Identifying the Effect of Changing the Policy Threshold in Regression Discontinuity Models - Supplemental Appendix

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Abstract

This is a Supplemental online Appendix, containing additional theoretical and empirical results.

1 Supplemental Online Appendix

Here we provide additional supplemental material. First is some details regarding extensions to higher order derivatives and larger than marginal changes in the threshold. Next is a second empirical application, showing application of our methods in a fuzzy design context.

1.1 Extension: Higher Order Derivatives and Nonmarginal Changes in the Threshold

Under local policy invariance, the expression $\tau(c_{new}) \approx D(c) + (c_{new} - c) D'(c)$ gives an estimate of the treatment effect $\tau(c_{new})$ when c_{new} is a marginal change in c. Here we discuss what can be

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done to consider larger changes in c. One possibility is to refine this expression using higher order derivatives.

Theorems 1 and 2 can be immediately extended to identify and estimate higher order derivatives. For Theorem 1, Let $D''(x) = \partial^2 D(x) / \partial^2 x$. If we replace the continuous differentiability in Assumption A2 with twice continuous differentiability for x in a neighborhood of c, then by taking second order instead of first order derivatives in the proof of Theorem 1 we obtain $D''(c) = g''_+(c) - g''_-(c)$, so $D''(c)$ is identified and can be estimated by this difference in second order one sided derivatives.

Analogous to the local policy invariance definition that $\partial S(X, C) / \partial C$ equals zero when $X = C = c$, define local policy invariance for second order derivatives to be that both $\partial S(X, C) / \partial C$ and $\partial^2 S(X, C) / \partial C^2$ equal zero when $X = C = c$. It follows immediately that if this condition holds then $\tau''(c) = D''(c)$ in addition to Theorem 1 and Corollary 1. If sufficient data are available to precisely estimate second derivatives in the neighborhood of $x = c$, then to refine estimates of the effects of small discrete changes in c, we can approximate $\tau(c_{new})$ based on a second order Taylor expansion, giving

$$\tau(c_{new}) \approx D(c) + (c_{new} - c) D'(c) + \frac{(c_{new} - c)^2}{2} D''(c). \tag{1}$$

In the same way, if $E(Y(t) \mid X = x)$ for $t = 0$ and $t = 1$ are bounded analytic functions, then derivatives $D^k(x) = \partial^\kappa D(x) / \partial^\kappa x$ at $x = c$ for all integers κ exist and can be correspondingly identified. Define strong local policy invariance to be the assumption that $S(c, C) = S(c, c)$ for all C in a neighborhood of c. Given strong local policy invariance, $\partial^k S(c, C) / \partial C^k$ equals zero when $C = c$ for all integers k. This then makes $\tau^k(c) = D^k(c)$. Under these assumptions, for any threshold c_{new} the local average treatment effect $\tau(c_{new})$ is exactly identified, and is given by the infinite order

Taylor expansion

$$\tau\left(c_{new}\right) = \tau\left(c\right) + \sum_{k=1}^{\infty} \frac{\left(c_{new} - c\right)^k}{k} D^k\left(c\right). \tag{2}$$

Given equation (2), one could construct a consistent estimator of $\tau\left(c_{new}\right)$ based on the method of sieves, using a K'th order Taylor expansion to estimate $\tau\left(c_{new}\right)$, with each $D^k\left(c\right)$ for $k = 0, ..., K$ estimated by $K'th$ order polynomial regressions, and letting $K \rightarrow \infty$ as the sample size goes to infinity at appropriate rates.

Another way to obtain a consistent estimator of $\tau\left(c_{new}\right)$ would be to assume a functional form for the treatment effect. For example, if we assume the function $D\left(c\right)$ is linear, then equation (9) will hold exactly rather than approximately and could then be applied to any size change to c_{new} from c. Similarly, if $\tau\left(c\right)$ is quadratic then equation (1) becomes exact. These assumptions would still be less restrictive than the requirement that one have a complete, correctly specified parametric model for Y.

1.2 Empirical Application - Superfund Cleanups

Here we provide a second empirical application, both to illustrate interpretation of TED and MTTE in another context, and to demonstrate estimation of these concepts in a fuzzy design RD. In this application, we follow Greenstone and Gallagher (2008) to estimate the effect of Superfund-sponsored cleanups of hazardous waste sites on housing prices in surrounding areas. Hedonic housing models predict that such cleanups should lead to increases in local housing prices if consumers value them. Greenstone and Gallagher (2008) show that a site's placement on the National Priorities List (NPL) for the Superfund cleanups leads to economically small and statistically insignificant changes in residential property values. However, these estimates are for sites right at the regulatory threshold, and nothing is known about sites surrounding the threshold. As they have noted, "it is important to highlight that the RD approach only provides estimates of the treatment effect at the regulatory discontinuity (i.e., HRS = 28.5). To extend the external validity of the RD estimates to the full 1982 HRS Sample, it is necessary to assume a homogeneous treatment effect in that sample."

