When the Levy Breaks: How Failing Renewal School Levies Effects Housing Prices

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Abstract

School districts in Ohio rely on tax levies voted on by the residents to increase their funding. Failure of a renewal school levy detracts money from a school's budget, but also lowers the tax burden on residents. It appears the decreased perceived value of the education system has a larger impact on home prices than the lower tax burden. Using a newly developed spatial regression discontinuity design approach, this paper finds failing a renewal school levy leads to a decrease in the price of homes by \$9,400, comprised of an average treatment on the treated of \$7,600, and an average treatment on the untreated of \$1,800.

The most recent version of this paper can be found at beausauley.weebly.com/research

1 Introduction

In the state of Ohio, schools are funded through a number of mechanisms including federal and state funds, Ohio lottery profits, and – at the local level – levied property taxes. These levies are voted on by the local population and generally take two main forms; general or operating levies, which are used to fund the operations of the local school district, and bond levies, which are used for both new school construction and maintenance. In the 2018 fiscal year Ohio had operating revenues slightly over twenty billion dollars. Of that, over nine billion was from property tax levies making it the single largest source of revenue for state districts.[1] Operating levies can be continuing, meaning that once enacted through a vote they are not subject to renewal, or limited, meaning that at some point in the near future the levy will be renewed or replaced by the voting population.[2] These limited levies are used to temporarily increase the operating budget of a school district, and a failure to renew or replace this levy when it expires amounts to a reduction in the schools future operating budget. Since this mechanism directly ties school spending to property values it begs the following question; if funds are removed from the local district by failing to renew a levy, what is the impact on local property values?

For context, the average levy in the state of Ohio has a duration of 5.1 years, and an average mill rate of 4.26.[3] With the average home price in a district where a levy took place of \$132,548, the average levy amount will be \$198 per year for the duration of the levy. Similar to Hainmueller and Kern (2008), Pettersson-Lidbom (2008), and Eggers et al. (2015), vote share in close, local elections is used to identify the treatment effect. However, this paper uses a spatial regression discontinuity (RD) design developed in Cornwall and Sauley (2020). Utilizing the new method, combined with a new formation of a directed real estate weight matrix, I develop average treatment on the treated (ATT) and average treatment on the untreated (ATU) measurements of effect size. These effects suggest failure to renew or replace an existing operating levy between 1999 and 2012, in the state of Ohio, reduces treated homes sale prices by approximately $7,800$, while decreasing untreated homes by approximately $1,800$.

Though research is mixed regarding the impact of increased school spending on quality (Hanushek, 1997; Hong and Zimmer, 2016; Conlin and Thompson, 2017), levies can act as a signaling mechanism to both the current and potential residents of a district (Brasington, 2016). Whether the purchasers have children of their own, or are considering the resale value of their purchase, the quality of local education often is a large factor in a home's value (Black, 1999; Cellini et al., 2010; Nguyen-Hoang and Yinger, 2011). But what happens when a school district loses funding by failing to renew an operating levy? On one hand we might expect local property values to increase since the

[1]See https://www.lsc.ohio.gov/documents/reference/current/schoolfunding/sfcr_feb2019.pdf for more information.

[2]The distinction between a renewal and a replacement is that renewal levies are under the same terms and conditions as the previously agreed upon tax while a replacement allows assessed property value to change in an effort to allow the district to benefit from local growth.

[3]A millage rate refers to the amount of tax liability a property owner faces for each $1,000$ of the property's assessed value. A mill rate of 1 would imply a single dollar in tax liability for each $\$1,000$ of property value. Moreover, the state assesses real property at 35% of the home value (more information can be found in the pdf of footnote 1), essentially making 1 mill a \$0.35 tax for every $\$1,000$ of property value. For example, a mill rate of 4.26 on a $\$100,000$ home produces an annual tax of \$149. See the Ohio tax code

tax burden is decreasing relative to its neighbors thus making the local property more valuable (Moulton et al., 2018). On the other hand a reduction of the schools operating budget may force cuts to programs (*e.g.* sports, music, field trips, etc.), teachers (salary or layoffs), and other educational opportunities the school may provide (*e.g.* external community programs). In some cases, the budgetary consequences can lead to closing of local school buildings. For example, according to a 2016 report prepared for the Ohio Legislature on districts in fiscal distress, East Knox Local district failed nine consecutive levies which forced the closure of an elementary building, elimination of administrative staff, and reduction of employee health benefits.[4] These impacts can certainly signal to perspective residents that the school district is no longer of high quality (even if there is no fundamental change in the quality of education) and reduce demand for property in the area.

The only way a school district can have a renewal levy is to have passed the same levy in a previous year. It is not surprising then that many of these renewal levies pass. From 1999 to 2012 there are $1,839$ levies covering 614 local school districts with only 245 failing. As a result, the majority of these levies will lead to minimal budget changes for the local school district. It is only when a levy fails that the budget is materially affected. While all voters are eligible to decide the fate of a school levy renewal, the impact of residential taxes fall entirely on property owners within the district. Only levies which fund public school districts are examined, and many areas have private or parochial schools which serve as alternatives. Since many private schools require tuition, it may be the case that local voters reject a levy so as to avoid paying for services they do not consume. Conversely, many financial transactions such as mortgage refinance, home equity loans, etc. may be intrinsically tied to the market value of a property, thus providing an incentive for owners to maximize their perceived property value at all times.

There is substantial evidence when evaluating property prices that the price of one's neighboring property, and their characteristics, are particularly relevant to the price of one's own property (Kim and Goldsmith, 2009; Bin et al., 2011; Mihaescu and Vom Hofe, 2012; Lazrak et al., 2014). This is not only empirically evident, but also transparent in the process of property transfers where appraisers use comparable sales to help determine a value.[5] This type of cross-sectional dependence creates spillover effects which, in a traditional RD setting, violate the *no-interference* assumption, a critical component of the potential outcome framework (see Imbens and Rubin (2015) and Athey and Imbens (2017) for a discussion). Since assuming away this dependence creates both bias and inefficiency in parameter estimates (Anselin, 1988; LeSage and Pace, 2009; Pace et al., 2011) a regression discontinuity design robust to cross-sectional dependence first outlined in Cornwall and Sauley (2020) is utilized. An unbiased treatment effect is calculated using a combination of Bayesian sampling, residualization, and numeric integration. The spillover effects are then recovered by conditioning a new spatial model on the unbiased parameter estimate.

Relying on close ballot results, this paper finds the failure to renew school levies has a negative impact on residential property sale prices. In a standard RD framework this amounts to a $\$20,000$ decline in sale prices on average. Incorporating the spatial model gives a more plausible estimate of a price decrease of $\$7,800$ on average, with an

[4] See http://education.ohio.gov/getattachment/Topics/Finance-and-Funding/District-Financial-Status/2016-Report.pdf.aspx for a complete discussion.

[5] See Ohio Administrative Code, section 5703-25-05 which governs appraisals of property. http://codes.ohio.gov/oac/5703-25 *accessed 9/25/2019*.

additional impact on untreated homes of approximately $\$1,800$.

The remainder of this paper is organized as follows. Section 2 outlines the data sources, while Section 3 provides context on the spatial regression discontinuity framework. In Section 4 the results using both standard RD methods and those from the aforementioned framework are discussed.

2 Data

School levy data was collected from the Ohio Secretary of State.[6] Additional school levies are often enacted when a public school system needs to raise money, which can lead to endogeneity issues with the timing of a levies placement on the ballot. Failure to pass a tax levy on the first attempt can cause a district to put the levy on the ballot in successive periods, violating the statistical independence of the votes (Cellini et al., 2010). By Ohio law, when a school district proposes a tax, it must specify the number of years for which the tax will be collected. The overwhelming majority (85%) of these levies are for five years. After the specified collection period has passed, the tax will expire unless voters choose to renew the tax levy. The Secretary of State classifies these as renewal levies. If the renewal levy fails, a school district can opt to put the issue back on the ballot in a successive period, but it will no longer be classified as a renewal levy: it will be classified as an 'additional' levy. Restricting attention to renewal tax levies addresses the potential non-independence of votes (Brasington, 2017). Other attempts to address non-independence include using only the largest tax levy Cellini et al. (2010) or the first tax levy Hong and Zimmer (2016). Figure 1 is a map of the renewal levies by school district in Ohio in 2012. The red indicates a levy failure, while blue indicates a passed levy.

While 6,505 levies took place in the state of Ohio from 1999-2012, this analysis is only interested in the effect of the 2,182 renewal levies that took place over the same period. To complete the analysis, only one levy in a school district can be utilized per year. In order to maximize the amount of school levies that were included in the analysis, if a district had multiple renewal levies in a single year the levy with a higher total number of votes cast is kept. This indicates a larger portion of the population is aware of the levy's occurrence. Table 2 displays the total number of levies by year, how many renewal levies there were, how many are used in the analysis, and of the levies in the analysis, how many were failures.

Information on all of the levies in the sample are displayed in Figures 2 - 5. The same plots only consisting of data within the 0.48-0.52 range of proportion of votes against is shown in Figures 7 - 10. Looking at Figure 2 and Figure 3 it is obvious most of the levies pass. In fact, nearly 87% of renewal levies over this period passed, which is the expected result as the estimation is only concerning renewal levies. Looking at the levies which will be used in the RD estimates in Figure 7 shows there is not a jump between the levy passes and failures, suggesting the first Stable Unit Treatment Value Assumption (SUTVA) assumption holds.

Over 85% of the levies are for a period of five years, as shown in Figure 4. Figure 5 shows these levies also average a millage of 4.26, meaning a property will be taxed \$1.49 for every \$1,000 of value.[7] By calculating the tax burden on each individual home

[6] The website is https://www.sos.state.oh.us/elections/election-results-and-data/

[7] While millage is calculated as $\$1$ per $\$1,000$ of property value, the state of Ohio assesses real property

assuming a levy passage, the average tax savings of a levy failure is $655 per year. When combined with the average duration of a levy, the average total tax savings from a renewal levy failure over this time period is $3,374. Note this number assumes an additional levy does not pass over this time period to make up for the lost school revenue from the failure of the renewal levy.

Housing data was collected from CoreLogic. The data was then trimmed to include home sales from 2000-2013, then further trimmed at the top and bottom 1% of each variable to avoid outliers biasing the estimates in an extreme way.

A data summary of all of the variables used in the following analysis is provided in Table 1. Each of the housing characteristics has been collected at the individual home level, while the community characteristics are collected at the school district level.

For reference, a plot of the median house price by school district from the year 2013 is provided in Figure 6. As expected, housing prices tend to be larger closer to metropolitan areas (Cincinnati, Cleveland, and Columbus), and lower in more rural areas, such as southeastern Ohio.

Housing data was then merged with school levy data from the year prior. Since most school levies occur in the month of November, and it takes time for the sale of a home to be completed, the effect of the levy should be seen in home sales in the year following the levy.

3 Methods

There is substantial evidence to suggest that cross-sectional dependence is a significant factor in home prices (see Kim and Goldsmith (2009); Bin et al. (2011); Mihaescu and Vom Hofe (2012); Wong et al. (2013) for example). In much of this literature the price of a home (i) is dependent not only upon its characteristics but also the price of neighboring homes (J), and often the characteristics of those homes. Simultaneously a great deal of effort has gone into isolating causal impacts of policy changes on home values (see Hidano et al. (2015); Moulton et al. (2018); Brasington (2017) among others). Many of the latter acknowledge that the *no interference* portion of the SUTVA is likely violated by the evidence from the former. Using the methodology outlined in Cornwall and Sauley (2020) incorporates these cross-sectional interactions, by utilizing a combination of Bayesian sampling, residualization, and numeric integration to recover an unbiased treatment effect.

The model shown below is an example of the SDM used in calculations shown in the Results section. Consider the following,

$$y_{ist} = \rho \sum_{j=1}^{N} w_{ij} y_{jst} + \sum_{k=1}^{K} \beta^k x_{ist}^k + \sum_{k=1}^{K} \sum_{j=1}^{N} \phi^k w_{ij} x_{jst}^k + \varepsilon_{ist}, \tag{1}$$

where $i \in (1:N)$ indicates an individual home sale, $s \in (1:614)$ represents the school district, and $t \in (1999:2012)$ indicates the year of the respective school levy. y_{ist} is the sale price of home i, in school district s, at time t. Further, let x_{ist} be a vector of characteristics, indexed by $k = (1, \dots, K)$ pertinent to home i sold at time t. These characteristics may include hedonic elements of the home itself as well as school district

values at 35% of the https://www.lsc.ohio.gov/documents/reference/current/schoolfunding/sfcr_feb2019.pdf for more information.

characteristics. See Table 1 for a complete list of these characteristics and their summary statistics.

