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Local Polynomial Order in Regression Discontinuity Designs

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ABSTRACT
Treatment effect estimates in regression discontinuity (RD) designs are often sensitive to the choice of bandwidth and polynomial order, the two important ingredients of widely used local regression methods. While Imbens and Kalyanaraman and Calonico, Cattaneo, and Titiunik provided guidance on bandwidth, the sensitivity to polynomial order still poses a conundrum to RD practitioners. It is understood in the econometric literature that applying the argument of bias reduction does not help resolve this conundrum, since it would always lead to preferring higher orders. We therefore extend the frameworks of Imbens and Kalyanaraman and Calonico, Cattaneo, and Titiunik and use the asymptotic mean squared error of the local regression RD estimator as the criterion to guide polynomial order selection. We show in Monte Carlo simulations that the proposed order selection procedure performs well, particularly in large sample sizes typically found in empirical RD applications. This procedure extends easily to fuzzy regression discontinuity and regression kink designs.

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1. Introduction

Regression discontinuity designs (RD designs or RDD) have been widely used in empirical social science research in recent years. Two important reasons for its appeal are that the research design permits clear and transparent identification of causal parameters of interest, and the design itself has testable implications similar in spirit to those in a randomized experiment (Lee 2008; Lee and Lemieux 2010).

Although the identification strategy is both transparent and credible in principle, many methods can be used to estimate the same causal parameter of interest. The key challenge is to estimate the values of the conditional expectation functions at the discontinuity cutoff without making strong assumptions about the shape of that function.

Typical practice in applied research is to employ a nonparametric local regression estimator. We surveyed leading economics journals between 1999 and 2017 and found that of the 110 studies employing RDD, 76 use a local polynomial regression as their main specification (Table A1, supplementary material). Among these 76 studies, local linear is the modal choice and is applied as the main specification in 45 studies, but the remaining 31 (about 40%) choose a different order.

As a practical matter, researchers often report results from using different polynomial orders, and feel reassured when their estimates are robust. But what are they to do when their conclusions *are* sensitive to polynomial order? This question mirrors the motivation behind optimal bandwidth proposals by Imbens and Kalyanaraman (2012) and Calonico, Cattaneo, and Titiunik (2014), and it is the focus of the present article.

Reasoning grounded in bias reduction of the RD estimator provides no guidance on this question. As both Hahn, Todd, and Van der Klaauw (2001) and Porter (2003) pointed out, higher order polynomials have a smaller asymptotic bias than lower orders. On the other hand, Gelman and Imbens (2019) argued that high-order polynomials can perform poorly in certain contexts.

In this article, we propose to extend the now widely used theoretical framework and data-driven approach of Imbens and Kalyanaraman (2012) and Calonico, Cattaneo, and Titiunik (2014)—which use estimated asymptotic mean squared error (AMSE or asymptotic MSE) of the RD estimator as an optimality criterion for bandwidth choice—to guide polynomial order selection. Thus, the proposed procedure is based on a local (as opposed to global) optimality criterion, as advocated by Gelman and Imbens (2019).

Our proposal is complementary to the recent work by Hall and Racine (2015), who call into question the practice of choosing the polynomial order ad hoc for nonparametric estimation at an interior point, and suggest a cross-validation method to select the polynomial order jointly with the bandwidth. Instead of cross-validation, we provide a formal justification for the application of a suggestion by Fan and Gijbels (1996) to RD designs, paralleling Imbens and Kalyanaraman (2012).

In order to assess the potential usefulness of the proposed procedure, we conduct Monte Carlo simulations based on two

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well-known examples (Lee 2008 and Ludwig and Miller 2007), where we use the exact same parameters as the simulations conducted by Imbens and Kalyanaraman (2012) and Calonico, Cattaneo, and Titiunik (2014). First, we illustrate the nature of the conundrum that researchers face in practice. Unsurprisingly, we find that in some cases the local linear specification performs the best, but in many other configurations, alternative polynomials fare better in terms of their MSE, coverage rate of the 95% confidence interval (CI), and size-adjusted CI length. Second, we find that the estimator chosen by comparing estimated AMSEs performs well, especially in larger sample sizes we often see employed in RD applications.

Finally, we compute the AMSE of the fuzzy RD estimator, the sharp and fuzzy estimators in the regression kink design (RK design or RKD), and the bias-corrected estimator of Calonico, Cattaneo, and Titiunik (2014) in all these contexts. We have implemented these computations in a Stata package `rdmse`. The installation instruction and program documentation are available online at *https://peizhuan.github.io/programs/*.

The remainder of the article is organized as follows. Section 2 summarizes the theory of local polynomial RD estimators, and the corresponding Appendix A (appendix, supplementary material) shows the consistency of our proposed polynomial order selection procedure. Section 3 presents simulation results. In Section 4, we discuss the extensions of our proposal to fuzzy RDDs and RKDs. Section 5 concludes.

2. RD Local Polynomial Order: Theoretical Considerations

In this section, we review and re-examine the theoretical justification for the choices in nonparametric RD estimation. In a sharp RD design, the binary treatment D is a discontinuous function of the running variable X: $D = 1_{[X \geqslant 0]}$ where we normalize the policy cutoff to 0. Hahn, Todd, and Van der Klaauw (2001) and Lee (2008) showed that under smoothness assumptions, the estimand:

$$\lim_{x \to 0^+} E[Y|X = x] - \lim_{x \to 0^-} E[Y|X = x] \tag{1}$$

identifies the treatment effect $\tau \equiv E[Y_1 - Y_0|X = 0]$, where Y_1 and Y_0 are the potential outcomes. To estimate (1), researchers typically use local polynomial regressions to separately estimate its two terms. Specifically, they solve the minimization problem using only observations above the cutoff as denoted by the $+$ superscript:

$$\min_{\{\tilde{\beta}_j^+\}} \sum_{i=1}^{n^+} \{Y_i^+ - \tilde{\beta}_0^+ - \tilde{\beta}_1^+ X_i^+ - \cdots - \tilde{\beta}_p^+ (X_i^+)^p\}^2 K\left(\frac{X_i^+}{h}\right). \tag{2}$$

The resulting $\hat{\beta}_0^+$ is the estimator for $\lim_{x \to 0^+} E[Y|X = x]$, and the estimator $\hat{\beta}_0^-$ for $\lim_{x \to 0^-} E[Y|X = x]$ is defined analogously. The RD treatment effect estimator is $\hat{\tau}_p \equiv \hat{\beta}_0^+ - \hat{\beta}_0^-$, where we emphasize its dependence on p by the subscript.

Any nonparametric RD estimator is generally biased in finite samples. Expressions for the exact bias require knowledge of the true underlying conditional expectation functions; thus, the econometric literature has focused on the first-order asymptotic approximations for the bias and variance. Applying these ideas, Lemma 1 of Calonico, Cattaneo, and Titiunik (2014) derived the AMSE of the pth order local polynomial estimator $\hat{\tau}_p$ as a function of bandwidth

$$\mathrm{AMSE}_{\hat{\tau}_p}(h) = h^{2p+2} B_p^2 + \frac{1}{nh} V_p \tag{3}$$

where B_p and V_p are unknown constants that depend on the properties of the data-generating process (DGP). The AMSE approximates the conditional MSE of $\hat{\tau}_p$ with bandwidth h: $\mathrm{MSE}_{\hat{\tau}_p}(h) \equiv E[(\hat{\tau}_p(h) - \tau)^2|\mathbf{X}]$, where $\mathbf{X} = [X_1, \ldots, X_n]$ consists of X of all n sample observations. The first term of the AMSE is the approximate squared bias, and the second term the approximate variance.

First-order approximations like the one above have been used in the literature in two ways. First, Hahn, Todd, and Van der Klaauw (2001) argued in favor of the local linear RD estimator ($p = 1$) over the kernel regression estimator ($p = 0$) for its smaller order of asymptotic bias—the biases of the two different estimators are $h^2 B_1$ and hB_0 and are of orders $O(h^2)$ and $O(h)$, respectively. However, by the same logic, the asymptotic bias of the local quadratic estimator ($p = 2$) is of order $O(h^3)$, and the bias of the local cubic is of order $O(h^4)$. More generally, the bias of the pth-order estimator is of order $O(h^{p+1})$. Therefore, if researchers were exclusively focused on the maximal shrinkage rate of the asymptotic bias, they would choose p to be as large as possible. Hahn, Todd, and Van der Klaauw (2001) recommended $p = 1$, implicitly recognizing that factors beyond bias shrinkage rate should also be taken into consideration.

Second, expression (3) is used as a criterion to determine the optimal bandwidth for a chosen order p. Since the AMSE is a convex function of h, one can solve for the optimal bandwidth that leads to the smallest value of AMSE: $h_{\mathrm{opt}}(p) \equiv \arg\min_h \mathrm{AMSE}_{\hat{\tau}_p}(h)$. Imbens and Kalyanaraman (2012) did precisely this to propose a bandwidth selector for local linear estimation (henceforth IK bandwidth) and Calonico, Cattaneo, and Titiunik (2014) further extended the selector to polynomial estimators of alternative orders (henceforth CCT bandwidth).

We now highlight that there is no theoretical ground to always prefer a specific polynomial order across all empirical contexts. By evaluating expression (3) at $h_{\mathrm{opt}}(p)$, which is of order $O(n^{-\frac{1}{2p+3}})$, $\mathrm{AMSE}_{\hat{\tau}_p}\left(h_{\mathrm{opt}}\left(p\right)\right)$ is equal to $\mathrm{C}_p \cdot n^{-\frac{2p+2}{2p+3}}$ with C_p being a function of the constants B_p and V_p. Therefore, as the sample size n increases, $\mathrm{AMSE}_{\hat{\tau}_p}\left(h_{\mathrm{opt}}\left(p\right)\right)$ shrinks faster for a larger p and will eventually, for the same n, fall *below* that of a lower order polynomial. Intuitively, if $E[Y|X = x]$ is close to being linear on both sides of the cutoff, then the local linear specification will provide an adequate approximation, and consequently $\hat{\tau}_1$ will have a smaller AMSE than that of $\hat{\tau}_2$ for a large range of sample sizes. On the other hand, if the curvature of $E[Y|X = x]$ is large near the cutoff, a higher p will have a lower AMSE, possibly even for small sample sizes. Although we expect higher order polynomials to have lower AMSE in sufficiently large samples, the precise sample size threshold at which that happens depends on the DGP through the constant C_p.