To investigate the external validity of their results for sites with slightly more or less hazardous, here we estimate 1) how the effect of Superfund cleanups depends on a site's initial hazard level, which is used to determine Superfund cleanup eligibility, and 2) how the effect of Superfund cleanups would change if the regulatory threshold were marginally changed (e.g., if EPA had lowered the regulatory threshold so that more sites are cleaned up.) The first corresponds our parameter TED and the second requires local policy invariance and hence TED can be interpreted as MTTE. Note that one cannot predict beforehand whether cleanups of more or less hazardous sites would have larger or smaller effects on nearby housing prices, since such an effect depends on current and potential residents' tastes and local housing markets characteristics.

Here the treatment T is an indicator for a site to be placed on the National Priorities List (NPL) and hence to be eligible for Superfund cleanups. The treatment is determined by scores from the Hazardous Ranking System (HRS) developed by EPA in 1982. The HRS score ranges from 0 to 100 based on the risk it posed, with 100 being the most dangerous. The running variable X is therefore the 1982 HRS score and the cutoff is 28.5 (normalized to be 0 in estimation). The outcome Y is the median housing price in the surrounding areas, including that in own Census tract, in adjacent Census tracts, within two-mile radii, within three-mile radii of hazardous waste sites. The RD design is fuzzy because some sites were rescored after the initial scoring in 1982, with the later scores determining whether they ended up on the NPL. Greenstone and Gallagher (2008) show that despite of the rescoring the distribution of 1982 HRS Scores does not show obvious bunching just above or below the threshold, suggesting that the RD model is valid.

We use the 1982 HRS sample from Greenstone and Gallagher (2008), which contains 487 sites

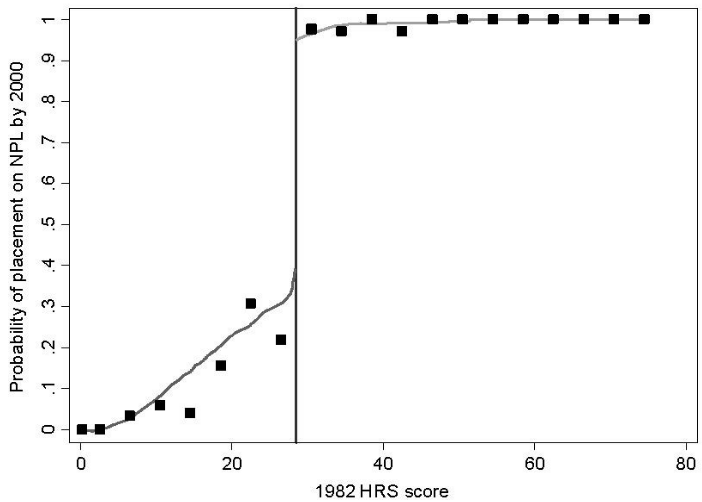

Figure 1: Probability of placement on NPL by 2000 at each 1982 HRS score

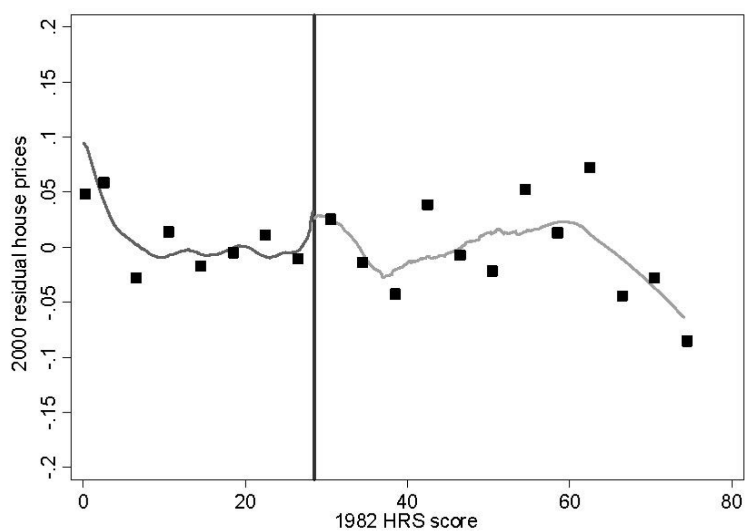

Figure 2: Residual housing prices in 2000 at each 1982 HRS score

with complete housing price data. Figures 2 and 3 reproduce figures IV and V in Greenstone and Gallagher (2008). Figure 2 plots the probability for a site to be placed on the NPL by 2000 against its initial HRS score. Figure 3 plots the year 2000 residual housing price within two-mile-radii from hazardous sites against the 1982 HRS score. Superimposed on both figures are fitted nonparametric regression lines above or below the threshold. As we can see the probability of being placed on NPL and hence being assigned for cleanups has a large jump and an obvious slope change at the HRS threshold 28.5, while the residual housing price show no obvious discontinuity or slope change.

