	(1)	(2)	(3)	(4)	(5)
Linear estimates					
Uniform	− 0.060 (0.83)	− 0.19 (0.40)	− 0.13 (0.62)	− 0.060 (0.83)	− 0.13 (0.63)
Triangular	− 0.091 (0.70)	− 0.040 (0.86)	− 0.071 (0.79)	− 0.071 (0.79)	− 0.046 (0.085)
Epanechnikov	− 0.058 (0.83)	− 0.055 (0.81)	− 0.083 (0.76)	− 0.084 (0.76)	− 0.071 (0.79)
Nonlinear estimates					
Uniform	0.077 (0.83)	0.093 (0.77)	0.096 (0.82)	0.096 (0.82)	− 0.063 (0.87)
Triangular	− 0.0021 (0.99)	0.16 (0.58)	0.30 (0.40)	0.30 (0.40)	0.15 (0.60)
Epanechnikov	0.17 (0.58)	0.35 (0.28)	0.29 (0.43)	0.29 (0.43)	0.27 (0.39)

Regression discontinuity treatment effect estimates shown with *p*-value in parentheses below using a variety of different options

*Statistically significant at the 5% level. Number of observations = 624. Bandwidth selection procedures are bias-corrected, coverage error-rate optimal bandwidths based on the rdrobust command in Stata, as detailed in Calonico, et al. (2017) and Calonico, et al. (2014). (1) is a robust bias-corrected bandwidth selection procedure that uses a common bandwidth on both sides of the cutoff; (2) allows two distinct bandwidths on either side of the cutoff; (3) selects the bandwidth for the sum of the estimates; (4) selects the minimum of (1) and (3); and (5) selects the median of (1), (2), and (3) for each side of the cutoff separately. The linear estimates use local linear regression for the point estimates of the treatment effect and a local quadratic regression for the bias correction, which are the defaults for the rdrobust command. The nonlinear estimates allow quadratic and cubic regression for the point estimates and bias correction. Uniform, triangular, and Epanechnikov are different kernel functions to construct the local-polynomial estimators. The covariates listed in Table 1 are included in all regressions. The default variance–covariance matrix estimator is used, which mandates that at least 3 nearest neighbors are used in the calculations

Table 12 Difference in house size in newly-constructed houses in cities that pass vs. fail police tax levies, 1 year before vote

	Bandwidth selection procedure				
	(1)	(2)	(3)	(4)	(5)
Linear estimates					
Uniform	− 151.9 (0.14)	56.0 (0.63)	− 148.0 (0.16)	− 148.0 (0.16)	− 152.3 (0.14)
Triangular	− 98.2 (0.31)	− 89.8 (0.35)	− 80.8 (0.40)	− 79.0 (0.41)	− 88.4 (0.36)
Epanechnikov	− 128.0 (0.21)	− 95.7 (0.34)	− 93.9 (0.37)	− 93.9 (0.37)	− 102.5 (0.32)
Nonlinear estimates					
Uniform	8.7 (0.95)	41.7 (0.74)	13.7 (0.92)	8.7 (0.95)	43.9 (0.73)
Triangular	93.5 (0.51)	57.0 (0.62)	69.1 (0.62)	93.5 (0.51)	69.1 (0.62)
Epanechnikov	189.9 (0.27)	− 22.8 (0.86)	153.9 (0.33)	189.9 (0.27)	153.9 (0.33)

Regression discontinuity treatment effect estimates shown with *p*-value in parentheses below using a variety of different options

*Statistically significant at the 5% level. Number of observations = 591. Bandwidth selection procedures are bias-corrected, coverage error-rate optimal bandwidths based on the rdrobust command in Stata, as detailed in Calonico, et al. (2017) and Calonico, et al. (2014). (1) is a robust bias-corrected bandwidth selection procedure that uses a common bandwidth on both sides of the cutoff; (2) allows two distinct bandwidths on either side of the cutoff; (3) selects the bandwidth for the sum of the estimates; (4) selects the minimum of (1) and (3); and (5) selects the median of (1), (2), and (3) for each side of the cutoff separately. The linear estimates use local linear regression for the point estimates of the treatment effect and a local quadratic regression for the bias correction, which are the defaults for the rdrobust command. The nonlinear estimates allow quadratic and cubic regression for the point estimates and bias correction. Uniform, triangular, and Epanechnikov are different kernel functions to construct the local-polynomial estimators. The covariates listed in Table 1 are included in all regressions. The default variance–covariance matrix estimator is used, which mandates that at least 3 nearest neighbors are used in the calculations

Acknowledgements The author is thankful for funding to secure the CoreLogic® housing data set from the James C. and Caroline Kautz Chair in Political Economy, the University of Cincinnati Third Century grant, and the Lindner College of Business. Thanks also to Melanie Poole, Serena Henderson, and Mia Yaniko of the Ohio Secretary of State's office for providing voting data, and to students for painful data work: Thai Binh Tran, Alex Rack, Rucha Patil, Dhanashree Pokale, Deepthi Arumalla, Duy Tran, Eugene Owusu-Awuah, Stormi Stevens, Vaibhav Kamble, and Disha Shende.

Funding James C. and Caroline Kautz Chair in Political Economy, the University of Cincinnati Third Century grant, and the Lindner College of Business.