This point is concretely illustrated in Figure 1, using the two DGPs we employ for subsequent simulations. The DGPs are based on Lee (2008) and Ludwig and Miller (2007) and

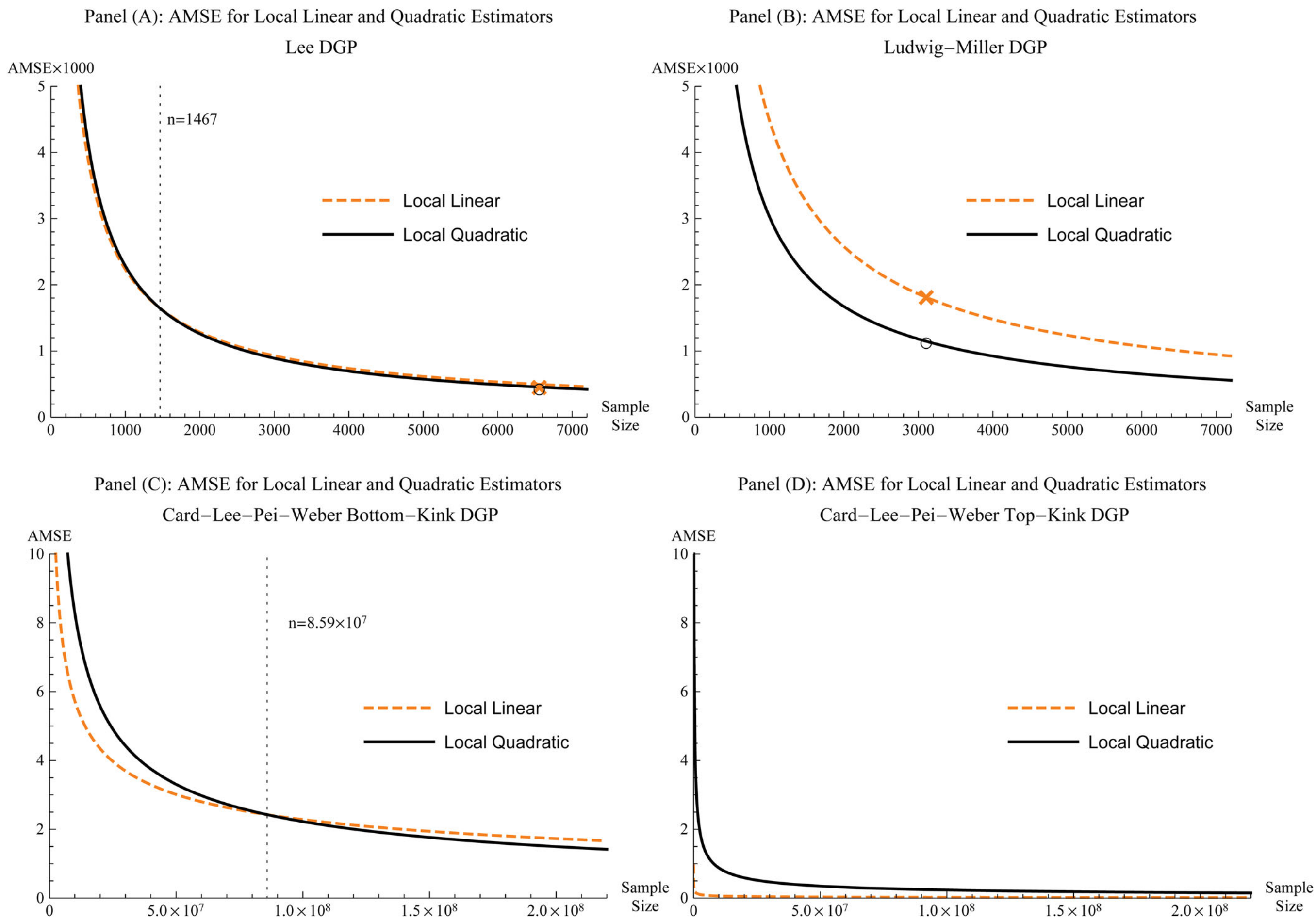

Figure 1. Asymptotic mean-squared-error as a function of sample size.
Note: We plot theoretical AMSEs as functions of sample size in two RD and two RK DGPs. We calculate the AMSEs for local linear and quadratic estimators with triangular kernel and the theoretical MSE-optimal bandwidth. In Panels (A) and (B), we superimpose the simulated MSEs of the local linear (cross) and quadratic (circle) estimators. These MSEs are taken from Tables 1 and 2. We discuss the rate at which the MSE-optimal polynomial order increases with sample size in the Remark below Proposition 1 in Appendix A (supplementary material).

described in greater detail in Appendix B.1 (supplementary material). Since we know the parameters of the underlying DGPs, we can analytically compute the quantities on the right hand side of equation (3). Using Lemma 1 of Calonico, Cattaneo, and Titiunik (2014), we plot in Figure 1 the $\mathrm{AMSE}_{\hat{\tau}_p}$ under the triangular kernel in the two DGPs as a function of sample size n for $p = 1, 2$ (see Appendix C.1 for details, supplementary material).

For the Lee (2008) DGP in Panel (A), $\mathrm{AMSE}_{\hat{\tau}_1}$ is marginally below $\mathrm{AMSE}_{\hat{\tau}_2}$ at small sample sizes but is larger at sample sizes over $n = 1467$. Therefore, for the actual sample size in Lee (2008), $n_{\text{actual}} = 6558$, local quadratic should be preferred to local linear based on the AMSE comparison—the associated reduction in AMSE is 8%. For the Ludwig and Miller (2007) DGP in Panel (B), the difference between $p = 1$ and $p = 2$ is much larger, and $\mathrm{AMSE}_{\hat{\tau}_2}$ dominates $\mathrm{AMSE}_{\hat{\tau}_1}$ for all n under 7000. At the actual sample size in Ludwig and Miller (2007), $n_{\text{actual}} = 3105$, the local quadratic estimator reduces the AMSE by a considerable 37%. It is worth noting that at n_{actual}, the AMSEs closely match the MSEs from our simulations in Section 3 below, which are marked by a cross for the local linear estimator and a circle for local quadratic.

In practice, Equation (3) cannot be directly applied because B_p and V_p depend on unknown quantities such as the derivatives of the conditional expectation function, conditional variances, and the density of X. Thus, Imbens and Kalyanaraman (2012) and Calonico, Cattaneo, and Titiunik (2014) used the empirical analog of Equation (3) for the local linear estimator

$$\widehat{\mathrm{AMSE}}_{\hat{\tau}_1}(h) = h^4 \hat{\mathrm{B}}_1^2 + \frac{1}{nh}\hat{\mathrm{V}}_1, \tag{4}$$

where B_1 and V_1 are replaced by consistent estimators $\hat{\mathrm{B}}_1$ and $\hat{\mathrm{V}}_1$, and the MSE-optimal feasible bandwidth is defined as $\hat{h}(1) \equiv \arg\min_h \widehat{\mathrm{AMSE}}_{\hat{\tau}_1}(h)$. The two studies differ in how they arrive at the estimates of B_1 and V_1. Additionally, Calonico, Cattaneo, and Titiunik (2014) generalized Imbens and Kalyanaraman (2012) by proposing bandwidth selectors for $\hat{\tau}_p$ for any p.

In this article, we simply extend the logic that justifies the optimal bandwidth by noting that we can choose the polynomial order corresponding to the lowest estimated AMSE. That is, we define

$$\hat{p} \equiv \arg\min_{p \in \Omega} \widehat{\mathrm{AMSE}}_{\hat{\tau}_p}\left(\hat{h}(p)\right),$$

where Ω consists of a finite number of candidate polynomial orders (Ω can contain as few as two elements if a researcher is just choosing between two orders; see Appendix A (supplementary material) for more discussion of Ω). For the AMSE of $\hat{\tau}_p$, no new quantities need to be computed beyond the estimators $\hat{\mathrm{B}}_p$ and $\hat{\mathrm{V}}_p$ and the optimal $\hat{h}\,(p)$, which must already be calculated when implementing, for example, the CCT bandwidth.

In summary, once one has already chosen an estimator (and the corresponding AMSE-minimizing bandwidth selector such as CCT), then it is straightforward to also report the resulting $\widehat{\mathrm{AMSE}}_{\hat{\tau}_p}$ for any given p and compare $\widehat{\mathrm{AMSE}}_{\hat{\tau}_p}$ across different candidate polynomial orders. Appendix C.2 (supplementary material) provides the exact expressions needed from Calonico, Cattaneo, and Titiunik (2014) for the calculation of the AMSE of $\hat{\tau}_p$, which is implemented in the Stata package `rdmse`.

Although this simple order selection approach was suggested by Fan and Gijbels (1996) for general local polynomial regression, to the best of our knowledge, a formal theoretical justification has yet to be discussed, and the approach has yet to be applied to RD designs. In Appendix A (supplementary material), we investigate the asymptotic property of the procedure and prove the consistency of $\hat{p}$ in two asymptotic frameworks that have been invoked in the literature.

Before proceeding to examine the finite sample performance of $\hat{p}$, we make several remarks.

Remark 1. We can also estimate the AMSE of the *bias-corrected estimator* of Calonico, Cattaneo, and Titiunik (2014) (denoted by $\hat{\tau}_p^{bc}$). Appendix C.2 (supplementary material) provides details, and the calculation is also implemented in the Stata package `rdmse`.

Remark 2. We can allow for different polynomial orders on two sides of the threshold, similar to recent developments that permit different bandwidths. Calonico et al. (2017, 2019) implemented bandwidths that are optimal for the left and right intercept estimators, respectively. Following this line of reasoning, our Stata package can calculate the AMSE of each intercept estimator of a given polynomial order with the Calonico et al. (2017, 2019) bandwidths. Another recent study by Arai and Ichimura (2018) proposed simultaneous left and right bandwidth selectors that are MSE-optimal for the sharp RD estimator. It is also possible to extend Arai and Ichimura (2018) and jointly select left and right polynomial orders that are optimal for the RD estimator itself. In fact, the finiteness of the polynomial choice set makes the exercise easier than the bandwidth selection by Arai and Ichimura (2018), who have to innovate to avoid a degenerate optimization problem.

Remark 3. Calonico et al. (2019) considered the identification, estimation, and inference in local RD regressions with covariates. Among other contributions, they propose covariate-adjusted MSE-optimal bandwidth selectors, which require the estimation of covariate-adjusted biases and variances. This article can be extended to select polynomial orders after covariate incorporation by building on Calonico et al. (2019).

Remark 4. Our MSE-optimal polynomial order selection procedure stems from the perspective of point estimation and not inference. Calonico, Cattaneo, and Farrell (2020) recently showed that the inference-optimal bandwidth that minimizes confidence interval coverage error rate is different from the MSE-optimal bandwidth (the former shrinks faster as a function of n). The same may also be true for polynomial order choices. Future work can study inference-optimal polynomial orders by building on the Edgeworth expansion approach in Calonico, Cattaneo, and Farrell (2020).

Remark 5. There exist alternative econometric estimation and inference approaches to the local polynomial paradigm, but many still require a polynomial order as input. Our proposal is applicable to frequentist approaches based on local approximation, for example, Otsu, Xu, and Matsushita (2015), whose empirical likelihood procedure relies on moment conditions formulated from the local linear RD estimator. One could adapt the Otsu, Xu, and Matsushita (2015) procedure by starting with our MSE-optimal polynomial order. In contrast, our way of calculating the AMSE does not apply to the local randomization approach by Cattaneo, Titiunik, and Vazquez-Bare (2017), where the polynomial choice amounts to a parametric assumption, or the order of global polynomial fit lines in RD graphs (Calonico, Cattaneo, and Titiunik 2015), for which Lee and Lemieux (2010) suggested selection procedures based on goodness-of-fit criteria. Finally, our frequentist proposal does not apply to the Bayesian RD approach of Geneletti et al. (2015), and we leave the polynomial order choice therein as an open question. (In another Bayesian study, Branson et al. 2019 largely circumvented this polynomial choice by modeling the potential outcome means conditional on X as Gaussian processes; although the mean functions of the Gaussian processes are still specified as polynomials, their choice is shown to be inconsequential in examples.)

