Does Extending Unemployment Benefits Improve Job Quality? Comment

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In contrast with a large body of existing literature, Nekoei and Weber (2017, NW henceforth) find a positive effect of unemployment insurance on job quality. This comment shows that NW's finding is driven by unnecessarily large bandwidths used in their regression discontinuity analysis. When the focus is on the data near the cutoff of the regression discontinuity design, the significantly positive effect documented in NW vanishes. Thus, re-examining NW's empirical analysis leads to results that are consistent with, rather than contrary to, many past studies. Our findings indicate the importance of using a range of bandwidths in future studies. (*JEL* J31, J64, J65)

The effect of unemployment insurance on job quality has attracted sizable attention in economics. By using an age-based regression discontinuity design, NW report that unemployment insurance increases reemployment wages. This positive effect, however, is in sharp contrast with many past studies that find either insignificant or negative wage effects; see, for example, Card, Chetty, and Weber (2007), Lalive (2007), Van Ours and Vodopivec (2008), and Schmieder, von Wachter, and Bender (2016).

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In this comment, we revisit the regression discontinuity analysis conducted by NW for estimating the wage effect. In particular, we show that the bandwidths used in NW appear to be unnecessarily large, in the sense that they substantially exceed those resulting from commonly used data-driven methods. The large bandwidths allow distant data points to be included in empirical analysis, leading to significant estimation outcomes that would have been insignificant and sign-reversed if smaller bandwidths derived from data-driven methods were adopted. As a result, the positive wage effect documented in NW is not driven by the data near the regression discontinuity cutoff, so whether it appropriately captures the causal effect of unemployment insurance on job quality is under doubt.

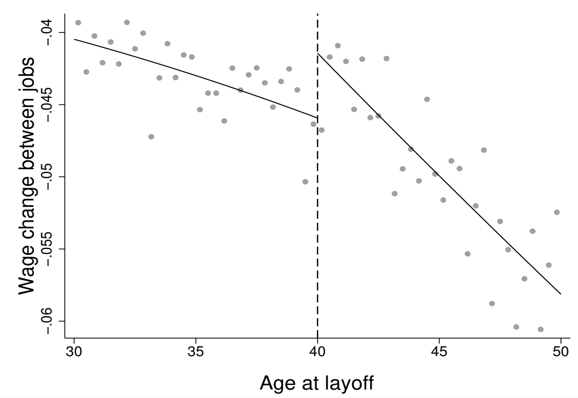
From the empirical perspective, our findings show the importance of reporting regression discontinuity estimates for a range of bandwidths in future studies. While practitioners commonly select several bandwidths for sensitivity analysis, this common practice unfortunately may still lead to misleading results as we show later on. To help alleviate this problem, we make several practical suggestions in the concluding remarks.

I. Data

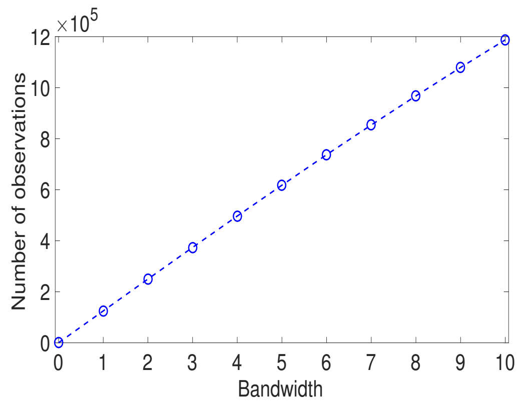
The two variables used for this comment are illustrated by Figure 1(a):[1] the horizontal running variable is the age at layoff of individuals between 30 and 50, while the vertical outcome variable is change in log wage between post- and pre- unemployment jobs. NW consider a regression discontinuity design where individuals older than 40 are eligible for extra unemployment insurance benefit, and report an estimated 0.45 percent point wage increase as reflected by the positive discontinuity at the cutoff 40.

Figure 1(b) presents the number of observations as the bandwidth increases. It shows that there are a large amount of data to facilitate the regression discontinuity analysis even if bandwidths are not large. For example, if we consider the bandwidth to be 1 year, then there are over 100,000

[1] Figure 1(a) corresponds to Figure 3 Panel C in NW, which we replicate by using the data from the *American Economic Review* website.