We estimate these discontinuities in levels and derivatives (slopes) in the treatment probability and the mean outcome by local linear regressions with a uniform kernel. We then use these estimates to construct our TED or MTTE and further calculate the counterfactual treatment effect at a marginally lowered regulatory threshold. Our estimation is based on a sample of hazardous sites with the 1982 HRS score within 20 points from the threshold, or HRS scores between 8.5 and 48.5. Note that this is not a wide range as the EPA considered HRS scores within 4 points to be statistically indistinguishable and reflect comparable risks to human health (Environmental Protection Agency 1991). Greenstone and Gallagher (2008) use both the full range of data and a sample for which the HRS score is within 12 points from the threshold in their RD analysis. We will show that our results, which are based on a sample in between their samples, are very similar to those reported in Greenstone and Gallagher (2008). Further, since the hazardous sites are located in different states in the United States and those below the threshold are not necessarily in the same states as those above, to mitigate the influence of localized housing market shocks, we control for the 1980 housing price, housing characteristics, economic and demographic variables and state fixed effects, similar to Greenstone and Gallagher (2008).

The estimation results are reported in Table 2. The first two rows report the estimated level and slope changes of the probability of being placed on NPL and hence being eligible for Superfund cleanups; the next two rows report similar estimates in the outcome equation. The rest of the table reports the estimated effect of Superfund cleanups on housing prices at the pre-determined regulatory threshold, the TED (or MTTE if local policy invariance holds), and the new treatment effect if the regulatory threshold were marginally lowered by 1 HRS points, so that less dangerous sites were also assigned for Superfund cleanups. Robust standard errors are reported. Standard errors for the estimated TED (MTTE) and the new treatment effect are calculated using the Delta method.

Consistent with the evidence presented in Figures 1 and 2, the estimated discontinuity and slope change in the treatment probability are all significant, while those in the mean outcome are small and insignificant. As a result, the estimated treatment effects, the effects of Superfund cleanups on median housing prices average less than 4% and are statistically insignificant. More importantly, the estimated TED is close to zero and is statistically insignificant, suggesting that the effect of Superfund cleanups does not significantly depend on the initial hazard level of the sites. Therefore the conclusion that Superfund cleanups have small and insignificant effects on housing prices holds not only for those marginal sites at the chosen regulatory threshold, but also among sites with slightly higher or lower HRS scores. It is worth noting that since the estimated discontinuity and derivative in the first stage are all significant, the insignificant estimate of TED is not entirely driven by the small sample used.

Further, local policy invariance in this case requires that the effect of Superfund cleanups can depend on the initial hazard level, or the 1982 HRS score, and possibly other characteristics, but not the regulatory threshold itself. This assumption might be violated if all the hazardous waste sites shared the same local housing market so that if the regulatory threshold changed and hence more or fewer sites were cleaned up would lead to a change in the equilibrium housing price. However, as noted in Greenstone and Gallagher (2008) the hazardous waste sites spread throughout the US, so such

Table 2 RD estimates of the effect of Superfund cleanups on house prices

	(1)	(2)	(3)	(4)
	Dependent Variable: Superfund Cleanup T			
$1(X > 28.5)$	0.592	0.582	0.602	0.596
	(0.082)***	(0.078)***	(0.076)***	(0.077)***
$1(X > 28.5) * (X - 28.5)$	-0.017	-0.015	-0.015	-0.016
	(0.007)**	(0.007)**	(0.007)**	(0.007)**
	Dependent Variable: Median Housing Price Y			
$1(X > 28.5)$	0.004	0.015	0.027	0.004
	(0.042)	(0.039)	(0.043)	(0.042)
$1(X > 28.5) * (X - 28.5)$	-0.002	-0.002	-0.001	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)
Treatment effect	0.031	0.057	0.035	0.031
	(0.105)	(0.058)	(0.059)	(0.105)
MTTE(TED)	-0.002	-0.001	0.000	-0.002
	(0.005)	(0.004)	(0.004)	(0.005)
Treatment effect - new	0.033	0.058	0.035	0.033
	(0.105)	(0.058)	(0.058)	(0.104)
Observations	336	336	333	333

Note: The sample includes sites with 1982 HRS scores between 8.5 and 48.5. The ln (2000 median house price) is the dependent variable. All specifications control for the 1980 housing price, housing characteristics, economic and demographic variables and state fixed effects. The units of observation are the Census tract that contains the site (Column (1)), tracts that share a border with the site (Column (2)), the areas within a circle of two-mile radius from the site (Column (3)), and the areas within a circle of three-mile radius from the site (Column (4)). Treatment effect - new refers to the RD treatment effect if the threshold were marginally lowered by 1 HRS point. Robust standard errors are in parentheses. *significant at the 10% level; ** significant at the 5% level; ***significant at the 1% level.

a general equilibrium effect is not likely. Given local policy invariance, MTTE is equal to TED. The fact that the estimated MTTE is close to be zero implies that the effect of Superfund cleanups would still be small and insignificant if the regulatory threshold were marginally lowered and hence less dangerous sites were cleaned up. This conclusion is formally supported by the small and insignificant estimates of the treatment effect at a lower threshold in the last row of Table 2.