3. Monte Carlo Results

Although AMSE provides the theoretical basis for bandwidth selection and our complementary proposal for polynomial order selection, it is nevertheless a first-order asymptotic approximation. In this section, we conduct Monte Carlo simulations to examine the finite sample performance of local polynomial estimators of various orders—which themselves use the CCT bandwidth selectors—and our proposed order selection procedure.

We employ DGPs from two well-known empirical examples, Lee (2008) and Ludwig and Miller (2007), and the specifications of these DGPs follow *exactly* those in Imbens and Kalyanaraman (2012) and Calonico, Cattaneo, and Titiunik (2014). The conditional expectation functions are specified as piecewise quintic polynomials (see Appendix B.1 for details, supplementary material). Because of the fifth-order specification of the DGPs, the highest polynomial order we allow is $p_{\max} = 4$ so that we do not mechanically favor estimators from correctly specified regressions.

Our simulations draw 10,000 repeated samples from the two DGPs. Below, we present results using a triangular kernel; additional results using the uniform kernel are available in the previous working article (Pei et al. 2020), and the qualitative conclusions are the same.

The simulation results are organized as follows. Tables 1 and 2 report on the performances of conventional RD estimators ($\hat{\tau}_p$) applied to the two DGPs, respectively, while Tables B.1 and B.2 (appendix, supplementary material) report on the bias-corrected RD estimators ($\hat{\tau}_p^{\text{bc}}$) and the associated robust confidence intervals as per Calonico, Cattaneo, and Titiunik (2014). Each of the four tables displays results corresponding to two sample sizes: the actual sample size in Panel A and large sample size in Panel B. The actual sample size is that of the analysis sample in the two empirical studies: $n_{\text{actual}} = 6558$ for Lee (2008) and $n_{\text{actual}} = 3105$ for Ludwig and Miller (2007). We set the large sample size to $n_{\text{large}} = 60{,}000$ for the Lee DGP and $n_{\text{large}} = 30{,}000$ for Ludwig–Miller. n_{large} is about $10 \times n_{\text{actual}}$ in both studies, and it is comparable to or lower than the n in many empirical papers.

In part (a) of each panel, we show the summary statistics for the local linear estimator with two bandwidths. The first bandwidth is the (infeasible) theoretical optimal bandwidth (h_{opt}), which minimizes AMSE using knowledge of the underlying DGP. Even though the theoretically optimal bandwidth is never known in an empirical application, we present simulation results for h_{opt} as a check on our theoretical intuition. As documented below, MSE decreases monotonically with p under h_{opt} with moderately large sample sizes, which is consistent with our discussion of the asymptotic behavior of $\text{AMSE}_{\hat{\tau}_p}(h_{\text{opt}}(p))$ in Section 2. The second bandwidth is the default CCT bandwidth selector from Calonico, Cattaneo, and Titiunik (2014) ($\hat{h}_{\text{CCT}}$).

We report averages and percentages across the simulations: average bandwidth in column (2), average number of observations within the bandwidth in column (3), MSE in column (4), coverage rate of the 95% CI in column (5), the average CI length in column (6), and the average size-adjusted CI length in column (7). While the other statistics are standard in Monte Carlo exercises, the size-adjusted CI length warrants further explanation. Size-adjustment is necessary because not all 95% CIs achieve the nominal coverage rate, in which case no standard metric tells us how to trade off a lower coverage rate for a shorter confidence interval. Therefore, we adapt the size-adjusted power proposal from Zhang and Boos (1994) to calculate size-adjusted 95% CIs. Specifically, instead of using 1.96 as the critical value for constructing the 95% CI, we find the smallest critical value so that the resulting size-adjusted 95% CI has the nominal coverage rate in the simulation. We simply report the average length of these size-adjusted CIs in column (7).

In part (b) of each table, we present the same statistics for different polynomial orders. In columns (4), (6), and (7), we express the quantities as a ratio to the quantity in the local linear specification for ease of comparison.

3.1. Performances of Alternative Polynomials

The set of polynomial orders we assess is limited by the piecewise quintic specification of the two DGPs. As mentioned above, since the kth-order derivative of the conditional expectation function is zero at the cutoff for $k > 5$, the highest-order estimator we allow is local quartic to ensure the finiteness of the theoretical optimal bandwidth. For the Lee DGP, the alternative polynomial orders are $p = 0, 2, 3, 4$, as well as the order $\hat{p}$ selected from the set $\{0, 1, 2, 3, 4\}$ that minimizes estimated AMSE. For Ludwig-Miller, we exclude $p = 0$ from the simulations under the actual sample size, because h_{opt} for $p = 0$ is so small (0.004) that the average effective sample size is only 17.

We highlight several findings from the four tables. First, although the *de facto* local linear estimator performs competitively in some cases (e.g., Lee DGP with CCT bandwidth selectors in Panel A of Table 1 and Table B.1, supplementary material), it does not deliver the lowest MSE. Looking down column (4) in part (b) of every table, there is at least one alternative estimator for which the MSE ratio is less than one. In these cases, the reduction in MSE ranges from 2% (local quadratic with $\hat{h}_{\text{CCT}}$ in Panel A of Table 2) to 72% (local quartic with h_{opt} in Panel B of Table 2).

Second, from column (5) in all tables, alternative estimators may improve upon the local linear in terms of its 95% CI coverage rate. It is worth noting that the coverage rate of the local linear CI is close to the nominal level in many instances, in which case the improvement by alternative estimators is small. But the improvement can sometimes be substantial. Given the analysis of Calonico, Cattaneo, and Titiunik (2014), it is not surprising that the conventional local linear CI sometimes undercover. The undercoverage is more serious under the Lee DGP: for example, the local linear CI coverage rate is 83% in simulations with n_{actual} and $\hat{h}_{\text{CCT}}$ (Part (a) of Panel A in Table 1). But this undercoverage is alleviated with the use of higher order alternatives, and the local quadratic, cubic and quartic estimators all lead to a coverage rate of at least 90%. The robust local linear CI has better coverage rates as shown in the appendix (Tables B.1 and B.2, supplementary material), and the use of alternative orders may bring further improvement.

Finally, we compare the length of confidence intervals across different choices of p. Table B.2 (supplementary material) shows that the coverage rates are close to the nominal 95% for all robust confidence intervals for the Ludwig-Miller DGP, and all of the polynomial orders greater than one yield confidence intervals that are smaller, and substantially so in many cases. In Tables 1, 2, and B.1, the CI coverage rates of local linear can fall noticeably below the nominal 95% rate. Thus, we rely on size-adjusted confidence intervals in column (7) to compare the precision of the estimates on equal footing. Of the 36 specifications that use higher order polynomials in those tables, 33 of them have shorter size-adjusted confidence intervals than local linear.

3.2. Performance of the Polynomial Order Selection Procedure

We have thus far provided both theoretical arguments and Monte Carlo evidence that point toward a more flexible view regarding the choice of p. We have presented simulation results on the performance of estimators that take p as given and use existing methods for choosing the $\widehat{\text{AMSE}}$-minimizing h, conditional on the given p. The evidence of the local linear specification performing well in some cases but not in others underscores the polynomial-order-choice conundrum researchers sometimes face.

Table 1. Simulation statistics for the conventional estimator of various polynomial orders: Lee DGP, actual and large sample sizes.

Panel A: Actual sample size ($n = 6558$)

(a): Simulation statistics for the local linear estimator ($p = 1$)

Bandwidth	(1) p	(2) Avg. h	(3) Avg. n	(4) MSE × 1000	(5) Coverage Rate	(6) Avg. CI Length	(7) Avg. Size-adj. CI length
Theo. Optimal	1	0.099	811	0.450	0.934	0.078	0.084
CCT	1	0.139	1140	0.518	0.831	0.067	0.097

(b): Simulation statistics for other polynomial orders as compared to $p = 1$

Bandwidth	p	Avg. h	Avg. n	Ratio of MSEs	Coverage Rate	Ratio of Avg. CI Lengths	Ratio of Avg. Size-adj. CI lengths
Theo. Optimal	0	0.022	183	1.583	0.896	1.109	1.245
	2	0.216	1766	0.932	0.942	0.995	0.965
	3	0.407	3321	0.853	0.945	0.958	0.913
	4	0.747	5739	0.764	0.942	0.898	0.867
	$\hat{p}$			0.790	0.941	0.911	
	Fraction of time $\hat{p}$=(0,1,2,3,4): (0, 0.001, 0, 0.228, 0.771)						
CCT	0	0.032	266	1.609	0.751	1.081	1.199
	2	0.248	2030	0.893	0.900	1.094	0.893
	3	0.344	2808	0.932	0.941	1.222	0.870
	4	0.390	3180	1.230	0.940	1.421	1.021
	$\hat{p}$			1.025	0.827	1.002	
	Fraction of time $\hat{p}$=(0,1,2,3,4): (0, 0.868, 0.105, 0.027, 0)						

Panel B: Large sample size ($n = 60{,}000$)

(a): Simulation statistics for the local linear estimator ($p = 1$)

Bandwidth	(1) p	(2) Avg. h	(3) Avg. n	(4) MSE × 1000	(5) Coverage Rate	(6) Avg. CI Length	(7) Avg. size-Adj. CI length
Theo. Optimal	1	0.064	4766	0.081	0.927	0.032	0.035
CCT	1	0.080	6020	0.091	0.851	0.029	0.039

(b): Simulation statistics for other polynomial orders as compared to $p = 1$

Bandwidth	p	Avg. h	Avg. n	Ratio of MSEs	Coverage Rate	Ratio of Avg. CI Lengths	Ratio of Avg. Size-adj. CI lengths
Theo. Optimal	0	0.011	798	2.051	0.893	1.287	1.420
	2	0.157	11782	0.805	0.939	0.933	0.899
	3	0.319	23847	0.681	0.939	0.865	0.835
	4	0.610	44516	0.568	0.939	0.786	0.755
	$\hat{p}$			0.568	0.939	0.786	
	Fraction of time $\hat{p}$=(0,1,2,3,4): (0, 0, 0, 0, 1)						
CCT	0	0.013	983	1.987	0.820	1.301	1.355
	2	0.181	13539	0.786	0.896	0.977	0.873
	3	0.323	24147	0.660	0.927	0.964	0.784
	4	0.400	29856	0.745	0.946	1.075	0.807
	$\hat{p}$			0.733	0.907	0.958	
	Fraction of time $\hat{p}$=(0,1,2,3,4): (0, 0.011, 0.102, 0.825, 0.062)						

Table 2. Simulation statistics for the conventional estimator of various polynomial orders: Ludwig-Miller DGP, actual and large sample sizes.