(a) Unemployment insurance effect on wage



(b) Number of observations as bandwidth increases

Figure 1: Regression discontinuity design in NW

Notes: (a) x-axis, age at layoff; y-axis, change in log wage between post- and pre- unemployment jobs. The dots show the sample mean of the vertical variable in each bin of the horizontal variable (30 bins on each side of the cutoff 40). The solid line represents the fitted second-order polynomial. As the bandwidth (distance to the cutoff 40) increases, (b) presents the number of observations within the corresponding bandwidth.

observations in the age group 39 ∼ 41 from the NW data. When 10 is used as the bandwidth, the total number of observations is over 1 million (1,187,476) in the age group 30 ∼ 50. As the bandwidth increases, however, a substantial portion of the data used in the regression discontinuity analysis will be further away from the cutoff 40, as indicated by Figure 1(b).

Figure 2 presents the data near the cutoff 40. The age group is 39 ∼ 41, so the bandwidth is 1, and the number of observations is 124,845. Unlike Figure 1(a), the discontinuity in Figure 2 does not appear significant; moreover, its sign is reversed from positive in Figure 1(a) to negative in Figure 2.

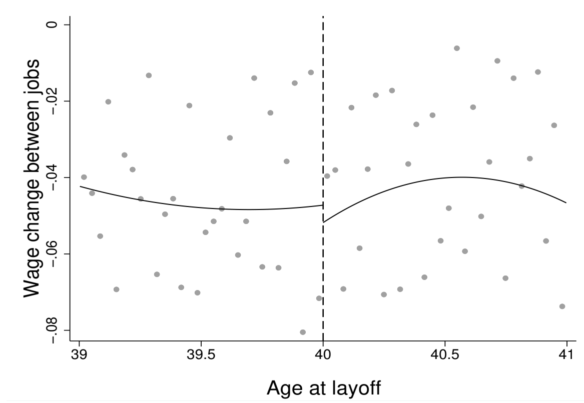


Figure 2: Unemployment insurance effect on wage, $39 < \text{age} < 41$

Notes: This figure is generated in the same manner as Figure 1(a) above, except that the age group is set to 39 ∼ 41. The number of observations is 124,845.

The comparison of Figure 1(a) and Figure 2 conveys the message that the choice of bandwidth matters for the NW study. If researchers focus on the data near the cutoff 40, then the estimated wage effect could be insignificantly negative as indicated by Figure 2. In contrast, once a large bandwidth is adopted, the estimated wage effect can become significantly positive as documented in NW and illustrated by Figure 1(a).

II. Bandwidth

The question now arises: What bandwidth should be used to analyze the NW data? Fortunately, prior research has provided guidance on bandwidth selection. A number of optimal bandwidth choices, which minimize some criteria such as mean squared errors of regression discontinuity estimators, have been proposed; see, for example, Imbens and Kalyanaraman (2012), Calonico, Cattaneo, and Titiunik (2014), and thereafter. Nowadays, popular software packages such as STATA, R, and MATLAB have programs that can be straightforwardly used by practitioners to derive data-driven bandwidths as reported in Table 1 for the NW data.

Table 1: Bandwidth for the NW data

		Bandwidth est. (h)		Bandwidth bias (b)	
	Program	Left of c	Right of c	Left of c	Right of c
IK	STATA, rd	1.008	1.008	-	-
	STATA, rdob	1.008	1.008	-	-
	R, IKbandwidth	1.008	1.008	-	-
	MATLAB, rd_optbandwidth	1.008	1.008	-	-
CCT	STATA, rdrobust: mserd	2.461	2.461	3.775	3.775
	STATA, rdrobust: msetwo	2.258	2.125	3.640	3.790
	STATA, rdrobust: msesum	3.018	3.018	5.599	5.599
	STATA, rdrobust: msecomb1	2.461	2.461	3.775	3.775
	STATA, rdrobust: msecomb2	2.461	2.461	3.775	3.790
CCF	STATA, rdrobust: cerrd	1.223	1.223	3.775	3.775
	STATA, rdrobust: certwo	1.122	1.056	3.640	3.790
	STATA, rdrobust: cersum	1.500	1.500	5.599	5.599
	STATA, rdrobust: cercomb1	1.223	1.223	3.775	3.775
	STATA, rdrobust: cercomb2	1.223	1.223	3.775	3.790
NW	STATA, altrdrobust: IK	4.936	4.936	5.060	5.060
	STATA, altrdrobust: CCT	3.114	3.114	4.681	4.681