Data Availability Restricted use data (CoreLogic housing data lease).

Code Availability User-written Stata code.

Declarations

Conflict of interest Not applicable.

References

Bhutta, N. (2012). GSE activity and mortgage supply in lower-income and minority neighborhoods: The effect of the affordable housing goals. *The Journal of Real Estate Finance and Economics, 45*(1), 238–261. https://doi.org/10.2139/ssrn.2904256

Boeckermann, L. M., Kaczynski, A. T., & King, S. B. (2019). Dreaming big and living small: Examining motivations and satisfaction in tiny house living. *Journal of Housing and the Built Environment, 34*(1), 61–71. https://doi.org/10.1007/s10901-018-9616-3

Brasington, D. M. (2017). What types of people sort to which public services? *Papers in Regional Science, 96*(3), 537–553. https://doi.org/10.1111/pirs.12210

Brasington, D. M. (2017b). School spending and new construction. *Regional Science and Urban Economics, 63*, 76–84. https://doi.org/10.1016/j.regsciurbeco.2017.01.001

Brasington, D., & Haurin, D. R. (2006). Educational outcomes and house values: A test of the value added approach. *Journal of Regional Science, 46*(2), 245–268. https://doi.org/10.1111/j.0022-4146.2006.00440.x

Calonico, S., Cattaneo, M. D., Farrell, M. H., & Titiunik, R. (2017). rdrobust: Software for regression-discontinuity designs. *The Stata Journal, 17*(2), 372–404. https://doi.org/10.1177/1536867x1701700208

Calonico, S., Cattaneo, M. D., Farrell, M. H., & Titiunik, R. (2019). Regression discontinuity designs using covariates. *Review of Economics and Statistics, 101*(3), 442–451. https://doi.org/10.1162/rest_a_00760

Calonico, S., Cattaneo, M. D., & Titiunik, R. (2014). Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica, 82*(6), 2295–2326. https://doi.org/10.3982/ecta11757

Calonico, S., Cattaneo, M. D., & Titiunik, R. (2015). Optimal data-driven regression discontinuity plots. *Journal of the American Statistical Association, 110*(512), 1753–1769. https://doi.org/10.1080/01621459.2015.1017578

Cattaneo, M. D., Jansson, M., & Ma, X. (2018). Manipulation testing based on density discontinuity. *The Stata Journal, 18*(1), 234–261. https://doi.org/10.1080/01621459.2019.1635480

Cattaneo, M. D., Jansson, M., & Ma, X. (2019). Simple local polynomial density estimators. *Journal of the American Statistical Association*. https://doi.org/10.1080/01621459.2019.1635480

Cellini, S. R., Ferreira, F., & Rothstein, J. (2010). The value of school facility investments: Evidence from a dynamic regression discontinuity design. *The Quarterly Journal of Economics, 125*(1), 215–261. https://doi.org/10.1162/qjec.2010.125.1.215

Fik, T. J., Ling, D. C., & Mulligan, G. F. (2003). Modeling spatial variation in housing prices: A variable interaction approach. *Real Estate Economics, 31*(4), 623–646. https://doi.org/10.1046/j.1080-8620.2003.00079.x

Gyourko, J., & Molloy, R. (2015). Regulation and housing supply. In G. Duranton, J. V. Henderson, & W. C. Strange (Eds.), *Handbook of regional and urban economics* (Vol. 5, pp. 1289–1337). Elsevier.

Karamon, K., McManus, D., & Zhu, J. (2017). Refinance and mortgage default: A regression discontinuity analysis of HARP's impact on default rates. *The Journal of Real Estate Finance and Economics, 55*(4), 457–475. https://doi.org/10.1007/s11146-016-9566-z

Shultz, S., & Schmitz, N. (2009). Augmenting housing sales data to improve hedonic estimates of golf course frontage. *Journal of Real Estate Research, 31*(1), 63–79. https://doi.org/10.1080/10835547.2009.12091233

smartasset.com (2020). *Ohio property taxes*. Retrieved August 7, 2020, from https://smartasset.com/taxes/ohio-property-tax-calculator#LgiVkeu9C2

Sun, W., Zheng, S., Geltner, D. M., & Wang, R. (2017). The housing market effects of local home purchase restrictions: Evidence from Beijing. *The Journal of Real Estate Finance and Economics, 55*(3), 288–312. https://doi.org/10.1007/s11146-016-9586-8

Tiebout, C. M. (1956). A pure theory of local expenditures. *Journal of Political Economy, 64*(5), 416–424. https://doi.org/10.1086/257839

Turnbull, G. K., Dombrow, J., & Sirmans, C. F. (2006). Big house, little house: Relative size and value. *Real Estate Economics, 34*(3), 439–456. https://doi.org/10.1111/j.1540-6229.2006.00173.x

U.S. Census Bureau (2020a). *Average length of time from authorization to start of new privately owned residential buildings*. Retrieved September 10, 2021, from https://www.census.gov/construction/nrc/lengthoftime.html, Accessed 9/10/2021

U.S. Census Bureau (2020b). *Average length of time from start to completion of new privately owned residential buildings*. Retrieved September 10, 2021, from www.census.gov/construction/chars/microdata.html, Accessed 9/10/2021

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.