Panel A: Actual Sample Size (n=3105)

(a): Simulation Statistics for the Local Linear Estimator (p=1)

Bandwidth	(1) p	(2) Avg. h	(3) Avg. n	(4) MSE × 1000	(5) Coverage Rate	(6) Avg. CI Length	(7) Avg. Size-adj. CI length
Theo. Optimal	1	0.057	222	1.809	0.918	0.150	0.170
CCT	1	0.064	247	1.942	0.884	0.142	0.178

(b): Simulation Statistics for Other Polynomial Orders as Compared to p=1

Bandwidth	p	Avg. h	Avg. n	Ratio of MSEs	Coverage Rate	Ratio of Avg. CI Lengths	Ratio of Avg. Size-adj. CI lengths
Theo. Optimal	2	0.181	702	0.618	0.930	0.824	0.789
	3	0.406	1566	0.457	0.938	0.729	0.681
	4	0.814	2881	0.354	0.948	0.660	0.589
	$\hat{p}$			0.373	0.944	0.665	
	Fraction of time $\hat{p}$=(1,2,3,4): (0, 0, 0.082, 0.918)						
CCT	2	0.198	770	0.610	0.904	0.831	0.780
	3	0.337	1304	0.542	0.934	0.844	0.719
	4	0.384	1484	0.717	0.937	0.980	0.834
	$\hat{p}$			0.563	0.917	0.823	
	Fraction of time $\hat{p}$=(1,2,3,4): (0, 0.271, 0.726, 0.003)						

Panel B: Large Sample Size (n=30,000)

(a): Simulation Statistics for the Local Linear Estimator (p=1)

Bandwidth	(1) p	(2) Avg. h	(3) Avg. n	(4) MSE × 1000	(5) Coverage Rate	(6) Avg. CI Length	(7) Avg. Size-adj. CI length
Theo. Optimal	1	0.036	1364	0.286	0.923	0.060	0.067
CCT	1	0.039	1158	0.318	0.901	0.060	0.071

(b): Simulation Statistics for Other Polynomial Orders as Compared to p=1

Bandwidth	p	Avg. h	Avg. n	Ratio of MSEs	Coverage Rate	Ratio of Avg. CI Lengths	Ratio of Avg. Size-adj. CI lengths
Theo. Optimal	0	0.003	109	4.299	0.886	1.861	2.065
	2	0.131	4904	0.546	0.938	0.773	0.728
	3	0.315	11802	0.379	0.942	0.658	0.612
	4	0.662	23874	0.279	0.947	0.573	0.523
	$\hat{p}$			0.279	0.947	0.573	
	Fraction of time $\hat{p}$=(0,1,2,3,4): (0, 0, 0, 0, 1)						
CCT	0	0.003	115	4.171	0.869	1.882	2.014
	2	0.141	5301	0.548	0.915	0.772	0.729
	3	0.315	11785	0.389	0.934	0.684	0.607
	4	0.399	14892	0.451	0.945	0.755	0.648
	$\hat{p}$			0.395	0.933	0.684	
	Fraction of time $\hat{p}$=(0,1,2,3,4): (0, 0, 0.001, 0.905, 0.094)						

We now turn to the performance of our proposed order selection procedure. Specifically, we designate our candidate set Ω to contain all of the polynomial orders considered in Section 3.1, and for a particular Monte Carlo draw, we compute the RD estimator for each p in Ω and their corresponding $\widehat{\text{AMSE}}_{\hat{\tau}_p}$. For that same draw, we choose the p with the lowest $\widehat{\text{AMSE}}$. By repeating this process over the Monte Carlo draws, we can examine how well this procedure performs in terms of MSE, coverage, and the length of the confidence interval.

We report the results in the rows labeled "$\hat{p}$" below the quartic in each table. Overall, our procedure tends to select a polynomial specification that performs well. Although the selected polynomial order varies across repeated sample draws, the modal value of $\hat{p}$ coincides with the lowest MSE order in the majority of cases. In fact, this happens for all 8 permutations (2 DGPs $\times$ 2 bandwidth selectors $\times$ 2 estimators) under the large sample size, n_{large}. Sometimes, our procedure leads to the local linear specification being the modal choice, but when it does not, it always results in an estimator with improved MSE over local linear. In these cases, the reduction in MSE ranges between 17% and 43% for the Lee DGP and between 46% than 72% for the Ludwig–Miller DGP. We see qualitatively similar results for the $\hat{p}$-selected estimator in terms of its CI coverage rate and length. When the procedure does not select linear as the modal choice, it maintains the coverage rate if the local linear CI coverage rate is close to 95%, and it improves coverage if the local linear CI undercovers. The procedure also helps to reduce the CI length relative to local linear, especially for the Ludwig–Miller DGP. As emphasized in Remark 4, however, our procedure is not theoretically grounded in inference, and the good performance of the CI here may not generalize to other contexts.

We show additional results in the appendix (Tables B.3 to B.4, supplementary material) for the sample size $n_{\text{small}} = 500$. This is the sample size used in the simulations of Imbens and Kalyanaraman (2012) and Calonico, Cattaneo, and Titiunik (2014). We see from Panel A of Table B.3 (supplementary material) that because $p = 1$ minimizes the MSE of the conventional estimator $\hat{\tau}_p$ under the Lee DGP, our polynomial selection procedure fares worse than always using local linear. As shown in Panel A of Table B.4, $\hat{p}$ does better for the bias-corrected estimator $\hat{\tau}_p^{\text{bc}}$, for which local constant is MSE-minimizing(!), leading to comparable or lower MSEs, but the corresponding CI may undercover. This somewhat underwhelming performance of $\hat{p}$ in small sample sizes is an important caveat, but we note that it is rare to find RD studies that rely on 500 or fewer observations. In our survey of 110 studies, only three papers use fewer than 500 observations, a third of the papers use fewer than 6000 observations, and the median sample size is 21,561. A sample size of 60,000, the largest sample size used in our simulations, sits at the 63rd percentile. Therefore, it is fairly common to see studies with $n \geqslant 60,000$, much more so than seeing studies with about 500 observations. But even with 500 observations, our selection procedure performs well under the Ludwig-Miller DGP as shown in Panel B of Tables B.3 and B.4 (supplementary material): the modal $\hat{p}$ always coincides with the MSE minimizing polynomial order, and relative to local linear, our procedure leads to improved MSE.

To summarize, we have implemented simulations under two DGPs (Lee and Ludwig–Miller), two bandwidth choices (h_{opt} and h_{CCT}), two types of estimators (conventional and bias-corrected), and three sample sizes (n_{small}, n_{actual}, and n_{large}). We see that the best performing polynomial order varies across context: the MSE minimizing specification ranges from local constant to local quartic (the highest order we consider). We also find that our polynomial selection procedure generally performs well, especially in larger sample sizes typically used in RD studies.

4. Extensions: Fuzzy RD and RKD

In this section, we briefly discuss how AMSE-based local polynomial order choice applies to two popular extensions of the sharp RD design. The first extension is the fuzzy RD design, where the treatment assignment rule is not strictly followed. We rely on Lemma 2 and Theorem A.2 of Calonico, Cattaneo, and Titiunik (2014) to estimate the AMSE of a fuzzy RD estimator by first linearizing it, and we implement the calculation in the Stata package `rdmse`.

The second extension is the regression kink design (Nielsen, Sørensen, and Taber 2010; Card et al. 2015a), which our Stata implementation also accommodates. For RKD, Calonico, Cattaneo, and Titiunik (2014) and Gelman and Imbens (2019) recommend using local quadratic ($p = 2$) by extending the Hahn, Todd, and Van der Klaauw (2001) argument. But similar to our RD discussion, the AMSE of local quadratic may or may not be lower than alternative orders, depending on the sample size and DGP characteristics.

To illustrate this once again, but in the case of fuzzy RKD, we specify DGPs based on the bottom- and top-kink samples of the application in Card et al. (2015b) (see Appendix B.2 for details, supplementary material). These DGPs again allow us to compute $\text{AMSE}_{\hat{\tau}_p}$ as a function of sample size for different p. As shown in Panel (C) of Figure 1, the AMSE of the local quadratic fuzzy estimator is asymptotically smaller. However, it takes about 86 million observations for the local quadratic to dominate local linear. In Panel (D) of Figure 1, the local linear fuzzy estimator dominates its local quadratic counterpart for sample sizes up to 200 million observations. Since these threshold sample sizes are far larger than the 270,000 observations in both the bottom- and top-kink samples, they give reason to prefer the local linear RK estimator.

5. Conclusion

This article is motivated by the question of what researchers should do when their RD estimates are sensitive to the choice of polynomial order used in local regressions. Since the existing literature does not provide a practical answer, we propose to extend the logic of the widely used approach of Imbens and Kalyanaraman (2012) and Calonico, Cattaneo, and Titiunik (2014) and use the estimated AMSE to guide polynomial order selection. In Monte Carlo simulations based on two well-known RD examples, we see that the best polynomial ranges from local constant to quartic (the maximum order we allow) and varies across sample size and DGP characteristics. Our proposed order selection procedure performs reasonably well, especially in larger sample sizes typically seen in RD applications.

As a concluding remark, we view the proposed polynomial selection procedure as a complement—not a substitute—to analyses that explore result robustness to order choice. In many cases, different polynomial orders may yield substantively similar results, and the procedure will not be needed. But when researchers are confronted with estimate sensitivity with respect to polynomial order, the procedure can be used to rule out suboptimal estimators which yield drastically different results, as in the RKD context of Card et al. (2017).

Supplemental Material

The supplemental materials contain the Appendix and replication programs.

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Appendix (For Online Publication Only)

A Theoretical Justification: Consistency of $\hat{p}$

This subsection presents a theoretical justification of choosing p on the basis of estimated AMSE. The justification parallels previous results on bandwidth selection, e.g. Imbens and Kalyanaraman (2012) and Calonico, Cattaneo and Titiunik (2014*b*) who prove the consistency of the bandwidth selector $\hat{h}(p)$ for $h_{opt}(p)$. There are two alternative asymptotic frameworks employed in the literature, and we show the consistency of $\hat{p}$ in both. The first asymptotic framework adopts bandwidths that shrink at the MSE-optimal rates. This is the framework that has been used to argue for the use of $p=1$ over $p=0$, as mentioned at the beginning of section 2; it is also the framework for the discussion about Figure 1. In the second framework, which Calonico, Cattaneo and Titiunik (2014*b*) use to derive their key inference results, we assume that bandwidths for polynomial estimators of different orders shrink at the same rate.

We first define

$$p_{opt} \equiv \arg\min_{p\in\Omega} \text{AMSE}_{\hat{\tau}_p}(h(p))$$

as the MSE-optimal polynomial order in the candidate set Ω, where $h(p)$ denotes the bandwidth choice for the pth order local regression estimator. In general, p_{opt} is a function of n, and consistency means $\hat{p}/p_{opt} \xrightarrow{\mathbb{P}} 1$. Using p_{max} to denote the largest candidate polynomial order ($p_{max} \equiv \max\{p|p\in\Omega\}$)—which can be as low as 1 if a researcher is choosing between local constant and local linear specifications—we state our assumptions.