The terms $\sum_{j=1}^{N} w_{ij} y_{jst}$ and $\sum_{j=1}^{N} \phi^k w_{ij} x_{jst}^k$ represent the weighted average of prices and characteristics for homes neighboring i. Let $w_{ij} = 1$ if i is a neighbor of j and zero otherwise. As is typical $w_{ii} = w_{jj} = 0$. In traditional spatial analysis, weight matrix would be undirected and right-stochastic, however since y_{ist} is the sale price of the home rather than the market value (which is unobserved) the weight matrix is constructed following a set of real estate market principles, to represent a set plausible homes home i would use as a comparable.

This directed weight matrix will differ heavily from the typical block diagonal matrix used in spatial analysis across time in two forms. First, the directed matrix construction allows for spillovers across all-time. When creating a block diagonal matrix, the researcher must choose a time period (s) to block the observations in, making home j_s a potential neighbor of home i_s, but home j_{s-1} can never be connected to home i_s, and will never receive any spillover effects from that time period. With real estate, s would typically be by month, or year, meaning a home sold in December of 2000 cannot effect the price of a home sold in January 2001. We know this is untrue, because the homes sold in January are likely to use the December or earlier sales as a comparable when negotiating price, or approving the mortgage.[8] Second, undirected block diagonal matrices allow spillovers within a time period (s) to flow both forwards and backwards. This is a faulty assumption, as the price of a home sold on December 31 cannot have an effect on the price of a home sold on December 1. Time, and causality can only go one way. Forcing the network to be directed, ensures spillover effects only flow into future homes, and not backwards in time.

Let $w_{ij} = 1$ if j is one of the six closest homes geographically which were sold between one and twelve months following the sale of home i. For example, if home i is sold in December of 2008, the plausible set of homes which would use home i as a comparable will include the six nearest homes (geographically) which sold between January of 2009 and December of 2009.[9] The lone exception is homes sold in the last year of the sample (2013). For example the neighbors of a home sold in June of 2013 could only be homes sold between July and December of the same year. December of 2013 is the last month data has been collected, so the six nearest homes which were also sold in December of 2013 will be used as home i's neighbors. There is no constraint that a comparable home must be in the same school district.

Since the observations are ordered by sale date, the current matrix only contains values to the right of the diagonal. To ensure the indirect effects only move forward, the transpose of this matrix is taken, creating a matrix with non-zero values only to the left of the diagonal. Each column in this new weight matrix contains six non-zeros values, but the number of neighbors in each row will differ with each home. This matrix is then row normalized and a can be seen in Figure 11. Recall this matrix is directed, forcing the spillover effects to only go into the future. This means the treatment effect on home i will spillover onto homes which could use home i as a comparable (J), then the effect on homes J spills over to their neighbors (sold after the sale of J), and so on. This is

[8] Ohio Administrative Code, section 5703-25-05 which governs appraisals of property, states the appraiser should use homes sold within the past year of the appraisal date. http://codes.ohio.gov/oac/5703-25 *accessed 9/25/2019*.

[9] This is very similar to the methods codified in Ohio Administrative Code, section 5703-25-05 which governs appraisals of property. http://codes.ohio.gov/oac/5703-25 *accessed 9/25/2019*.

different than an undirected or block-diagonal weight matrix, where the spillover effect from home i to homes J will come back to home i.

Using the weight matrix described above, equation 1 written in matrix form is as follows,

$$Y = \rho WY + X\beta + WX\phi + \varepsilon, \tag{2}$$

with reduced form,

$$Y = (I_N - \rho W)^{-1}(X\beta + WX\phi + \varepsilon). \tag{3}$$

Using a spatial model not only controls for the effect of neighbors on house prices, but will also enrich the findings of the model. Incorporating spatial dependence changes the partial derivative of β (see equation 4), which leads to the parameter estimates being separable into the direct, indirect, and total effects (see LeSage and Pace (2009) for a complete discussion).

$$\begin{gathered} \delta y/\delta x^k = S_k(W) = (I_N - \rho W)^{-1}(I_N\beta^K + W\phi^k) \\ \underbrace{n^{-1}(\iota_n' S_k(W))\iota_n}_{\text{Total Effects}} = \underbrace{n^{-1}tr(S_k(W))}_{\text{Direct Effects}} + \underbrace{n^{-1}(\iota_n' S_k(W))\iota_n - n^{-1}tr(S_k(W))}_{\text{Indirect Effects}} \end{gathered} \tag{4}$$

While these additional estimates provide a richer analysis, developing a causal relationship requires the model be placed in a causal framework. The nature of school levies presents a perfect situation to utilize RD will to disentangle causal effects of school funding on the price of a home.

RD exploits a cutoff point (Z_0) in a continuous variable (z_i) at which some individuals will be treated and others will not. Two important assumptions are made here to develop this causal relationship. First, agents cannot manipulate their position around the cutoff, meaning they cannot effect whether or not they, themselves, receive the treatment. The second assumption says the individuals must be randomly assigned the treatment. This is ensured by keeping only individuals within a bandwidth near Z_0. The bandwidth selection can be done many different ways (see Calonico et al. (2014) or Lee and Lemieux (2010) for an explanation), but each way works on the same assumption: the observations within the bandwidth are randomly assigned the treatment, and thus the estimate can be considered a causal effect. The combination of these assumptions allows the treatment, defined as,

$$q_i = \begin{cases} 1 & z_i > Z_0 \\ 0 & z_i \leq Z_0 \end{cases}, \tag{5}$$

to be considered randomly assigned, and thus allows the researcher to consider the effect of the treatment a causal effect.

In this setting, the running variable (z_i) is the percentage of votes against the levy, and the cutoff (Z_0) is 0.5. Thus, any school district with a renewal levy receiving more than half of the votes against will be considered treated.

While there have been debates about the best way to estimate the treatment parameter (γ), this paper will be following Gelman and Imbens (2019) and using a combination of residualization and local-linear method of estimation moving forward. Re-writing equation 3 as a function of the residuals grants

$$\varepsilon = Y - (I_N - \rho W)^{-1}(X\beta + WX\phi). \tag{6}$$

This is a function of ρ and W, which presents problems when cutting to the bandwidth for RD, since some neighbors of the treated group will likely be left out. To manage this, it is necessary to understand the distribution of the residuals, given below

$$\varepsilon \sim N(0, (I_N - \rho W)^{-1}(I_N - \rho W)^{-1'}\sigma^2). \tag{7}$$

Knowing the variance is a function of ρ and W, the residuals can be filtered by numerically integrating over the values of ρ, β, and ϕ. For each draw of the Markov Chain Monte Carlo sampler, a new vector of filtered residuals is created

$$\tilde{\varepsilon} = (I_N - \rho W)[Y - (I_N - \rho W)^{-1}(X\beta + WX\phi)], \tag{8}$$

which is distributed

$$\tilde{\varepsilon} \sim N(0, I_N\sigma^2). \tag{9}$$

These filtered residuals no longer contain ρ or W and can now be the dependent variable for the RD technique. For the remainder of the text, $\bar{\cdot}$ will denote observations above the cutoff and within the bandwidth, and $\underline{\cdot}$ will denote observations below the cutoff and within the bandwidth. After calculating the bandwidth, Equation 10 shows the estimation procedure for the local linear approximation on either side of the cutoff

$$\begin{aligned} \bar{\tilde{\varepsilon}} &= \bar{\gamma} + \bar{Z}\bar{\zeta} + \bar{\mu} \\ \underline{\tilde{\varepsilon}} &= \underline{\gamma} + \underline{Z}\underline{\zeta} + \underline{\mu}, \end{aligned} \tag{10}$$

where Z is the proportion of votes for the school levy, minus 0.50. This centers the treatment effect at zero, and allows the treatment effect to be calculated as follows

$$\gamma = \underline{\gamma} - \bar{\gamma}. \tag{11}$$

Inserting this estimate of the treatment effect back into an SDM allows for calculations of the direct, indirect, and total treatment effects, as well as these same estimates for each of the covariates included in the model. This can be seen in Equation 12 below,

$$Y = (I_N - \rho W)^{-1}(X\beta + WX\phi + D\gamma + \eta), \tag{12}$$

where γ is the treatment effect calculated in Equation 11, η is the residuals from the estimation, and D is a dummy indicator equal to one if the house is located in a school district which failed a renewal levy the year prior to the home sale and zero otherwise.

4 Results

Section 4.1 presents the results of base regression discontinuity models, while section 4.2 discusses the results of SDM, incorporating spatial dependence into the model.

Though the estimation runs across multiple years, the treatment is identified through regression discontinuity, not panel data techniques such as fixed effects. The effect on home price is measured the year following the failure of a levy. The small time frame from levy vote to home sale combined with the assumptions of regression discontinuity allow the results to be interpreted as the average effect of failing a renewal levy on housing prices.

4.1 Regression Discontinuity

As a reminder, though the figures displayed as maps of Ohio are aggregated up to the school district level, these estimates are at the individual house level. While there could be multiple levies in a single school district during a single year, only one levy is used in the analysis, then merged with the housing sales the following year, as outlined in Section 2.

Regression discontinuity can be done on just price. Figure 12 shows price against the percentage of votes for the renewal levy, binned at every 0.000625, or every 0.0625% of the vote against. Figure 13 shows the RD estimate on either side of the cutoff within the bandwidth. Though this is a simple and straightforward method of regression discontinuity, Gelman and Imbens (2019) suggests residualization and local linear estimation should be used to estimate the treatment effects. Table 3 shows the results of the local linear model run with price as the dependent variable, as well as the residuals. Each of these estimates use bandwidth selection from Calonico et al. (2014). The table also provides estimates with common robustness checks such as doubling or halving the bandwidth.

As discussed earlier in this, and many other papers (see Section 1 and Section 3 for further discussion), if there is cross-sectional dependence between these observations, the results here are likely to be biased, and inconsistent. A simple test of spatial dependence is to map the residuals. If there is no spatial dependence, the values of the residuals should be randomly distributed across the map. If there is spatial dependence, these values will be clustered together. Figure 14 shows the sum of the residuals from the OLS regression above, in each school district, across all years. Examining this figure, it should be clear the values of the residuals are clustering together, with overestimation in the rural areas of Ohio, and undervaluing homes in the suburbs.

A second, more formal test of spatial dependence is a Moran's I test. The null hypothesis here is there is no spatial dependence, with the alternative being spatial dependence is present. Running this test on housing sales from the year 2013, gives a test statistic of 148.8, which against a critical value of 1.96 is substantial evidence to reject the null.

4.2 Spatial Regression Discontinuity

To control for spatial dependence, an SDM will be utilized following the methods discussed earlier, as well as in Cornwall and Sauley (2020). The same covariates are used in the first estimation of the SDM as were used in the previous model. The next model does not include school district specific characteristics, and the final estimation only includes continuous housing characteristics. Estimates of the coefficients on the covariates can be found in Table 4.

The direct effect here is the same as the treatment effect, which is to be expected given the construction of the directed W matrix. Since home i can only be a neighbor of homes sold prior to the sale of home i, the indirect effects will spill to homes sold in the future, with no chance to come back to home i. While the indirect effects are large, they are not able to spill back to the original home, and they do die out exponentially across neighbors. The total effect of the school levy is calculated by adding the direct and indirect effects together, as the direct effect is the average of the diagonal, and the indirect effect is the average of the off-diagonal. This is the true effect of the failure of a school levy, as it shows the spillover effect onto nearby properties which will be using the treated home as a comparable property while selling, or appraising the house.

When comparing these results to the results from Section 4.1, it should be noted here the non-spatial regression estimates the same value for γ, the direct effect, and the total effect. By utilizing a non-spatial model, this analysis is assuming there is no cross-sectional dependence, thus no indirect effects, and no spill-over effects. Tables 5-7 display these traditional spatial effect estimates.