Notes: IK, Imbens and Kalyanaraman (2012); CCT, Calonico, Cattaneo, and Titiunik (2014); CCF, Calonico, Cattaneo, and Farrell (2018); NW, Nekoei and Weber (2017). "Bandwidth est. (h)" stands for the main bandwidth used in local linear regression to produce the regression discontinuity estimate. "Bandwidth bias (b)" stands for the pilot bandwidth used in local quadratic regression to correct the bias in the regression discontinuity estimate. "Left of c" and "Right of c" stand for the left and right of the regression discontinuity cutoff, respectively. "rd" and "rdrobust" are build-in commands in STATA. "rdob" for STATA and "rd_optbandwidth" for MATLAB are downloaded from the website of Guido Imbens. R is a free software. "altrdrobust" is used in NW. The triangular kernel is used for calculating all the bandwidths reported in the table. More details on the adopted programs can be found in their descriptions.

What Table 1 shows foremost is that the bandwidth h for calculating the regression discontinuity estimate does not need to be large. Specifically, most of the suggested values for h based on the algorithms of Imbens and Kalyanaraman (2012), Calonico, Cattaneo, and Titiunik (2014), and Calonico, Cattaneo, and Farrell (2018) are between 1 and 3 in Table 1. These values are substantially smaller than 10, the bandwidth used in NW to produce their main result.

III. Estimation by Second-Order Polynomial

The main estimation result in NW for the wage effect of unemployment insurance is based on the quadratic polynomial with the bandwidth of 10 years to the left and the right of the cutoff (see their Table 2, Column 4). NW also consider the bandwidth of 5 years for additional check (see their Appendix Table A2, Columns 1 and 4). Page 538 of NW states: "Our results are robust to variations in the polynomial degrees of the supporting functions or the choice of bandwidth."

In Figure 3, we consider a sequence of bandwidths ranging from 1 to 10 with step size 0.5: 1, 1.5, 2, 2.5, 3, ..., 10. The purpose is to illustrate how the bandwidth choice might affect the finding of NW, since Table 1 suggests small bandwidths while NW use large ones. For ease of exposition, we present both the estimated wage effect $\pm$ 1.96 standard error and the resulting t-statistic as a function of the bandwidth.

Figure 3 shows that the two significant results documented in NW, which are highlighted in red circles, rely on the large bandwidth they select. For smaller bandwidths such as those around $1 \sim 3$, which are favored by Table 1, the t-statistics in Figure 3 are insignificant at the commonly used 5% level, so the 95% confidence intervals of the wage effect contain zero. Moreover, the point estimate of the wage effect is negative if the bandwidth is around 1. Thus, Figure 3 reveals that the significantly positive wage effect found by NW is caused by including the data that are not close to the regression discontinuity cutoff. The findings presented in Figure 3 are therefore consistent with the comparison of Figure 1(a) and Figure 2 discussed in Section I above.

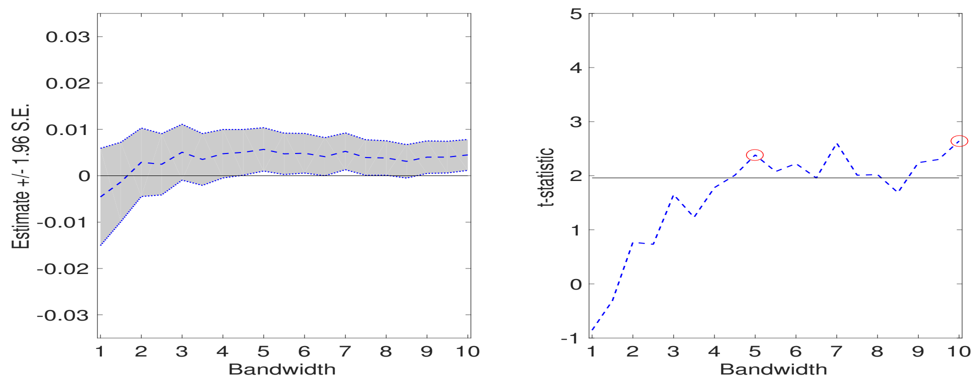


Figure 3: Estimation of the wage effect by using the second-order polynomial

Notes: The left panel presents the point estimate $\pm$ 1.96 standard error of the estimated wage effect as a function of the bandwidth. The right panel presents the t-statistic (estimate/standard error) as a function of the bandwidth. NW use 5 and 10 as the bandwidth, leading to the two t-statistics in red circles. The 0 and 1.96 benchmark lines are also plotted.