Assumption 1. *p_{max} is constant.*

Assumption 2. *a) Assumptions 1 and 2 in Calonico, Cattaneo and Titiunik (2014*b*) hold with $S = p_{max}+1$; b) for all $p\in\Omega$, $\hat{B}_p$ and $\hat{V}_p$ in equation (4) are consistent estimators for B_p and V_p in equation (3).*[1]

[1] Assumption 1 in Calonico, Cattaneo and Titiunik (2014*b*) consists of regularity conditions for the fourth moment

Assumption 3. *$h(p) = H_p \cdot n^{-\frac{1}{2p+3}}$ with $H_p > 0$, and $\hat{h}(p)/h(p) \xrightarrow{\mathbb{P}} 1$ for all $p \in \Omega$.*

Assumption 1 states that p_{max} does not change with n. This is consistent with the standard approach in other contexts, such as choosing the order of a time series autoregression from a fixed candidate set by the Akaike or Bayesian Information Criterion that penalizes model complexity (Stock and Watson, 2011), or selecting from a fixed set of covariate polynomial terms in propensity score matching or LASSO (the candidate set in Imbens and Rubin, 2015 for propensity score matching and Chernozhukov et al., 2018 for LASSO consists of linear, linear interactions and quadratic terms). In addition, Assumption 1 is not restrictive by itself as the researcher may always pick a large enough p_{max} a priori regardless of n. However, care is needed as Calonico, Cattaneo and Titiunik (2015) and Gelman and Imbens (2019) express concerns regarding high-order global RD polynomial estimators related to the Runge phenomenon. The Runge phenomenon arises in the polynomial interpolation of a function $f(x)$ over an interval $[a,b]$: using a polynomial of order n to interpolate a function through $n+1$ equispaced knots when n is large does not imply uniform convergence to f. In fact, large departures from the function may result outside the interpolation knots, especially toward the edge of $[a,b]$. One textbook remedy (Ch. 4 of Dahlquist and Björck, 2008 and Ch. 8 of Björck, 1996) to guard against the Runge phenomenon is to employ least squares regression as opposed to interpolation. As a rule of thumb, the textbooks recommend using a polynomial order no larger than $2\sqrt{n}$ where n is the number of (equispaced) observations. However, this rule of thumb does not cater to local RD estimators, and researchers typically choose polynomial orders from a set with a much smaller p_{max}. The Stata package `rdrobust` (Calonico, Cattaneo and Titiunik, 2014*a* and Calonico et al., 2017) caps the polynomial order at 8, and 107 of the 110 RD papers we surveyed use local orders no larger than 5. Given the concerns voiced by Calonico, Cattaneo and Titiunik (2015) and Gelman and Imbens (2019) and the status quo of the econometric and applied literature, it is advisable to always limit p_{max} to be at or below 8 and in

of Y given X, the density of X, and the conditional expectation and variance functions of the potential outcomes given X. In particular, the conditional expectation functions of the potential outcomes are assumed to be S-times differentiable in a neighborhood around zero. Assumption 2 in Calonico, Cattaneo and Titiunik (2014*b*) requires the kernel function $K(\cdot)$ in the minimization problem (2) to have compact support, be nonnegative, and be continuous.

most cases at or below 5.[2]

Part a) of Assumption 2 consists of standard regularity conditions that allow for the asymptotic approximation of MSE, and part b) encompasses the estimators $\hat{\mathrm{B}}_p$ and $\hat{\mathrm{V}}_p$ in Imbens and Kalyanaraman (2012) for $p = 1$ and Calonico, Cattaneo and Titiunik (2014*b*) as special cases. Note that a larger p_{max} translates to a higher degree of smoothness in Assumption 2, which may seem undesirable ostensibly. But it is also arbitrary to assume, for example, that the conditional expectation functions $E[Y_1|X = x]$ and $E[Y_0|X = x]$ have continuous second derivatives ($S = 2$) but not continuous third derivatives ($S = 3$). The technicality of Assumption 2 notwithstanding, for all practical purposes, we treat these conditional expectation functions as infinitely smooth.

Assumption 3 is the key assumption of the first asymptotic framework we consider. It states that the theoretical bandwidth for each p shrinks at the MSE-optimal rate and that the bandwidth selector is consistent. The CCT bandwidth selector, for example, satisfies this property.

Proposition 1. *Under Assumptions 1, 2 and 3,* $p_{opt} \to p_{max}$ *and* $\hat{p}/p_{opt} \xrightarrow{\mathbb{P}} 1$.

Proof. First we show that $p_{opt} \to p_{max}$. As mentioned in section 2, Assumption 3 implies that

$$\mathrm{AMSE}_{\hat{\tau}_p}(h(p)) = \mathrm{C}_p \cdot n^{-\frac{2p+2}{2p+3}}, \tag{A1}$$

where C_p is a constant for each p and does not depend on n. It follows that for any $p \neq p_{max}$

$$\frac{\mathrm{AMSE}_{\hat{\tau}_{p_{max}}}(h(p_{max}))}{\mathrm{AMSE}_{\hat{\tau}_p}(h(p))} \to 0$$

as $n \to \infty$. In other words, the AMSE of $\hat{\tau}_{p_{max}}$ is asymptotically smaller than a lower-order polynomial estimator, when the bandwidths shrink at the MSE-optimal rate. Therefore, $p_{opt} \to p_{max}$.

Next we show that $\hat{p} \xrightarrow{\mathbb{P}} p_{max}$. Under part b) of Assumption 2, Lemma A1 of Calonico, Cattaneo

[2] Another practical consideration is multicollinearity. As the polynomial order increases, multicollinearity is more likely when executing the regression. Using the Lee (2008) data, for example, `rdrobust` reports issues in bandwidth computation when $p = 7$.

and Titiunik (2014*b*) shows that

$$\frac{\widehat{\text{AMSE}}_{\hat{\tau}_p}(h(p))}{\text{AMSE}_{\hat{\tau}_p}(h(p))} \xrightarrow{\mathbb{P}} 1$$

for each $p \in \Omega$. It follows that

$$\frac{\widehat{\text{AMSE}}_{\hat{\tau}_{p_{max}}}(h(p_{max}))}{\text{AMSE}_{\hat{\tau}_p}(h(p))} \xrightarrow{\mathbb{P}} 0$$

for any $p \neq p_{max}$, which implies $\hat{p} \xrightarrow{\mathbb{P}} p_{max}$. Since $p_{opt} \to p_{max}$, $\hat{p} \xrightarrow{\mathbb{P}} p_{opt}$ as $n \to \infty$. □

Remark. We can calculate the rate at which p_{opt} converges to p_{max} based on equation (A1). For example, if a researcher is choosing between local linear and quadratic i.e. $\Omega = \{1,2\}$ as in Figure 1, quadratic is MSE-optimal when

$$n^{2/35} > \text{C}_2/\text{C}_1.$$

In this case, $|p_{opt} - p_{max}| = |p_{opt} - 2| < (\text{C}_2/\text{C}_1)n^{-2/35}$. Similarly, we can derive that for a general Ω where $\tilde{p}$ is the highest order in the set other than p_{max}, $|p_{opt} - p_{max}| = O(n^{-2(p_{max}-\tilde{p})/(2p_{max}+3)(2\tilde{p}+3)})$.

Proposition 1 says that under standard asymptotics as provided by Assumption 3, a) the optimal polynomial order is the "corner solution" p_{max} when the sample size is large; b) the order we select will also converge to p_{max} in probability. Point a) echos the insight from Porter (2003) and our discussion above that a higher order estimator will dominate in a sufficiently large sample when using optimal bandwidths. However, to reiterate our point made at the beginning of section 2, which we illustrate again in section 4 using the RKD example, the "corner solution" here reflects the theoretical property that $\text{AMSE}_{\hat{\tau}_p}$ decreases at a higher rate as a function of the sample size when p is larger.

It is clear from Figure 1 and the remark above that although p_{opt} converges to p_{max} asymptotically, p_{opt} may not coincide with p_{max} in any finite sample. This is true even in sample sizes conventionally considered to be large, as is the case with our RKD example in section 4. It is worth emphasizing that this is not a statement about the finite sample performance of $\hat{p}$—p_{opt} is not subject to sampling variation; instead, as discussed in section 2, it is about the important role of the constants (B_p and V_p for $p \in \Omega$) in determining p_{opt}, beyond the asymptotic rates in the remark above that push p_{opt} toward p_{max}.

To highlight the role of these constants, we consider a second, alternative, asymptotic framework used in the literature, in which p_{opt} can be an "interior solution". That is, even in the limit as the sample size tends to infinity, we can still have $p_{opt} < p_{max}$. The key assumption of this alternative asymptotic framework is:

Assumption 4. *$h(p) = H_p \cdot n^{-\alpha}$ with $H_p > 0$ and $\alpha \in (0,1)$ for all $p \in \Omega$.*

Unlike in Assumption 3, all bandwidths shrink at the same rate in Assumption 4 regardless of the polynomial order p. It is analogous to the defining assumption of the asymptotic framework in Calonico, Cattaneo and Titiunik (2014*b*): for their inference result, Calonico, Cattaneo and Titiunik (2014*b*) assume that the bandwidth for estimating the bias and the bandwidth for estimating the treatment effect shrink at the same rate. Calonico, Cattaneo and Titiunik (2014*b*) maintain this assumption even though the bias term contains higher order derivatives of the conditional expectation functions than the treatment effect and that their corresponding bandwidth selectors in Calonico, Cattaneo and Titiunik (2014*b*) shrink at different rates as the sample size increases.

We now establish the consistency of $\hat{p}$ in this alternative asymptotic framework.

Proposition 2. *Under Assumptions 1, 2 and 4 and provided that p_{opt} is unique asymptotically, $\hat{p}/p_{opt} \xrightarrow{\mathbb{P}} 1$.*

Proof. We show that the probability $\Pr(\hat{p}/p_{opt} \neq 1)$ is arbitrarily small as $n \to \infty$.

$$\begin{aligned}
&\Pr\left(\frac{\hat{p}}{p_{opt}} \neq 1\right) \\
=&\Pr\left(\frac{\widehat{\text{AMSE}}_{\hat{\tau}_{\hat{p}}}(h(\hat{p}))}{\widehat{\text{AMSE}}_{\hat{\tau}_{p_{opt}}}(h(p_{opt}))} < 1\right) \\
\leqslant& \sum_{p \neq p_{opt}} \Pr\left(\frac{\widehat{\text{AMSE}}_{\hat{\tau}_{p}}(h(p))}{\widehat{\text{AMSE}}_{\hat{\tau}_{p_{opt}}}(h(p_{opt}))} < 1\right) \\
=& \sum_{p \neq p_{opt}} \Pr\left(\frac{\widehat{\text{AMSE}}_{\hat{\tau}_{p}}(h(p))}{\text{AMSE}_{\hat{\tau}_{p}}(h(p))} \frac{\text{AMSE}_{\hat{\tau}_{p}}(h(p))}{\text{AMSE}_{\hat{\tau}_{p_{opt}}}(h(p_{opt}))} \frac{\text{AMSE}_{\hat{\tau}_{p_{opt}}}(h(p_{opt}))}{\widehat{\text{AMSE}}_{\hat{\tau}_{p_{opt}}}(h(p_{opt}))} < 1\right)
\end{aligned} \tag{A2}$$