These measures of spatial effects are more consistent with previous findings of school quality's effect on housing values. The plots of the full model treatment estimates can be seen in Figures 15 and 16. The second, and preferred model, estimates can be found in Figures 17 and 18. The first reason this is preferred is the majority of neighbors are from within the same school district, so the spillover effects of those covariate effects should be very small, and leaving them in the estimation will bias the estimates of ρ and ϕ towards zero. The third estimation method does not include quality dummy variables for individual houses. This is done as another robustness check, since these dummy variables are competing with the treatment indicator over information contained in the intercept. While these estimates are slightly smaller than the results when just omitting school district characteristics, they remain similar.

Though the treatment effect is measured by γ again here, when incorporated back into the SDM, the direct, indirect, and total effects can also be calculated. As laid out in Section 3, the direct effect here is the average of the trace of the matrix of estimates. Because of the structure of the weight matrix, spill-outs can only go forward in time. This means the direct effects will be the same as the estimate of the treatment effect. The direct effect can be interpreted as the effect of the treatment (failing a renewal levy) on the treated (the homes in the school district sold within one year of the levy failure). The indirect effect is the average of the off diagonal, and the total effect is the sum of the two. Because of the structure of the weight matrix, the indirect effect is the effect on future homes sales. Combining these effects leads to the measure of the total effect. Total, direct, and indirect effects for each coefficient in each model can be found in Tables 5-7.

While these spillover effects are a start, they still do not quantify the effect of failing a renewal school levy on houses within the school district. By splitting the indirect effects of the treatment into a treated and untreated homes, I can calculate the average effect of treatment on the treated (ATT) homes, as well as the average effect of treatment on the untreated (ATU) homes. ATT is calculated by taking the total effect of all observations within treated school districts. Consider home i, which can either be treated ($q_i = 1$) or untreated ($q_i = 0$), and home j. If $q_i = 0$, all of the associated treatment effects are zero. But if $q_i = 1$, we can calculate the direct effect on home i, as well as the indirect on home j. ATT is calculated by measuring the total effect on homes where $q_i = 1$, and $q_j = 1$. This measures both the home within a treated school district, as well as the effect on any neighboring home which is also in a treated school district. ATU is calculated using the indirect effect $q_i = 1$, and $q_j = 0$. This will grant the effect of treatment on neighboring homes which are in a school district which did not fail a renewal levy.

The results of the ATT and ATU can be found in Table 8. Looking at the results from the preferred model which does not include school district characteristics, the average treatment on the treated is estimated to be \$7,600 and the average treatment on the untreated is \$1,800. Given the average home value of \$127,000, this equates to a 6% decrease in house price, which is much more consistent with previous studies. The negative value for the average treatment on the untreated suggests failing a renewal levy decreases home values both within the school district which the levy failed, and in the neighboring school districts.

5 Conclusion

Spatial dependence is an important factor in hedonic models, and costly to exclude from the estimation procedure. Utilizing a spatial regression discontinuity approach, this analysis finds a failure of a renewal school levy leads to a decrease in home values caused by a lower perception of school quality, which outweighs the effect of the decreased tax burden from a failed renewal levy.

Incorporating SDM allows for a richer interpretation of the results, granting multiple parameter estimates instead of the one treatment effect estimated using traditional methods. The resulting matrix of the treatment effect and spillovers is then chopped to create two separate estimates of the treatment effect. Using the preferred model, homes within a school district which failed a renewal levy the previous year can expect to see a $7,600 decrease in value on average, while the average treatment on the untreated is estimated to be a decrease of $1,800.

6 Tables

Table 1: Summary of Statistics

Variable	Mean	SD	Min	Max
Price (Thousands)	127.10	87.56	5.16	843.80
Acres	0.60	1.15	0.02	10.30
Square Feet	1,734.73	687.59	688	4,579
Bedrooms	3.11	0.74	1	6
Baths	2.04	0.89	1	5
Excellent	0.01	0.10	0	1
Very Good	0.04	0.20	0	1
Good	0.29	0.45	0	1
Poor	0.01	0.11	0	1
Race Het.	0.08	0.06	0	0.49
Disadvantaged	0.34	0.22	0	0.95
Inc. per Capita	27.24	8.54	11.80	117.03
nobs	261,694			

Table 2: Levies by Year

Year	Total	Renew	Final	Fails
1999	469	93	84	18
2000	481	206	177	10
2001	356	156	138	13
2002	231	149	125	20
2003	314	152	128	15
2004	500	168	132	13
2005	415	152	124	22
2006	348	143	115	20
2007	290	171	130	14
2008	317	164	140	13
2009	227	178	152	18
2010	286	183	156	11
2011	248	140	124	10
2012	233	127	114	12
Total	6,505	2,182	1,839	209

Table 3: Non-spatial Results

		CCT	CCT Robust	CCT 2x BW	CCT 1/2 BW	CCT w Covariates
Raw Data	Estimate (γ)	8285.58	9065.40	11685.71	-19213.99	-12267.41
	S.E. (γ)	2013.14	2242.37	1385.39	3006.571	1360.64
	Interval	[4339.91, 12231.26]	[4670.43, 13460.37]	[8970.41 , 14401.016]	[-25106.76 , -13321.22]	[-14934.22 , -9600.61]
	Nobs	261689	261689	261689	261689	261689
	Eff. Nobs	19666	19666	45936	10239	26150
	BW	0.018	0.018	0.037	0.009	0.023
Residualized	Estimate (γ)	-19148.09	-19997.01	-11914.80	-12762.70	-
	S.E. (γ)	1727.09	1804.32	1205.02	2501.38	-
	Interval	[-22533.134 , -15763.05]	[-23533.41 , -16460.61]	[-14276.60 , -9553.00]	[-17665.32 , -7860.08]	-
	Nobs	261689	261689	261689	261689	-
	Eff. Nobs	17574	17574	36067	9406	-
	BW	0.015	0.015	0.031	0.008	-

Table 4: Model Estimates: Spatial RD Parameters

	Full Model			Omitting SD Information			Omitting SD and Quality		
Variable	Estimate	S.D.	Interval	Estimate	S.D.	Interval	Estimate	S.D.	Interval
Acres	2025.86	0.911	[2024.034 , 2027.628]	1976.82	1.536	[1973.72 , 1979.86]	1866.81	1.514	[1863.83 , 1869.83]
Square Feet	52.90	0.002	[52.897 , 52.904]	58.31	0.002	[58.3 , 58.31]	60.22	0.001	[60.22 , 60.22]
Bedrooms	-7155.42	1.372	[-7158.125 , -7152.757]	-8563.96	0.084	[-8564.12 , -8563.8]	-9549.13	0.515	[-9550.17 , -9548.12]
Bathrooms	21134.27	2.77	[21128.888 , 21139.581]	25388.41	3.772	[25380.38 , 25395.77]	26864.37	4.447	[26855.68 , 26873.47]
Excellent	30195.37	6.281	[30182.798 , 30207.447]	31189.63	5.84	[31178.02 , 31200.79]			
Very Good	32199.02	4.902	[32189.124 , 32208.431]	34537.72	3.481	[34530.73 , 34544.68]			
Good	14551.66	1.89	[14548.03 , 14555.261]	16476.46	1.572	[16473.31 , 16479.52]			
Poor	-41850.80	14.904	[-41879.188 , -41821.424]	-48078.12	18.512	[-48114.46 , -48039.11]			
Race Het.	2101.54	0.84	[2099.917 , 2103.229]						
Disadvantaged	2887.48	19.89	[2847.449 , 2925.75]						
Inc. per Capita	-19472.35	48.696	[-19567.657 , -19376.175]						
W*Acres	-1083.22	1.846	[-1086.926 , -1079.648]	-1483.71	1.355	[-1486.4 , -1481.12]	-1483.22	0.864	[-1484.95 , -1481.52]
W*Square Feet	-17.05	0.133	[-17.312 , -16.807]	-16.22	0.169	[-16.58 , -15.89]	-16.85	0.174	[-17.19 , -16.5]
W*Bedrooms	4787.30	60.827	[4675.167 , 4906.535]	348.32	68.113	[215.36 , 492.86]	115.9	75.364	[-38.75 , 262.79]
W*Bathrooms	-3357.49	85.307	[-3524.908 , -3201.354]	-4192.99	112.491	[-4433.01 , -3973.91]	-4440.32	123.776	[-4681.22 , -4185.82]
W*Excellent	-14788.55	26.017	[-14839.22 , -14737.83]	-18588.58	27.415	[-18643.82 , -18533.89]			
W*Very Good	-14126.37	21.923	[-14168.362 , -14083.338]	-14133.78	24.786	[-14185.54 , -14084.77]			
W*Good	-3775.02	17.962	[-3809.29 , -3739.732]	-5456.18	21.777	[-5500.91 , -5412.84]			
W*Poor	1953.41	233.665	[1523.41 , 2413.232]	6280.28	322.223	[5652.75 , 6967.3]			
W*Race Het.	-534.19	5.298	[-544.615 , -524.444]						
W*Disadvantaged	-8276.77	54.406	[-8376.979 , -8169.704]						
W*Inc. per Capita	11050.84	54.317	[10948.492 , 11156.841]						
ρ	0.277	0.003	[0.272 , 0.282]	0.306	0.002	[0.301 , 0.311]	0.306	0.002	[0.301 , 0.311]
Levy Fail	-12151.19	92.139	[-12326.925 , -11971.703]	-7305.31	82.297	[-7475.03 , -7142.04]	-5920.98	45.103	[-6012.47 , -5839.56]
Bandwidth	0.02210	0.00011	[0.02188 , 0.02231]	0.01960	0.00000	[0.01945, 0.01976]	0.02072	0.00009	[0.02052 , 0.02087]
Effective Nobs	$\approx$ 24130			$\approx$ 20770			$\approx$ 22577		

Table 5: Effect Estimates: Full Model

	Total			Direct			Indirect		
Variable	Estimate	S.D.	Interval	Estimate	S.D.	Interval	Estimate	S.D.	Interval
ρ	0.277	0.003	[0.272 , 0.282]						
Acres	1303.44	6.053	[1291.46 , 1315.11]	2025.66	0.912	[2023.83 , 2027.43]	-722.22	5.560	[-733.12 , -711.62]
Square Feet	49.57	0.257	[49.09 , 50.06]	52.90	0.002	[52.90 , 52.90]	-3.33	0.258	[-3.81 , -2.84]
Bedrooms	-3274.56	83.126	[-3439.20 , -3114.25]	-7154.35	1.349	[-7157.00, -7151.72]	3879.79	84.447	[3712.63 , 4042.76]
Baths	24581.08	151.543	[24285.25 , 24876.98]	21135.23	2.804	[21129.77 , 21140.61]	3445.85	149.28	[3152.59 , 3736.93]
Excellent	21303.98	84.759	[21134.30 , 21468.57]	30192.90	6.278	[30180.33 , 30204.97]	-8888.92	85.465	[-9060.95 , -8722.61]
Very Good	24990.19	94.770	[24799.73 , 25173.08]	32197.01	4.896	[32187.14 , 32206.41]	-7206.82	95.859	[-7399.20 , -7021.92]
Good	14901.54	60.434	[14779.76 , 15019.13]	14551.76	1.893	[14548.10 , 14555.36]	349.78	60.045	[228.84 , 467.13]
Poor	-55168.65	398.963	[-55944.95 , -54400.91]	-41854.50	14.996	[-41883.09 , -41824.98]	-13314.15	386.071	[-14066.29 , -12572.82]
Race Het.	2167.27	11.575	[2144.92 , 2189.35]	2101.55	0.842	[2099.93 , 2103.25]	65.72	11.009	[44.81 , 86.58]
Disadvantaged	-7452.12	66.687	[-7583.08 , -7322.05]	2884.61	19.879	[2844.62 , 2922.92]	-10336.73	75.581	[-10485.12 , -10191.09]
Inc. per Capita	-11644.96	46.552	[-11735.57 , -11552.41]	-19470.18	48.681	[-19565.45 , -19374.02]	7825.22	71.368	[7686.29 , 7964.42]
Levy Fail	-16737.18	126.913	[-16979.24, -16489.95]	-12152.46	92.149	[-12328.21 , -11972.95]	-4584.72	34.765	[-4651.03 , -4517.00]

Table 6: Effect Estimates: Omitting SD Characteristics

Variable	Total			Direct			Indirect		
	Estimate	S.D.	Interval	Estimate	S.D.	Interval	Estimate	S.D.	Interval
ρ	0.306	0.002	[0.301 , 0.311]						
Acres	710.30	4.828	[700.769 , 719.776]	1976.44	1.537	[1973.334 , 1979.475]	-1266.14	3.613	[-1273.112 , -1259.118]
Square Feet	60.62	0.326	[59.987 , 61.25]	58.31	0.002	[58.305 , 58.313]	2.31	0.325	[1.680 , 2.940]
Bedrooms	-11834.16	106.759	[-12045.719 , -11620.892]	-8564.95	0.111	[-8565.170 , -8564.731]	-3269.21	106.662	[-3480.554 , -3056.161]
Bathrooms	30530.81	199.230	[30140.052 , 30914.361]	25389.97	3.822	[25381.853 , 25397.425]	5140.84	196.002	[4758.232 , 5516.733]
Excellent	18151.10	72.867	[18007.123 , 18292.046]	31185.68	5.834	[31174.096 , 31196.827]	-13034.58	74.395	[-13180.890 , -12890.334]
Very Good	29390.73	108.329	[29175.124 , 29610.978]	34536.16	3.472	[34529.179 , 34543.086]	-5145.44	109.232	[-5362.624 , -4925.421]
Good	15874.09	64.740	[15746.538 , 15997.471]	16476.28	1.576	[16473.114 , 16479.341]	-602.18	64.337	[-729.759 , -479.152]
Poor	-60207.43	535.057	[-61266.079 , -59150.366]	-48081.80	18.655	[-48118.394 , -48042.505]	-12125.63	517.955	[-13148.573 , -11098.088]
Levy Fail	-10526.39	118.584	[-10770.943 , -10291.122]	-7306.29	82.308	[-7476.034 , -7142.994]	-3220.10	36.276	[-3294.908 , -3148.128]

Table 7: Effect Estimates: Omitting SD & Quality Characteristics

Variable	Total			Direct			Indirect		
	Estimate	S.D.	Interval	Estimate	S.D.	Interval	Estimate	S.D.	Interval
ρ	0.306	0.002	[0.301 , 0.311]						
Acres	552.85	3.948	[545.162 , 560.576]	1866.43	1.514	[1863.444 , 1869.445]	-1313.58	2.756	[-1319.021 , -1308.150]
Square Feet	62.51	0.335	[61.846 , 63.163]	60.22	0.001	[60.220 , 60.226]	2.28	0.334	[1.625 , 2.939]
Bedrooms	-13595.59	119.007	[-13829.673 , -13361.656]	-9550.31	0.547	[-9551.412 , -9549.234]	-4045.28	118.501	[-4278.634 , -3812.389]
Bathrooms	32318.52	216.608	[31888.891 , 32732.064]	26865.96	4.499	[26857.172 , 26875.166]	5452.57	212.803	[5029.883 , 5860.416]
Levy Fail	-8543.98	65.084	[-8676.008 , -8426.492]	-5921.74	45.109	[-6013.252 , -5840.315]	-2622.23	19.975	[-2662.756 , -2586.178]

Table 8: Average Treatment Effects

	All Variables			No School			No School & No Quality		
Variable	Estimate	S.D.	Interval	Estimate	S.D.	Interval	Estimate	S.D.	Interval
ρ	0.277	0.003	[0.272 , 0.282]	0.306	0.002	[0.301 , 0.311]	0.306	0.002	[0.301 , 0.311]
ATT				-7583.70	85.43968	[-7751.16, -7416.24]	-6146.95	46.81324	[-6238.70, -6055.19]
ATU				-1804.41	124.9617	[-2049.34, -1559.49]	-1464.63	87.36683	[-1635.87, -1293.39]
TE				-9388.11	107.3506	[-9598.52, -9177.70]	-7611.57	59.76399	[-7728.71, -7494.44]

ATT: Average Treatment on the Treated

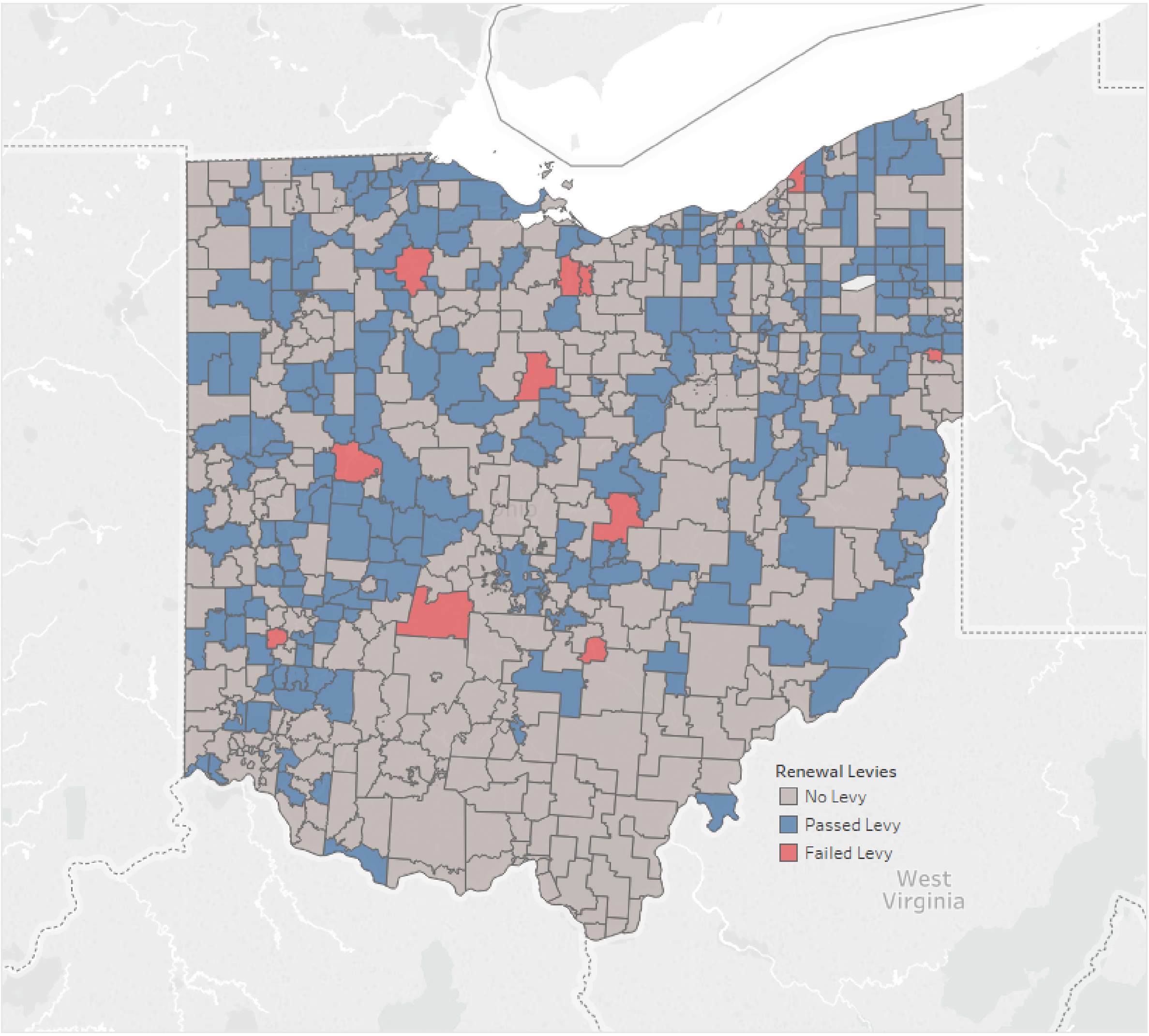
ATU: Average Treatment on the Untreated

TE: Total Effect

Note: The All Variables calculations have not finished running yet.

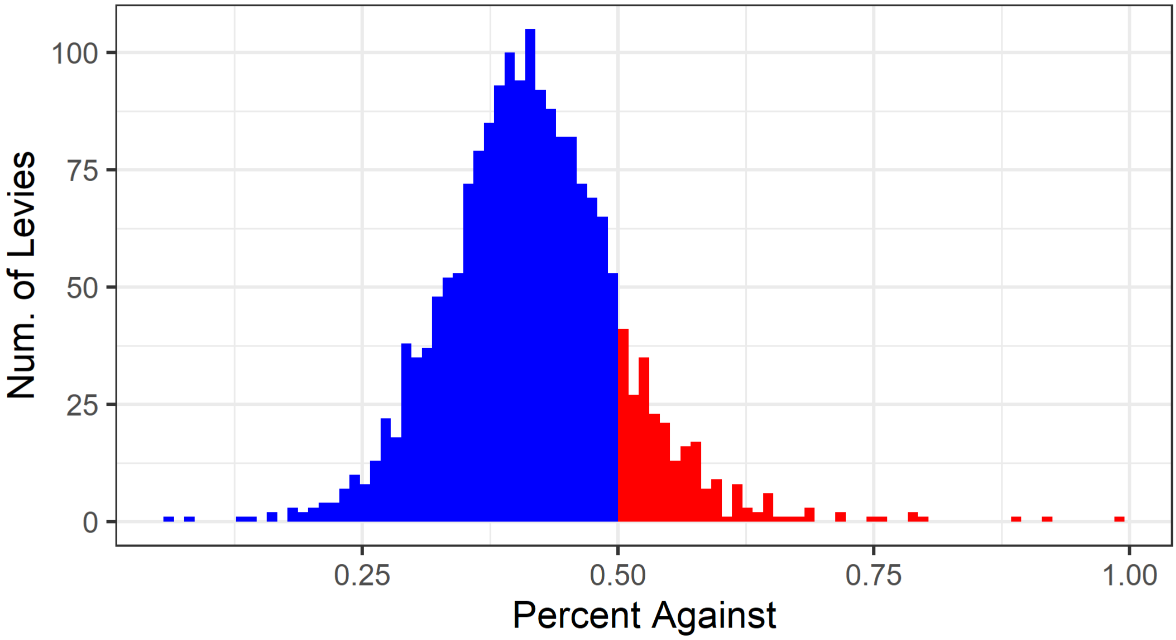
7 Figures

Figure 1: Renewal levies in 2012



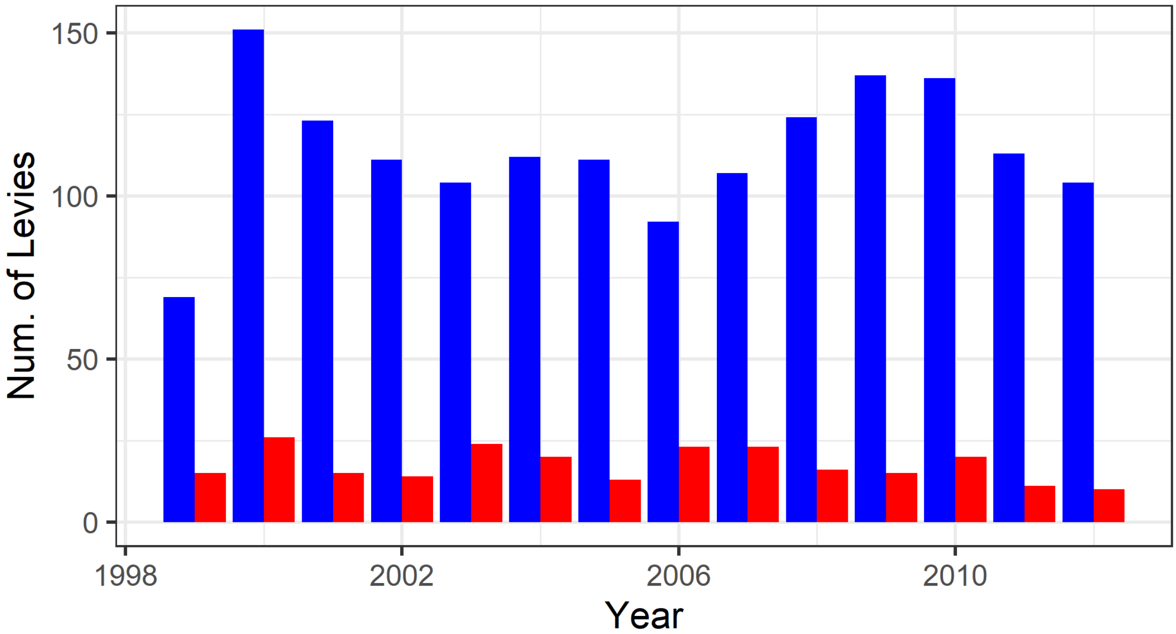
Note: Similar plots have been created for each year in the sample. The districts with renewal levies are not constant over time. In every year the majority of school districts do not have a renewal levy, but those who do overwelmingly pass.