Now we examine the three fractions inside the probability statement of (A2) one by one. For the first fraction, Lemma A1 of Calonico, Cattaneo and Titiunik (2014*b*) again implies that

$$\frac{\widehat{\text{AMSE}}_{\hat{\tau}_p}(h(p))}{\text{AMSE}_{\hat{\tau}_p}(h(p))} \xrightarrow{\mathbb{P}} 1 \tag{A3}$$

for all p. The second fraction

$$\frac{\text{AMSE}_{\hat{\tau}_p}(h(p))}{\text{AMSE}_{\hat{\tau}_{p_{opt}}}(h(p_{opt}))} > 1$$

for all p by the definition and uniqueness of p_{opt}. For the third fraction, notice that for any $\varepsilon > 0$

$$\Pr\left(\left|\frac{\text{AMSE}_{\hat{\tau}_{p_{opt}}}(h(p_{opt}))}{\widehat{\text{AMSE}}_{\hat{\tau}_{p_{opt}}}(h(p_{opt}))} - 1\right| > \varepsilon\right) \leqslant \sum_{p\in\Omega} \Pr\left(\left|\frac{\text{AMSE}_{\hat{\tau}_p}(h(p))}{\widehat{\text{AMSE}}_{\hat{\tau}_p}(h(p))} - 1\right| > \varepsilon\right). \tag{A4}$$

By Assumption 1 and condition (A3), the right hand side of (A4) can be made arbitrarily small by choosing a large enough sample size. It follows that

$$\frac{\widehat{\text{AMSE}}_{\hat{\tau}_{p_{opt}}}(h(p_{opt}))}{\text{AMSE}_{\hat{\tau}_{p_{opt}}}(h(p_{opt}))} \xrightarrow{\mathbb{P}} 1.$$

Putting all three fractions together, we know that, for each p,

$$\Pr\left(\frac{\widehat{\text{AMSE}}_{\hat{\tau}_p}(h(p))}{\text{AMSE}_{\hat{\tau}_p}(h(p))} \frac{\text{AMSE}_{\hat{\tau}_p}(h(p))}{\text{AMSE}_{\hat{\tau}_{p_{opt}}}(h(p_{opt}))} \frac{\text{AMSE}_{\hat{\tau}_{p_{opt}}}(h(p_{opt}))}{\widehat{\text{AMSE}}_{\hat{\tau}_{p_{opt}}}(h(p_{opt}))} < 1\right)$$

can be made arbitrarily small by choosing a large enough sample size. It follows that $\Pr(\hat{p}/p_{opt} \neq 1) \to 0$ as $n \to \infty$ and that $\hat{p}/p_{opt} \xrightarrow{\mathbb{P}} 1$. □

Under Assumption 4, $\text{AMSE}_{\hat{\tau}_p}$ shrinks at the same rate for all p. Therefore, the limit of p_{opt} is generally not p_{max}, and the AMSE of $\hat{\tau}_{p_{max}}$ does not always dominate that of alternative polynomial orders as is the case under Assumption 3. Instead, the optimal polynomial order depends on the magnitudes of the constants B_p and V_p from equation (3) even asymptotically. In another contrast with Assumption 3, under which p_{opt} is unique as $n \to \infty$, there exist DGPs for which the AMSEs are the same for different p. We therefore assume the uniqueness of p_{opt} in Proposition 2, but even if the uniqueness assumption is relaxed, $\hat{p}$ still has the desirable asymptotic no-regret per Li (1987) and Imbens and Kalyanaraman (2012). Namely, there is no loss asymptotically by using $\hat{p}$, as compared to any of the optimal orders that deliver the lowest MSE.

In summary, Propositions 1 and 2 establish the consistency of our polynomial order selection procedure in two asymptotic frameworks that have been invoked in the literature. In the first and more conventional framework, p_{opt} converges asymptotically to p_{max}, the largest polynomial order in the candidate set. But even in a sample typically considered large, p_{opt} may not coincide with p_{max} depending on the bias and variance constants (B_p and V_p for $p \in \Omega$). Our second asymptotic framework, which is analogous to that of Calonico, Cattaneo and Titiunik (2014*b*), further emphasizes the role of the constants, which justifies $\hat{p}$ as consistent for p_{opt} when p_{opt} is distinct from p_{max}.

B Specifications of Data Generating Processes

B.1 Lee and Ludwig-Miller DGPs

To obtain the conditional expectation functions in the Lee and Ludwig-Miller DGPs, Imbens and Kalyanaraman (2012) and Calonico, Cattaneo and Titiunik (2014*b*) first discard the outliers in the empirical data (i.e. observations for which the absolute value of the running variable is very large) and then fit a separate quintic function on each side of the cutoff to the remaining observations. The conditional expectation functions are

$$\text{Lee: } E[Y|X=x] = \begin{cases} 0.48 + 1.27x + 7.18x^2 + 20.21x^3 + 21.54x^4 + 7.33x^5 & \text{if } x < 0 \\ 0.52 + 0.84x - 3.00x^2 + 7.99x^3 - 9.01x^4 + 3.56x^5 & \text{if } x \geqslant 0 \end{cases} \tag{A5}$$

$$\text{Ludwig-Miller: } E[Y|X=x] = \begin{cases} 3.71 + 2.30x + 3.28x^2 + 1.45x^3 + 0.23x^4 + 0.03x^5 & \text{if } x < 0 \\ 0.26 + 18.49x - 54.81x^2 + 74.30x^3 - 45.02x^4 + 9.83x^5 & \text{if } x \geqslant 0. \end{cases} \tag{A6}$$

Equations (A5) and (A6) are graphed in Appendix Figure A.1. The assignment variable X is specified as following the distribution $2\mathscr{B}(2,4)-1$, where $\mathscr{B}(a,b)$ denotes a beta distribution with shape parameters a and b. The outcome variable is given by $Y = E[Y|X=x] + \varepsilon$, where $\varepsilon \sim N(0, \sigma_\varepsilon^2)$ with $\sigma_\varepsilon = 0.1295$.

B.2 Card-Lee-Pei-Weber DGPs

The process of specifying the Card-Lee-Pei-Weber DGPs are described in section 4.4.3 of Card et al. (2017). In both the bottom- and top-kink DGPs, the first-stage and reduced-form conditional expectation functions are specified as

$$\text{First-stage: } E[B|X=x] = \begin{cases} \beta_0 + \beta_1^+ x + \beta_2^+ x^2 + \beta_3^+ x^3 + \beta_4^+ x^4 + \beta_5^+ x^5 & \text{if } x < 0 \\ \beta_0 + \beta_1^- x + \beta_2^- x^2 + \beta_3^- x^3 + \beta_4^- x^4 + \beta_5^- x^5 & \text{if } x \geqslant 0 \end{cases} \tag{A7}$$

$$\text{Reduced-form: } E[Y|X=x] = \begin{cases} \gamma_0 + \gamma_1^+ x + \gamma_2^+ x^2 + \gamma_3^+ x^3 + \gamma_4^+ x^4 + \gamma_5^+ x^5 & \text{if } x < 0 \\ \gamma_0 + \gamma_1^- x + \gamma_2^- x^2 + \gamma_3^- x^3 + \gamma_4^- x^4 + \gamma_5^- x^5 & \text{if } x \geqslant 0. \end{cases} \tag{A8}$$

We also specify $\sigma_B^2(0^+)$, $\sigma_B^2(0^-)$, $\sigma_Y^2(0^+)$, and $\sigma_Y^2(0^-)$, which are the conditional variances of B and Y given X just above and below the cutoff. Finally, we specify $f_X(0)$, the density of X at the cutoff. The values of these parameters are provided in Appendix Table B.5.

C AMSE Calculation and Estimation

C.1 Theoretical AMSE Calculation

After the full specification of a data generating process, we can calculate $\mathrm{AMSE}_{\hat{\tau}_p}(h)$ by applying Lemma 1 of Calonico, Cattaneo and Titiunik (2014*b*) in a sharp design and Lemma 2 in a fuzzy design. The lemmas provide the expressions for the constants in the squared-bias and variance terms, B_p^2 and V_p, that make up $\mathrm{AMSE}_{\hat{\tau}_p}(h)$ according to equation (3). Specifically, B_p^2 depends on the $(p+1)$th derivatives on both sides of the cutoff, and V_p depends on the conditional variances on both sides of the cutoff as well as the density of the running variable at the cutoff. With B_p^2 and V_p computed, we can calculate the infeasible optimal bandwidth h_{opt} for a given sample size, which is simply a function of B_p^2 and V_p. Finally, plugging h_{opt} back into $\mathrm{AMSE}_{\hat{\tau}_p}(h)$ yields the AMSE for that given sample size, and Figure 1 is the graphical representation of this mapping across different sample sizes.

C.2 AMSE Estimation

To estimate $\mathrm{AMSE}_{\hat{\tau}_p}$, we rely on the proposed procedure in Calonico, Cattaneo and Titiunik (2014*a*,*b*). Our program `rdmse_cct2014` takes user-specified bandwidths as inputs and estimates $\hat{\mathrm{B}}_p^2$ and $\hat{\mathrm{V}}_p$ for the conventional estimator in the same way as Calonico, Cattaneo and Titiunik (2014*b*). The correspondences between $\hat{\mathrm{B}}_p$ and $\hat{\mathrm{V}}_p$ in this paper and their notations in Calonico, Cattaneo and Titiunik (2014*b*) are laid out in Table C.1. We also provide another program `rdmse`, which speeds up the computation in `rdmse_cct2014` by modifying variance estimations. As with Calonico, Cattaneo and Titiunik (2014*b*), `rdmse` implements a nearest-neighbor estimator as per Abadie and Imbens (2006) and sets the number of neighbors to three. However, in the event of a tie, while Calonico, Cattaneo and Titiunik (2014*b*) selects all of the closest neighbors, we randomly select three neighbors. We adopt the same modification in Card et al. (2015).

Additionally, `rdmse` estimates the AMSE of the bias-corrected RD or RK estimator $\hat{\tau}_p^{bc}$:

$$\widehat{\text{AMSE}}_{\hat{\tau}_p^{bc}}(h,b) = \left(\tilde{\text{B}}_p^{bc}(h,b)\right)^2 + \tilde{\text{V}}_p^{bc}(h,b),$$

where b is the pilot bandwidth used in Calonico, Cattaneo and Titiunik (2014*b*) to estimate the bias of $\hat{\tau}_p$. According to Theorems A.1 and A.2 of Calonico, Cattaneo and Titiunik (2014*b*), the bias of $\hat{\tau}_p^{bc}$ has two terms: the first term is the higher-order approximation error post bias-correction, and the second term captures the bias in estimating the bias of $\hat{\tau}_p$. These two terms involve the $(p+2)$th derivatives of the conditional expectation function on both sides of the cutoff, which are estimated via local polynomial regressions in the CCT bandwidth selection procedure for the sharp design, and in the "fuzzy CCT" bandwidth selection procedure of Card et al. (2015). We follow the same algorithm to arrive at $\tilde{\text{B}}_p^{bc}$. $\tilde{\text{V}}_p^{bc}$ is simply the estimated variance of $\hat{\tau}_p^{bc}$, and its computation is covered in detail in Calonico, Cattaneo and Titiunik (2014*b*). In Table C.1, we provide details on the AMSE calculations in our software implementation by presenting the correspondence between the expressions in this paper to those in Calonico, Cattaneo and Titiunik (2014*a*,*b*).

Finally, as mentioned in Appendix A, our AMSE estimator is consistent for the true MSE in a sharp design. Consistency in the fuzzy design and for $\widehat{\text{AMSE}}_{\hat{\tau}_p^{bc}}(h,b)$ can be similarly established.