Figure 2: Count of levies by the percent of votes against



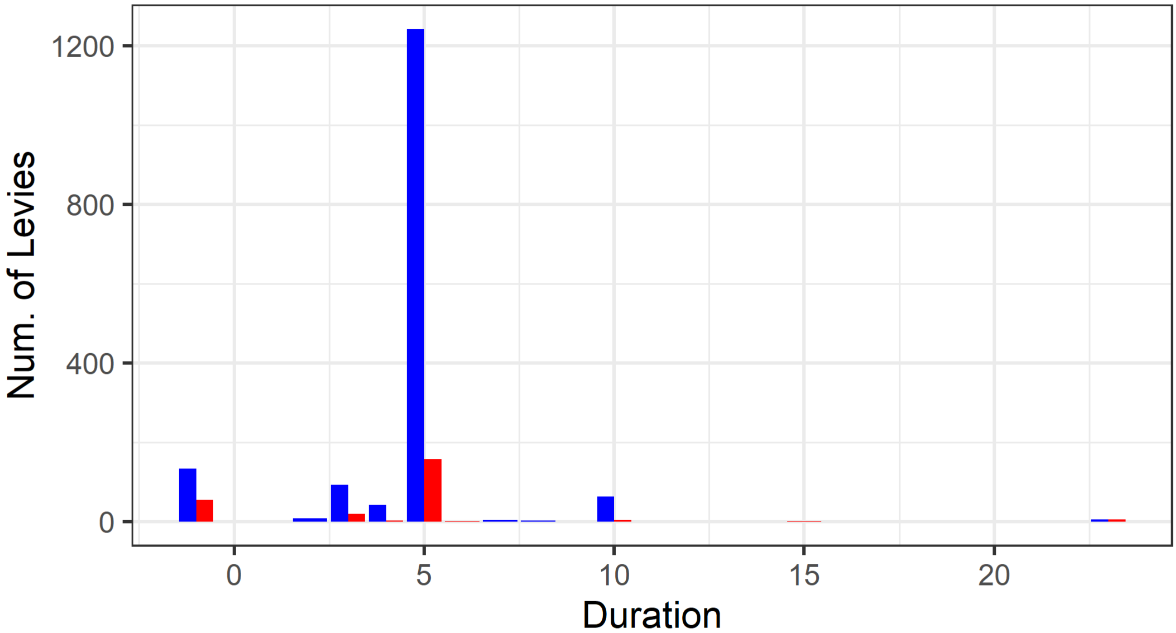
Note: Blue represents a passed levy, while red represents a failure

Figure 3: Count of levies by year



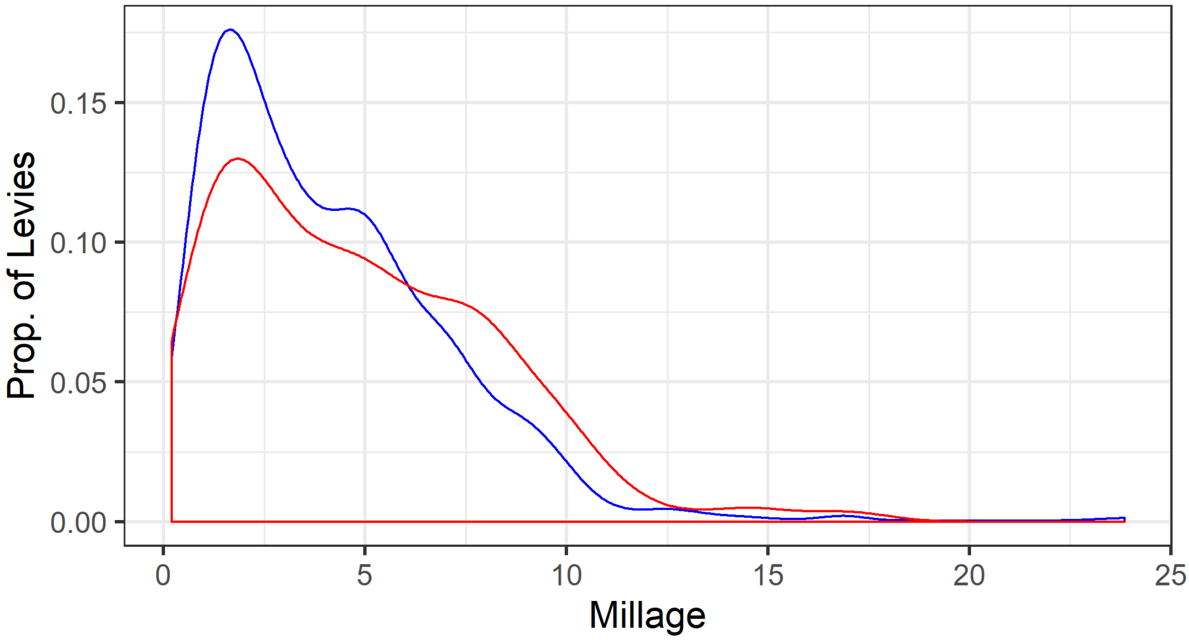
Note: Blue represents a passed levy, while red represents a failure

Figure 4: Count of levies by duration



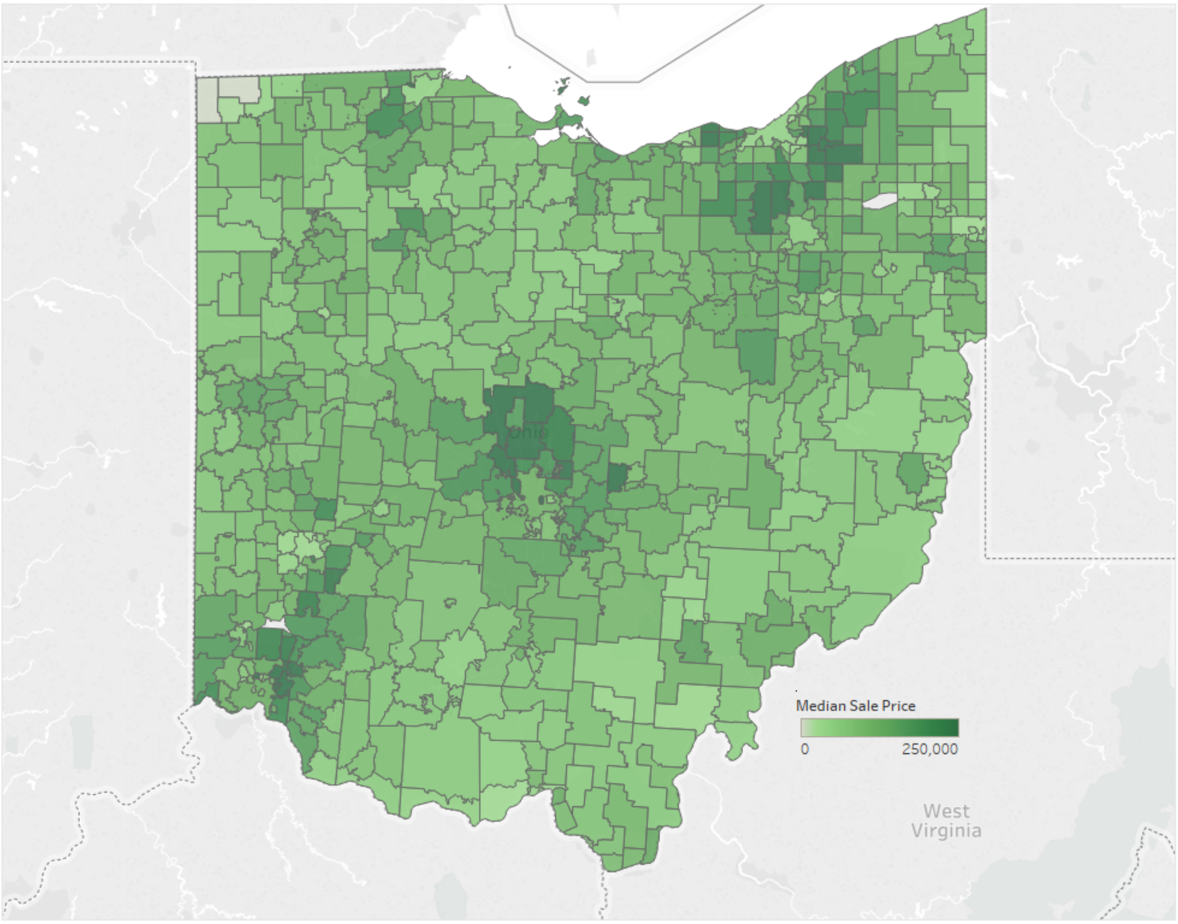
Note: Blue represents a passed levy, while red represents a failure

Figure 5: Density of levies by millage



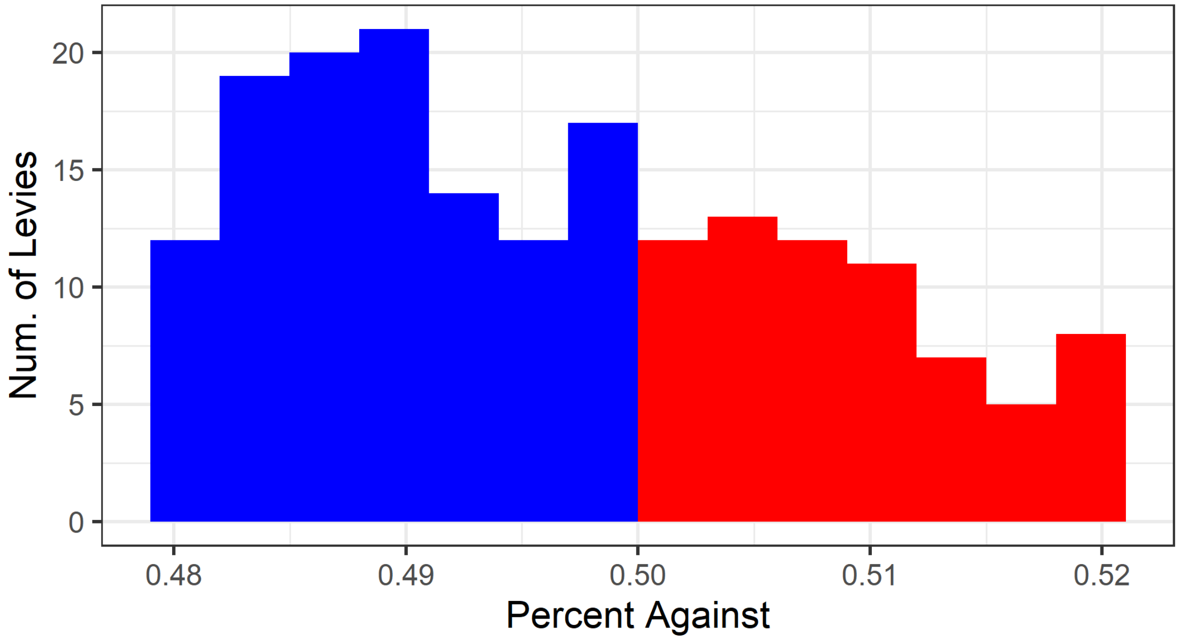
Note: Blue represents a passed levy, while red represents a failure

Figure 6: Median Home Price



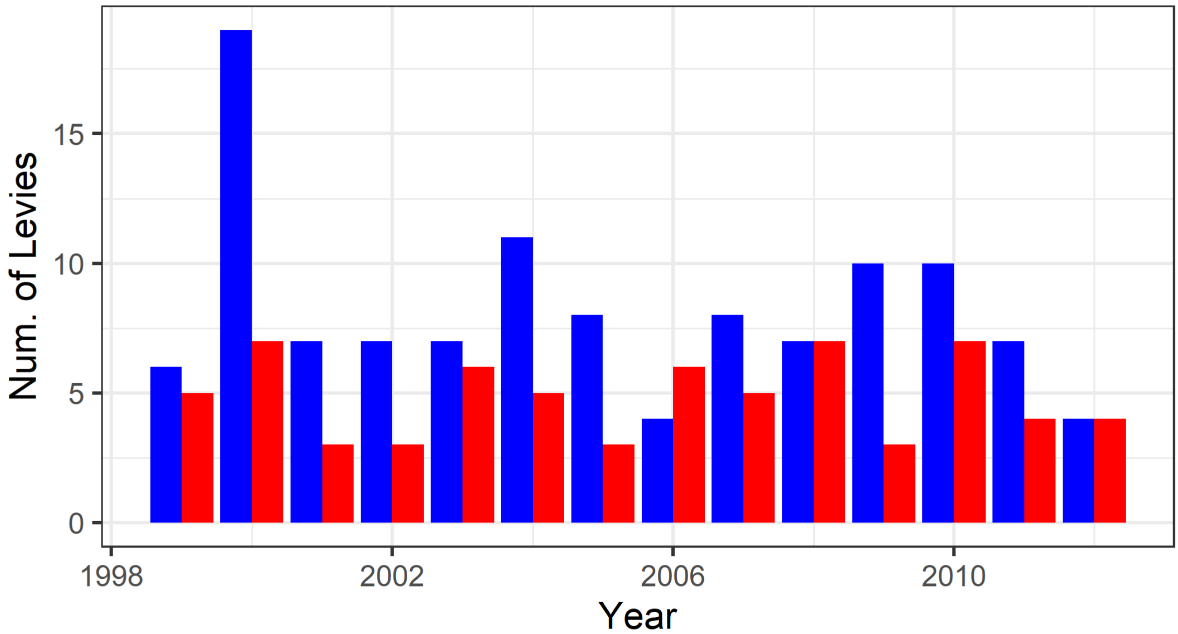
Note: Median home price is by school district in year 2013

Figure 7: Count of levies by percent of votes against



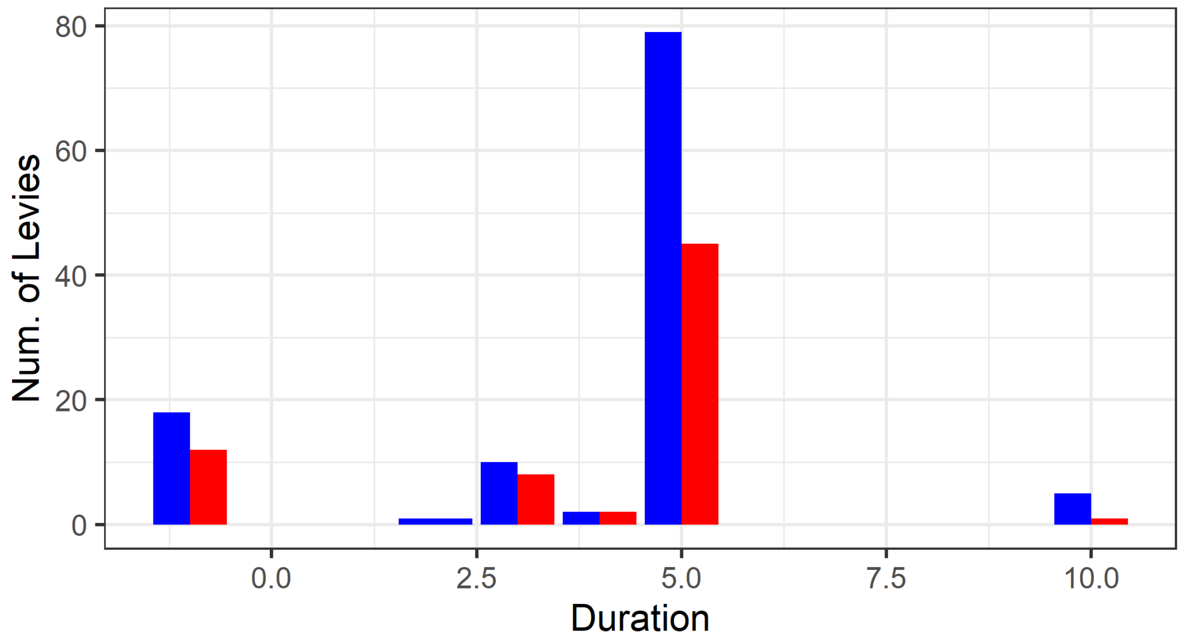
Note: Only levies within 0.48-0.52 proportion of votes against are plotted. Blue represents a passed levy, while red represents a failure

Figure 8: Count of levies by year



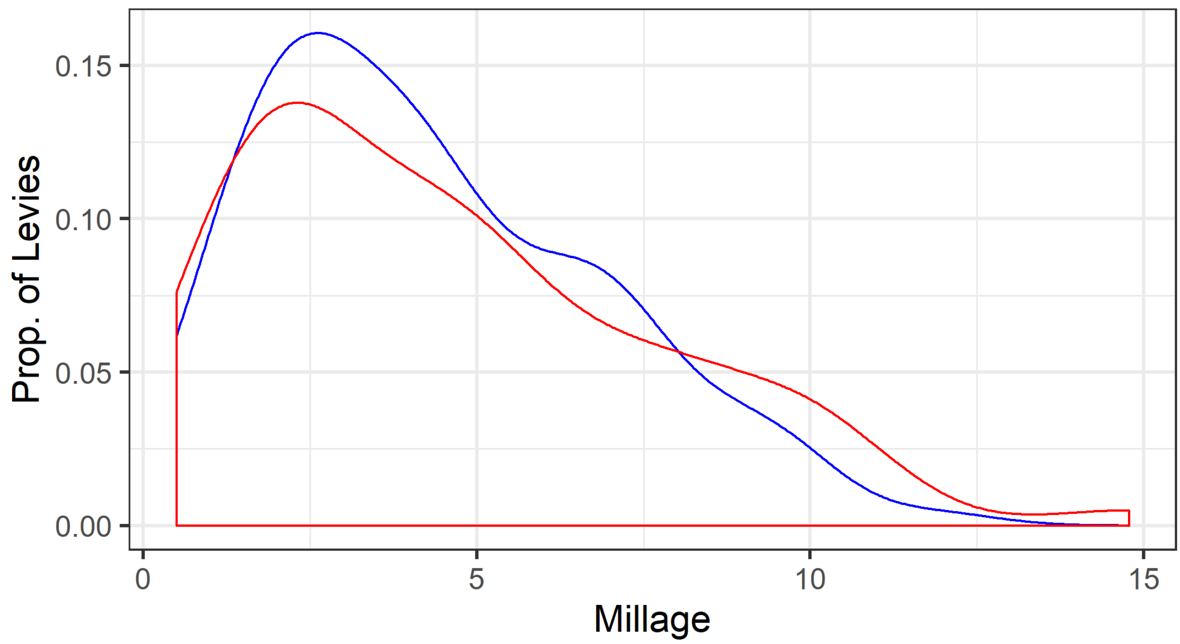
Note: Only levies within 0.48-0.52 proportion of votes against are plotted. Blue represents a passed levy, while red represents a failure

Figure 9: Count of levies by duration



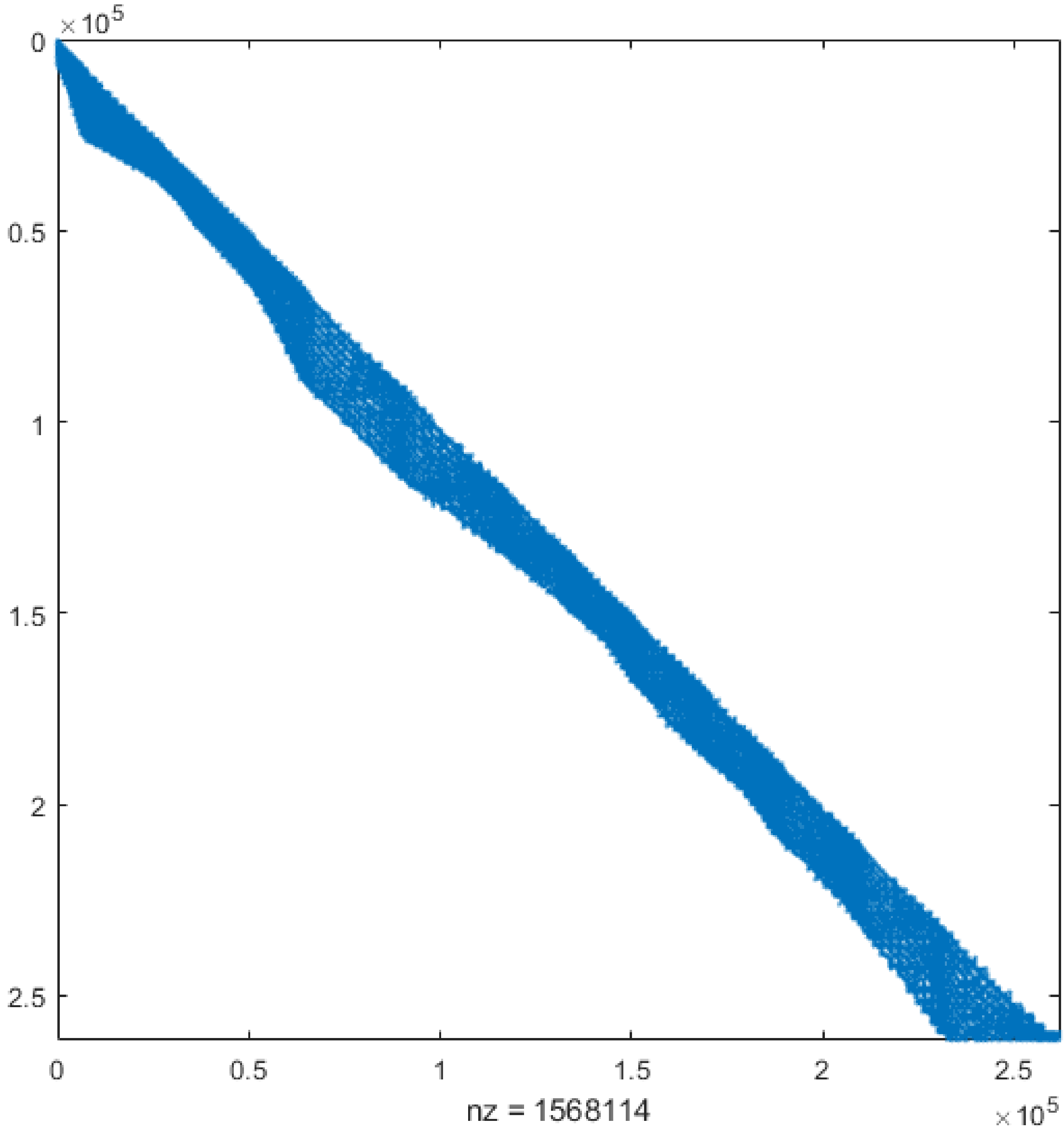
Note: Only levies within 0.48-0.52 proportion of votes against are plotted. Blue represents a passed levy, while red represents a failure

Figure 10: Density of levies by millage



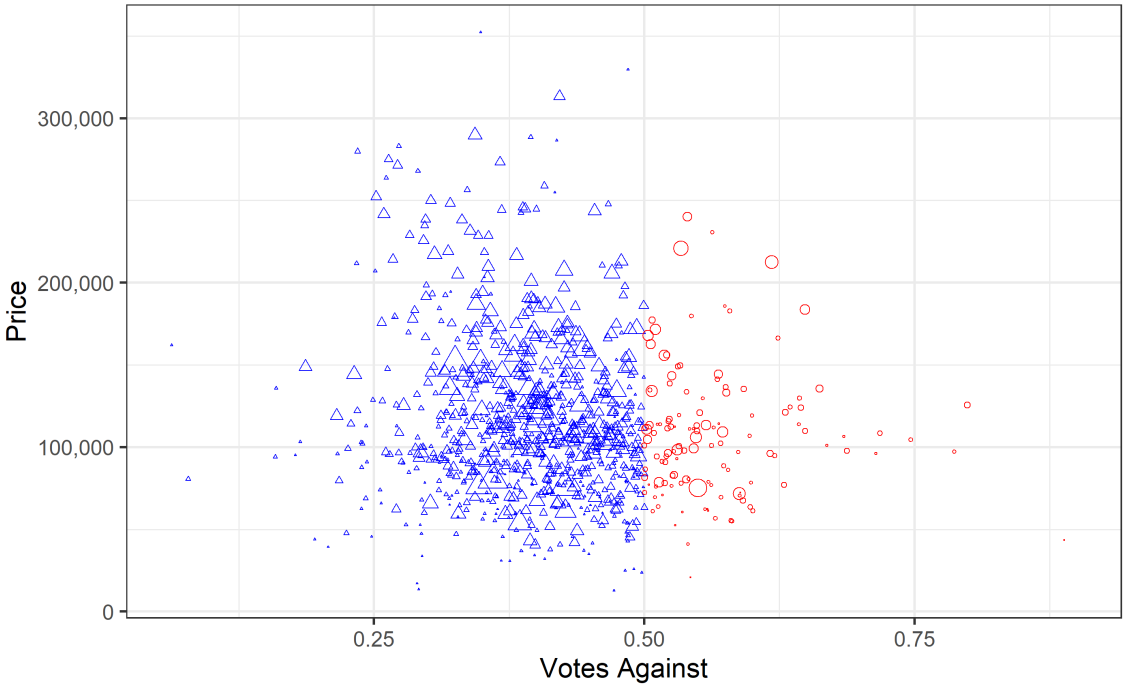
Note: Only levies within 0.48-0.52 proportion of votes against are plotted. Blue represents a passed levy, while red represents a failure