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Figure A.1: Conditional Expectation Functions in RDD DGPs

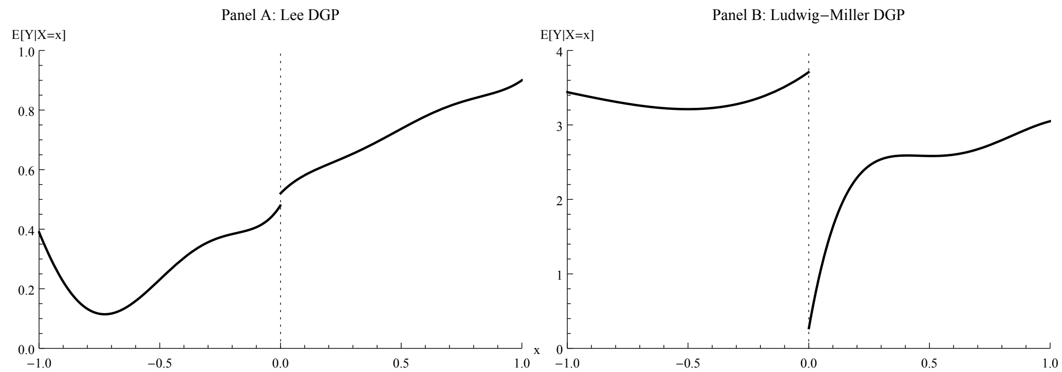

Figure A.2: Conditional Expectation Functions in RKD DGPs

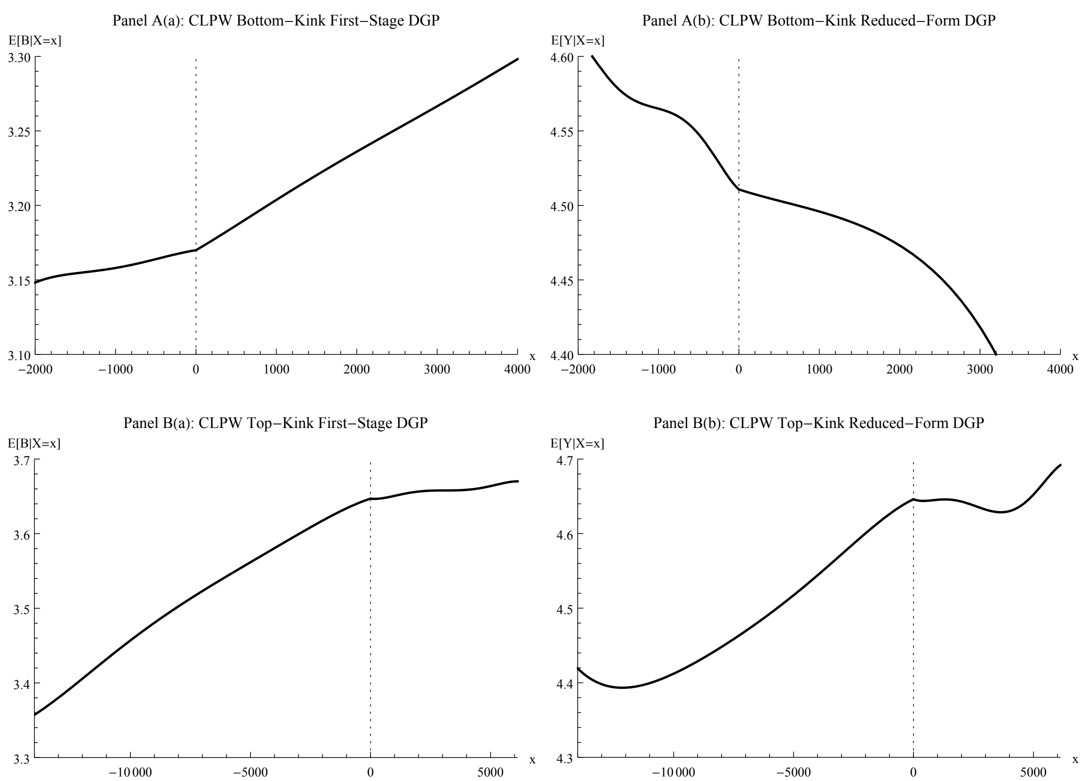

Table A.1: Main Specification of RD Papers Published in Leading Journals

Main Specification	Number of Papers	1999-2010	2011-2017
Local constant	11	8	3
Local linear	45	9	36
Local quadratic	6	1	5
Local cubic	5	4	1
Local quartic	2	2	0
Local 7th-order	1	1	0
Local 8th-order	1	0	1
Local but did not mention preferred polynomial	5	0	5
Total local	76	25	51
Global linear	4	1	3
Global quadratic	4	0	4
Global cubic	11	5	6
Global quartic	4	2	2
Global 5th-order	1	0	1
Global 8th-order	1	0	1
Global but did not mention preferred polynomial	1	0	1
Total global	26	8	18
Did not mention preferred specification	8	2	6
Total	110	35	75

Note: Our survey includes empirical RD papers published between 1999 and 2017 in the following journals: *American Economic Review*, *American Economic Journals*, *Econometrica, Journal of Political Economy*, *Journal of Business and Economic Statistics*, *Quarterly Journal of Economics*, *Review of Economic Studies*, and *Review of Economics and Statistics*.

Table B.1: Simulation Statistics for the Bias-corrected Estimator of Various Polynomial Orders: Lee DGP, Actual and Large Sample Sizes

Panel A: Actual Sample Size (n=6,558)

(a): Simulation Statistics for the Local Linear Estimator (p=1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bandwidth	p	Avg. h	Avg. n	MSE ×1000	Coverage Rate	Avg. CI Length	Avg. Size-adj. CI length
Theo. Optimal	1	0.099	811	0.483	0.947	0.085	0.086
CCT	1	0.139	1140	0.481	0.906	0.077	0.089

(b): Simulation Statistics for Other Polynomial Orders as Compared to p=1

Bandwidth	p	Avg. h	Avg. n	Ratio of MSE's	Coverage Rate	Ratio of Avg. CI Lengths	Ratio of Avg. Size-adj. CI lengths
Theo. Optimal	0	0.022	183	1.298	0.945	1.132	1.145
	2	0.216	1766	0.905	0.949	0.959	0.951
	3	0.407	3321	0.800	0.952	0.904	0.887
	4	0.747	5739	0.770	0.952	0.890	0.873
	$\hat{p}$			0.814	0.948	0.898	
	Fraction of time $\hat{p}$=(0,1,2,3,4): (0, 0, 0, .607, .392)						
CCT	0	0.032	266	1.056	0.909	1.034	1.025
	2	0.248	2030	0.980	0.938	1.061	0.953
	3	0.344	2808	1.141	0.946	1.166	1.018
	4	0.390	3180	1.503	0.945	1.337	1.182
	$\hat{p}$			1.009	0.903	0.993	
	Fraction of time $\hat{p}$=(0,1,2,3,4): (.219, .668, .101, .012, 0)						

Panel B: Large Sample Size (n=60,000)

(a): Simulation Statistics for the Local Linear Estimator (p=1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bandwidth	p	Avg. h	Avg. n	MSE ×1000	Coverage Rate	Avg. CI Length	Avg. Size-adj. CI length
Theo. Optimal	1	0.064	4766	0.080	0.945	0.034	0.035
CCT	1	0.080	6020	0.075	0.931	0.032	0.034

(b): Simulation Statistics for Other Polynomial Orders as Compared to p=1

Bandwidth	p	Avg. h	Avg. n	Ratio of MSE's	Coverage Rate	Ratio of Avg. CI Lengths	Ratio of Avg. Size-adj. CI lengths
Theo. Optimal	0	0.011	798	1.624	0.948	1.290	1.283
	2	0.157	11782	0.815	0.950	0.909	0.894
	3	0.319	23847	0.677	0.948	0.829	0.822
	4	0.610	44516	0.568	0.947	0.763	0.757
	$\hat{p}$			0.596	0.944	0.766	
	Fraction of time $\hat{p}$=(0,1,2,3,4): (0, 0, 0, .054, .946)						
CCT	0	0.013	983	1.493	0.935	1.248	1.237
	2	0.181	13539	0.883	0.942	0.964	0.936
	3	0.323	24147	0.827	0.946	0.941	0.893
	4	0.400	29856	1.021	0.950	1.047	0.976
	$\hat{p}$			0.832	0.942	0.934	
	Fraction of time $\hat{p}$=(0,1,2,3,4): (0, .002, .196, .780, .023)						

Table B.2: Simulation Statistics for the Bias-corrected Estimator of Various Polynomial Orders: Ludwig-Miller DGP, Actual and Large Sample Sizes

Panel A: Actual Sample Size (n=3,105)

(a): Simulation Statistics for the Local Linear Estimator (p=1)

Bandwidth	(1) p	(2) Avg. h	(3) Avg. n	(4) MSE ×1000	(5) Coverage Rate	(6) Avg. CI Length	(7) Avg. Size-adj. CI length
Theo. Optimal	1	0.057	222	1.617	0.939	0.155	0.164
CCT	1	0.064	247	1.562	0.935	0.151	0.162

(b): Simulation Statistics for Other Polynomial Orders as Compared to p=1

Bandwidth	p	Avg. h	Avg. n	Ratio of MSE's	Coverage Rate	Ratio of Avg. CI Lengths	Ratio of Avg. Size-adj. CI lengths
Theo. Optimal	2	0.181	702	0.665	0.940	0.819	0.815
	3	0.406	1566	0.507	0.945	0.720	0.699
	4	0.814	2881	0.484	0.946	0.709	0.684
	$\hat{p}$			0.515	0.941	0.715	
	Fraction of time $\hat{p}$=(1,2,3,4): (0, 0, .700, .300)						
CCT	2	0.198	770	0.692	0.938	0.836	0.819
	3	0.337	1304	0.769	0.941	0.870	0.848
	4	0.384	1484	1.011	0.939	0.998	0.978
	$\hat{p}$			0.685	0.939	0.828	
	Fraction of time $\hat{p}$=(1,2,3,4): (0, .706, .294, .001)						

Panel B: Large Sample Size (n=30,000)

(a): Simulation Statistics for the Local Linear Estimator (p=1)

Bandwidth	(1) p	(2) Avg. h	(3) Avg. n	(4) MSE ×1000	(5) Coverage Rate	(6) Avg. CI Length	(7) Avg. Size-adj. CI length
Theo. Optimal	1	0.036	1364	0.251	0.947	0.062	0.063
CCT	1	0.039	1469	0.244	0.945	0.061	0.062

(b): Simulation Statistics for Other Polynomial Orders as Compared to p=1

Bandwidth	p	Avg. h	Avg. n	Ratio of MSE's	Coverage Rate	Ratio of Avg. CI Lengths	Ratio of Avg. Size-adj. CI lengths
Theo. Optimal	0	0.003	109	3.456	0.943	1.849	1.871
	2	0.131	4904	0.590	0.951	0.771	0.759
	3	0.315	11802	0.422	0.950	0.652	0.644
	4	0.662	23874	0.340	0.951	0.588	0.576
	$\hat{p}$			0.373	0.944	0.594	
	Fraction of time $\hat{p}$=(0,1,2,3,4): (0, 0, 0, .105, .896)						
CCT	0	0.003	115	3.425	0.943	1.849	1.859
	2	0.141	5301	0.602	0.948	0.776	0.766
	3	0.315	11785	0.499	0.949	0.702	0.691
	4	0.399	14892	0.627	0.947	0.781	0.773
	$\hat{p}$			0.499	0.948	0.701	
	Fraction of time $\hat{p}$=(0,1,2,3,4): (0, 0, .010, .961, .029)						