Figure 11: Weight Matrix



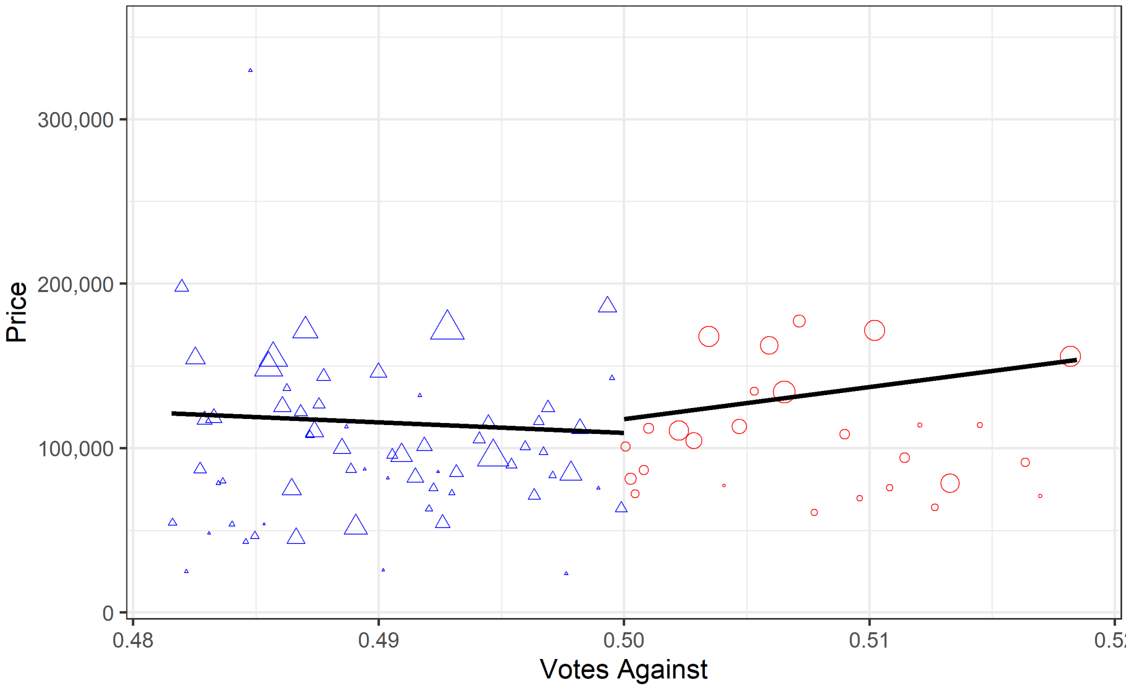
Note: A blue dot indicates house j is a neighbor of house i. Homes are ordered by sale date and school district. Because of each neighbor, j, of home i must be sold prior to the sale of home i, each of the dots must be to the lower left of the diagonal.

Figure 12: Price by vote share



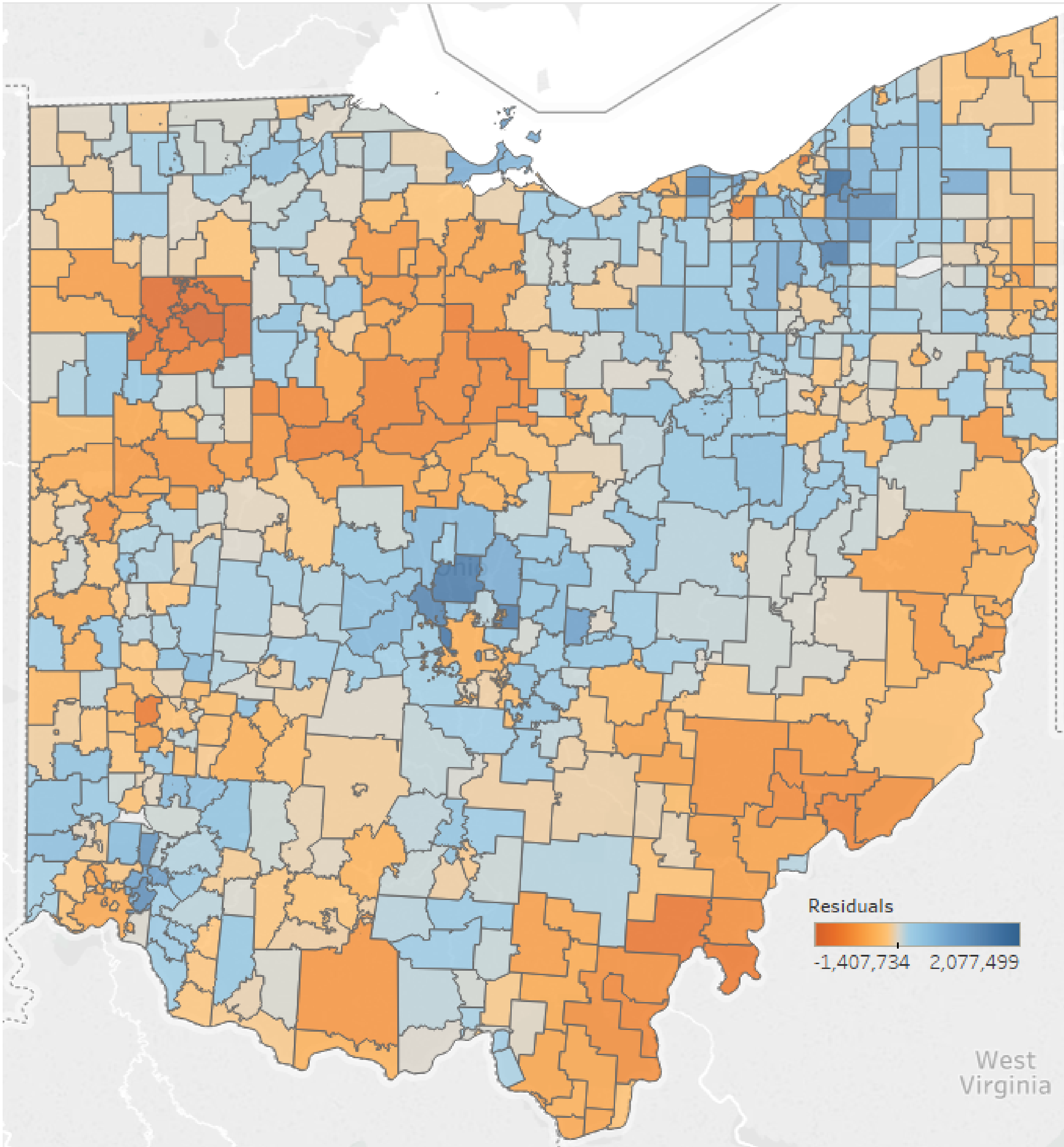
Note: Blue indicates a passage of a levy, while red indicates failure. Observations are binned every 0.0625% of vote share. The size of the object indicates the number of home sales averaged within the bin.

Figure 13: RD plot of price by vote share



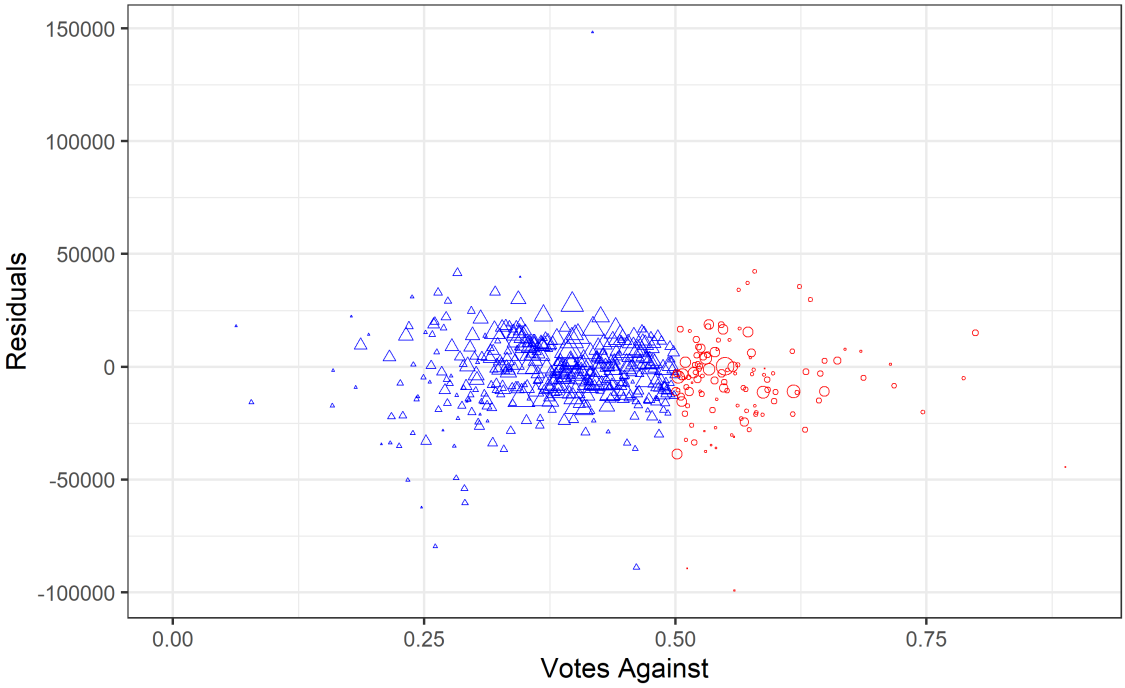
Note: Blue indicates a passage of a levy, while red indicates failure. Observations are binned every 0.0625% of vote share. The size of the object indicates the number of home sales averaged within the bin.

Figure 14: Statewide residuals from non-spatial regression



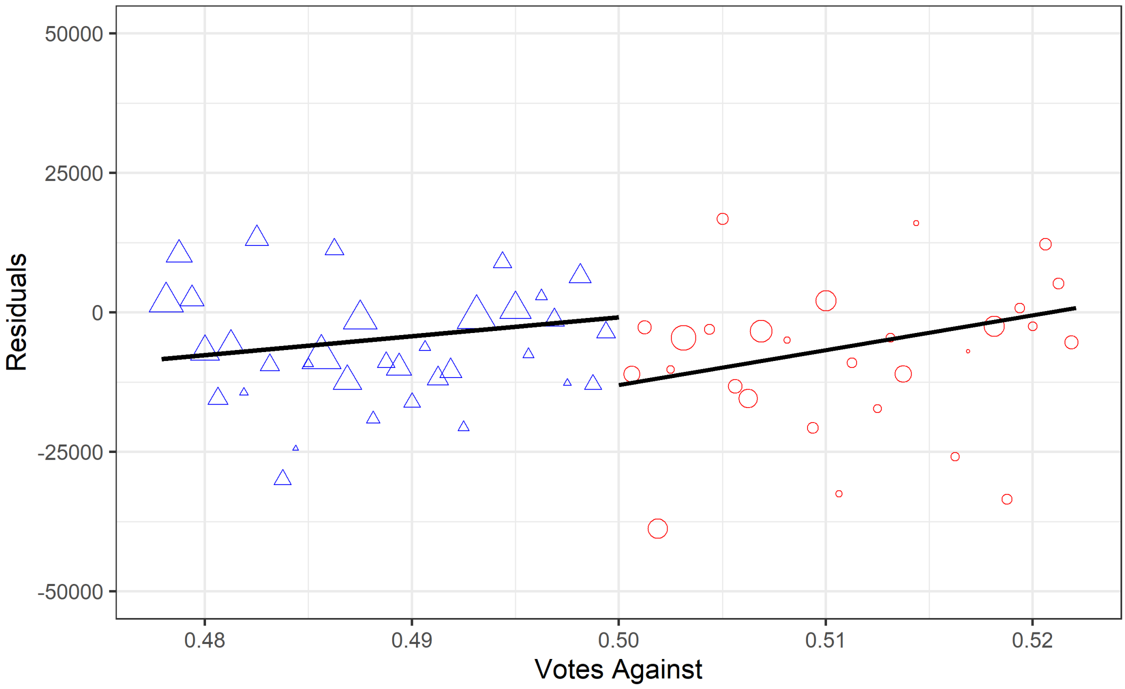
Note: This displays the sum of the residuals across all years for all homes sold inside each school district. The clustering of the low and high amounts suggests spatial dependence.

Figure 15: Residuals from full SDM



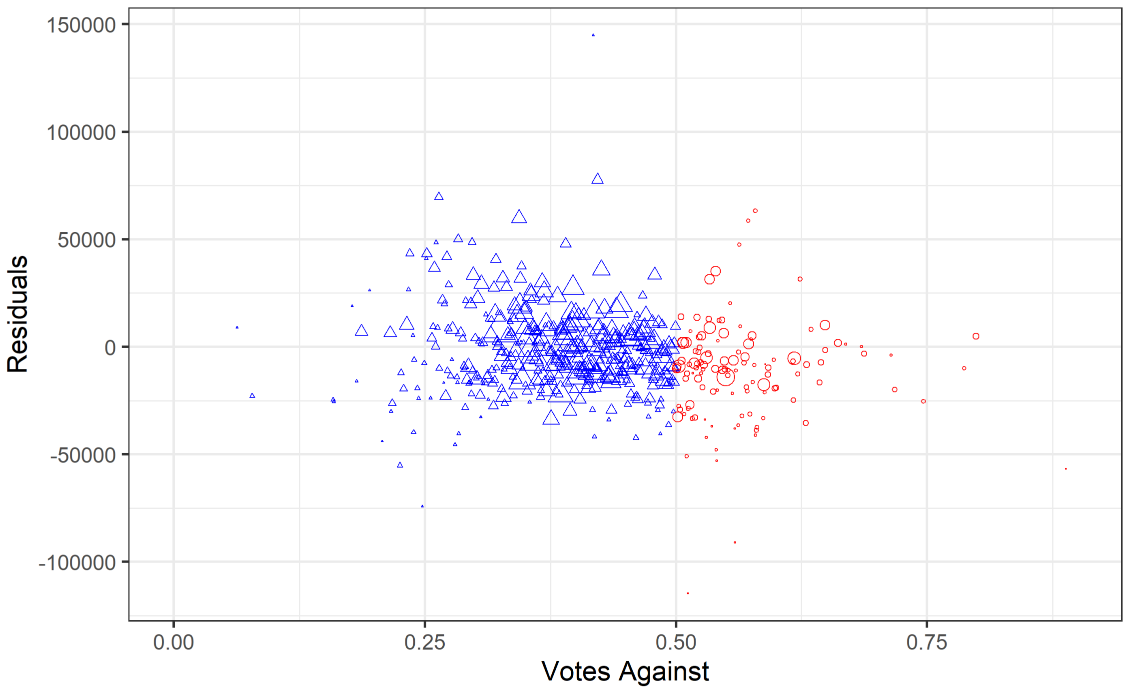
Note: Blue indicates a passage of a levy, while red indicates failure. Observations are binned every 0.0625% of vote share. The size of the object indicates the number of home sales averaged within the bin.

Figure 16: RD plot of residuals from full SDM



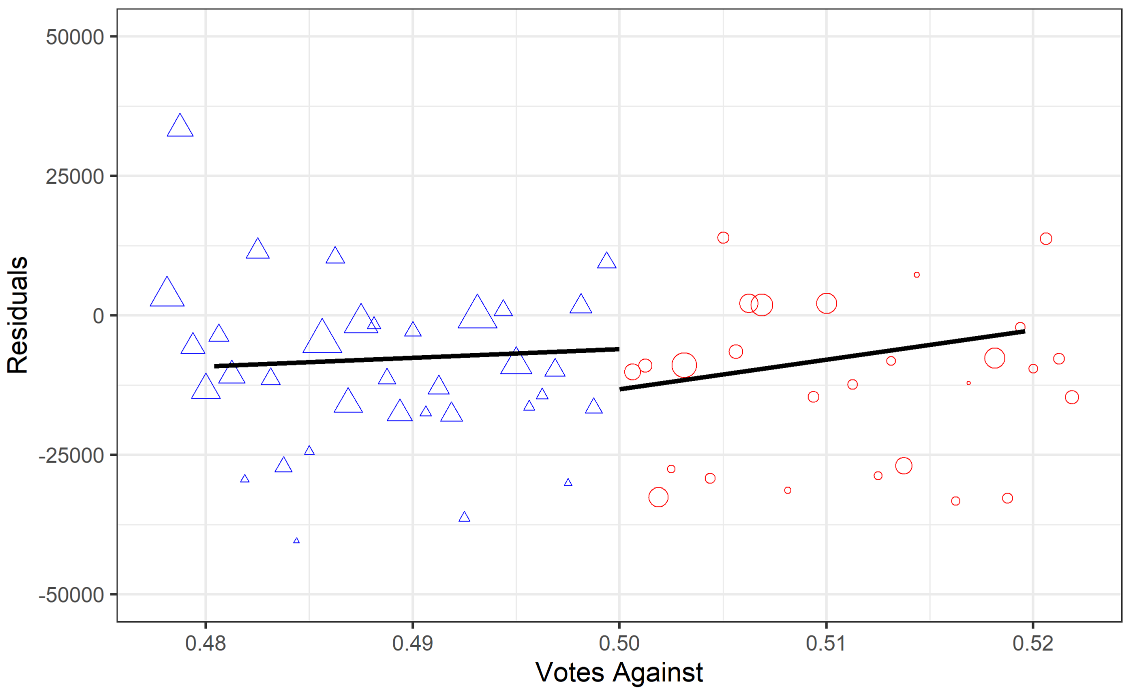
Note: Blue indicates a passage of a levy, while red indicates failure. Observations are binned every 0.0625% of vote share. The size of the object indicates the number of home sales averaged within the bin.

Figure 17: Residuals from SDM without school characteristics



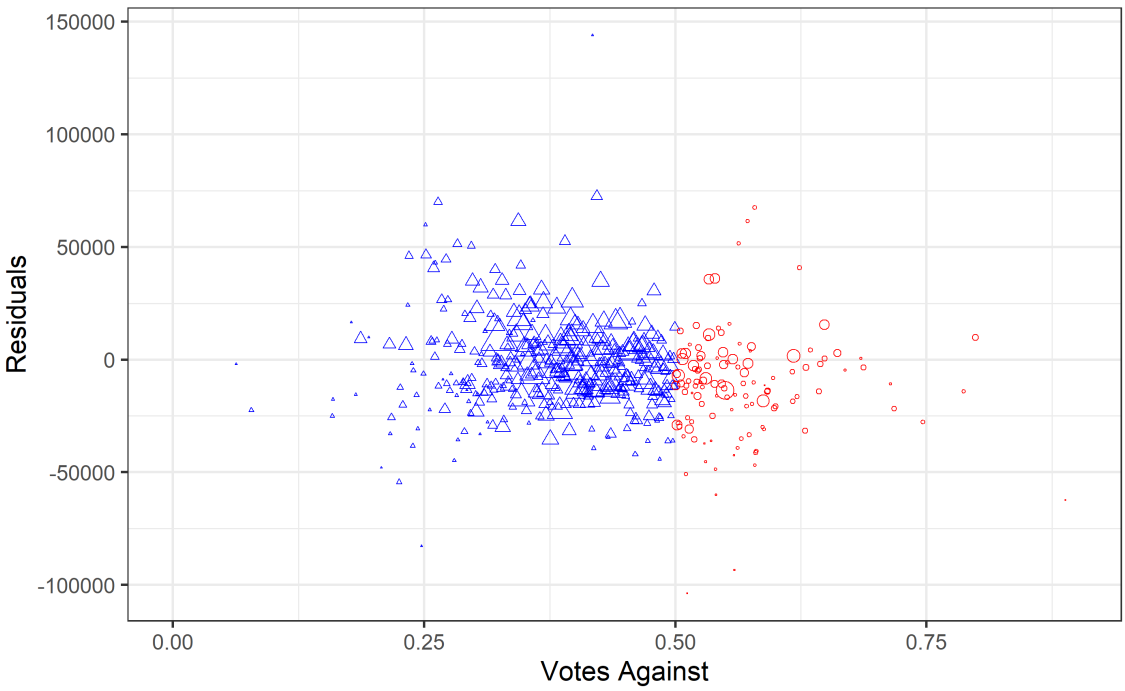
Note: Blue indicates a passage of a levy, while red indicates failure. Observations are binned every 0.0625% of vote share. The size of the object indicates the number of home sales averaged within the bin.

Figure 18: RD plot of residuals from SDM without school characteristics



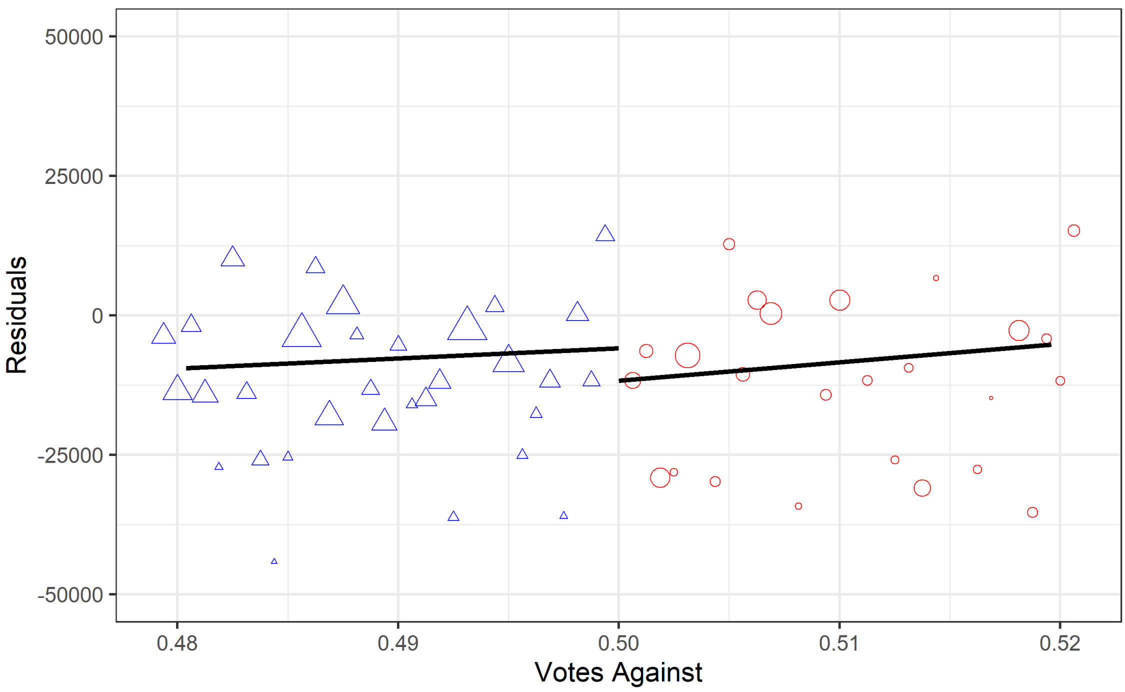
Note: Blue indicates a passage of a levy, while red indicates failure. Observations are binned every 0.0625% of vote share. The size of the object indicates the number of home sales averaged within the bin.

Figure 19: Residuals from SDM without school characteristics or quality



Note: Blue indicates a passage of a levy, while red indicates failure. Observations are binned every 0.0625% of vote share. The size of the object indicates the number of home sales averaged within the bin.

Figure 20: RD plot of residuals from SDM without school characteristics or quality



Note: Blue indicates a passage of a levy, while red indicates failure. Observations are binned every 0.0625% of vote share. The size of the object indicates the number of home sales averaged within the bin.

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