Table B.3: Simulation Statistics for the Conventional Estimator of Various Polynomial Orders: Lee and Ludwig-Miller DGP, Small Sample Size

Panel A: Lee DGP, Small Sample Size (n=500)

(a): Simulation Statistics for the Local Linear Estimator (p=1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bandwidth	p	Avg. h	Avg. n	MSE ×1000	Coverage Rate	Avg. CI Length	Avg. Size-adj. CI length
Theo. Optimal	1	0.166	103	3.692	0.922	0.222	0.250
CCT	1	0.205	128	3.901	0.893	0.202	0.246

(b): Simulation Statistics for Other Polynomial Orders as Compared to p=1

Bandwidth	p	Avg. h	Avg. n	Ratio of MSE's	Coverage Rate	Ratio of Avg. CI Lengths	Ratio of Avg. Size-adj. CI lengths
Theo. Optimal	0	0.053	33	1.101	0.878	0.929	1.077
	2	0.311	194	1.121	0.927	1.076	1.050
	3	0.542	333	1.137	0.928	1.087	1.056
	4	0.943	496	1.150	0.928	1.092	1.066
	$\hat{p}$			1.187	0.871	0.954	
	Fraction of time $\hat{p}$=(0,1,2,3,4): (.525, .430, .013, .018, .015)						
CCT	0	0.084	52	1.162	0.729	0.811	1.123
	2	0.271	169	1.386	0.919	1.269	1.194
	3	0.318	198	1.977	0.920	1.551	1.457
	4	0.351	219	2.778	0.918	1.848	1.729
	$\hat{p}$			1.138	0.742	0.831	
	Fraction of time $\hat{p}$=(0,1,2,3,4): (.731, .269, .001, 0, 0)						

Panel B: Ludwig-Miller DGP, Small Sample Size (n=500)

(a): Simulation Statistics for the Local Linear Estimator (p=1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bandwidth	p	Avg. h	Avg. n	MSE ×1000	Coverage Rate	Avg. CI Length	Avg. Size-adj. CI length
Theo. Optimal	1	0.082	51	8.618	0.910	0.354	0.419
CCT	1	0.097	60	9.377	0.869	0.319	0.430

(b): Simulation Statistics for Other Polynomial Orders as Compared to p=1

Bandwidth	p	Avg. h	Avg. n	Ratio of MSE's	Coverage Rate	Ratio of Avg. CI Lengths	Ratio of Avg. Size-adj. CI lengths
Theo. Optimal	2	0.235	147	0.658	0.933	0.843	0.762
	3	0.497	307	0.521	0.944	0.762	0.664
	4	0.961	498	0.463	0.951	0.733	0.618
	$\hat{p}$			0.519	0.940	0.741	
	Fraction of time $\hat{p}$=(1,2,3,4): (.004, .005, .519, .473)						
CCT	2	0.246	154	0.660	0.915	0.904	0.764
	3	0.323	201	0.798	0.933	1.062	0.856
	4	0.357	222	1.141	0.930	1.287	1.046
	$\hat{p}$			0.677	0.912	0.903	
	Fraction of time $\hat{p}$=(1,2,3,4): (.014, .913, .072, .001)						

Table B.4: Simulation Statistics for the Bias-corrected Estimator of Various Polynomial Orders: Lee and Ludwig-Miller DGP, Small Sample Size

Panel A: Lee DGP, Small Sample Size (n=500)

(a): Simulation Statistics for the Local Linear Estimator (p=1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bandwidth	p	Avg. h	Avg. n	MSE ×1000	Coverage Rate	Avg. CI Length	Avg. Size-adj. CI length
Theo. Optimal	1	0.166	103	4.514	0.928	0.252	0.277
CCT	1	0.205	128	4.831	0.913	0.239	0.274

(b): Simulation Statistics for Other Polynomial Orders as Compared to p=1

Bandwidth	p	Avg. h	Avg. n	Ratio of MSE's	Coverage Rate	Ratio of Avg. CI Lengths	Ratio of Avg. Size-adj. CI lengths
Theo. Optimal	0	0.053	33	0.987	0.921	0.985	1.018
	2	0.311	194	1.026	0.932	1.017	1.003
	3	0.542	333	1.013	0.932	1.013	0.995
	4	0.943	496	1.282	0.933	1.139	1.128
	p̂			0.999	0.920	0.971	
	Fraction of time p̂=(0,1,2,3,4): (.626, .227, .032, .115, 0)						
CCT	0	0.084	52	0.725	0.900	0.825	0.859
	2	0.271	169	1.354	0.928	1.219	1.182
	3	0.318	198	1.895	0.925	1.461	1.416
	4	0.351	219	2.628	0.924	1.720	1.689
	p̂			0.729	0.899	0.825	
	Fraction of time p̂=(0,1,2,3,4): (.977, .023, 0, 0, 0)						

Panel B: Ludwig-Miller DGP, Small Sample Size (n=500)

(a): Simulation Statistics for the Local Linear Estimator (p=1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bandwidth	p	Avg. h	Avg. n	MSE ×1000	Coverage Rate	Avg. CI Length	Avg. Size-adj. CI length
Theo. Optimal	1	0.082	51	8.026	0.933	0.372	0.401
CCT	1	0.097	60	7.562	0.928	0.346	0.385

(b): Simulation Statistics for Other Polynomial Orders as Compared to p=1

Bandwidth	p	Avg. h	Avg. n	Ratio of MSE's	Coverage Rate	Ratio of Avg. CI Lengths	Ratio of Avg. Size-adj. CI lengths
Theo. Optimal	2	0.235	147	0.708	0.942	0.835	0.802
	3	0.497	307	0.586	0.947	0.757	0.712
	4	0.961	498	0.716	0.946	0.846	0.801
	p̂			0.630	0.940	0.762	
	Fraction of time p̂=(1,2,3,4): (.021, .124, .843, .012)						
CCT	2	0.246	154	0.862	0.939	0.928	0.873
	3	0.323	201	1.188	0.937	1.096	1.044
	4	0.357	222	1.681	0.934	1.315	1.272
	p̂			0.866	0.932	0.919	
	Fraction of time p̂=(1,2,3,4): (.186, .793, .021, 0)						

Table B.5: Parameter Values in the Card-Lee-Pei-Weber DGPs

	Bottom-Kink DGP		Top-Kink DGP	
Parameter	Above Cutoff	Below Cutoff	Above Cutoff	Below Cutoff
β_0	3.17	3.17	3.65	3.65
β_1	3.14×10^{-5}	8.40×10^{-6}	-3.70×10^{-6}	1.03×10^{-5}
β_2	5.30×10^{-9}	-1.21×10^{-8}	1.25×10^{-8}	-3.18×10^{-9}
β_3	-3.82×10^{-12}	-1.01×10^{-11}	-6.17×10^{-12}	-5.72×10^{-13}
β_4	9.54×10^{-16}	-7.56×10^{-16}	1.16×10^{-15}	-4.83×10^{-17}
β_5	-8.00×10^{-20}	7.89×10^{-19}	-7.43×10^{-20}	-1.42×10^{-21}
γ_0	4.51	4.51	4.65	4.65
γ_1	-1.76×10^{-5}	-4.75×10^{-5}	-1.29×10^{-5}	1.51×10^{-5}
γ_2	7.00×10^{-9}	1.64×10^{-7}	2.35×10^{-8}	-5.69×10^{-9}
γ_3	-5.00×10^{-12}	3.04×10^{-10}	-1.42×10^{-11}	-1.07×10^{-12}
γ_4	1.00×10^{-15}	1.82×10^{-13}	3.04×10^{-15}	-8.49×10^{-17}
γ_5	-2.00×10^{-19}	3.53×10^{-17}	-2.06×10^{-19}	-2.65×10^{-21}
σ_B^2	2.05×10^{-4}	2.07×10^{-4}	1.20×10^{-3}	9.60×10^{-4}
σ_Y^2	1.51	1.49	1.62	1.63
f_X	1.53×10^{-4}	1.53×10^{-4}	2.35×10^{-5}	2.35×10^{-5}

Note: For $j = 1, \ldots, 5$, the values of β_j, γ_j, σ_B^2, and σ_Y^2 above the cutoff correspond, respectively, to those of β_j^+, γ_j^+, $\sigma_B^2(0^+)$, and $\sigma_Y^2(0^+)$, which are defined in Appendix B.2. The values of β_j, γ_j, σ_B^2, and σ_Y^2 below the cutoff correspond, respectively, to those of β_j^-, γ_j^-, $\sigma_B^2(0^-)$, and $\sigma_Y^2(0^-)$. By construction, the values of β_0, γ_0, and f_X are the same on both sides of the cutoff.

Table C.1: Correspondence to the Expressions in Calonico, Cattaneo and Titiunik (2014*a*,*b*)

Expression in this paper	Expression in Calonico, Cattaneo and Titiunik (2014*a*,*b*) for the case of	
	Sharp RD ($\nu = 0$)/RK ($\nu = 1$)	Fuzzy RD ($\nu = 0$)/RK ($\nu = 1$)
B_p	$\mathrm{B}_{\nu,p,p+1,0}$[SAp.38]	$\mathrm{B}_{\mathrm{F},\nu,p,p+1}$[SAp.39]
V_p	$\mathrm{V}_{\nu,p}$[SAp.38]	$\mathrm{V}_{\mathrm{F},\nu,p}$[SAp.39]
$\hat{\mathrm{B}}_p$	$\hat{B}_{n,p,q}$[SJp.920]	$\hat{B}_{n,p,q}$[SJp.920]
$\hat{\mathrm{V}}_p$	$\hat{V}_p$[SJp.920]	$\hat{V}_p$[SJp.920]
$\tilde{\mathrm{B}}_p^{bc}(h,b)$	Estimator of $h_n^{p+2-\nu}\mathrm{B}_{\nu,p,p+1}(h_n) - h_n^{p+1-\nu}b_n^{q-p}\mathrm{B}^{\mathrm{bc}}_{\nu,p,q}(h_n,b_n)$[p.2321]	Estimator of $h_n^{p+2-\nu}\mathrm{B}_{\mathrm{F},\nu,p,p+1}(h_n) - h_n^{p+1-\nu}b_n^{q-p}\mathrm{B}^{\mathrm{bc}}_{\mathrm{F},\nu,p,q}(h_n,b_n)$[p.2323]
$\tilde{\mathrm{V}}_p^{bc}(h,b)$	$\hat{V}^{\mathrm{bc}}_{n,p,q}$[SJp.922]	$\hat{V}^{\mathrm{bc}}_{n,p,q}$[SJp.922]

Note: The number after "p." and "SAp." refers to the page on which the particular expression appears in the main article or the Supplemental Appendix of Calonico, Cattaneo and Titiunik (2014*b*), respectively. The number after "SJp." refers to the page on which the particular expression appears in Calonico, Cattaneo and Titiunik (2014*b*). We set $q = p + 1$ for all of our estimators, which is the default used by Calonico, Cattaneo and Titiunik (2014*b*).