It is worth noting that Figure 3 also helps explain conflicting empirical findings on the wage effect of unemployment insurance. Depending on the selected bandwidth, the estimated wage effect could be negative or positive, insignificant or significant.

IV. Estimation by Local Linear Regression

NW further use the local linear regression to infer the wage effect in their Appendix Table A2. Following Calonico, Cattaneo, and Titiunik (2014), the local linear regression estimator has a bias that can be corrected. This leads to two bandwidth choices: (i) the main bandwidth h used for estimating the wage effect in the local linear regression; (ii) the pilot bandwidth b used in a quadratic regression for estimating the bias of the linear regression estimator. In Figure 4, we present the resulting t-statistics on the wage effect for h and b ranging from 1 to 10.

The message conveyed by Figure 4 is similar to that in Figure 3: significantly positive t-statistics on the wage effect (the high yellow area in Figure 4) come with large bandwidths. When either h or b is not large as suggested by data-driven methods, the t-statistics are found to be mostly insignificant in Figure 4, some of which even become negative.

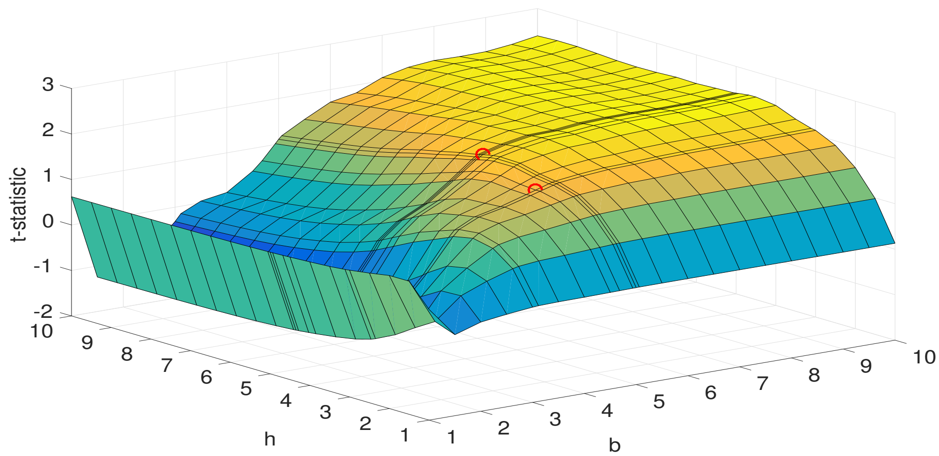


Figure 4: t-statistic on the wage effect based on local linear regression

Notes: h is the bandwidth for the local linear regression. b is the bandwidth used in the quadratic regression for estimating the bias of the linear regression estimator. NW consider two pairs of h and b: $h = 3.114$, $b = 4.681$; $h = 4.936$, $b = 5.06$, leading to the two t-statistics in red circles (see their Appendix Table A2, Columns 8 and 11). The t-statistics presented in this figure use the bias correction and robust standard error of Calonico, Cattaneo, and Titiunik (2014) with the triangular kernel.

Other than the quadratic polynomial and local linear regression with bias correction discussed above, we also explore the other functional forms used in NW for robustness check, such as higher order polynomials, and local linear regression without bias correction. They lead to the bandwidth issue similar to those in Figures 3 and 4, so we relegate them to the Appendix.

Overall, it is well understood that credibility of causal inference in regression discontinuity designs primarily relies on the data near the cutoff/threshold. As stated in Lee and Lemieux (2000): "... there seems little reason to prefer a specification that uses all the data if using the same specification, but restricting to observations closer to the threshold, gives a substantially (and statistically) different answer." From this perspective, whether the positive wage effect documented in NW properly reflects the causal effect of unemployment insurance on job quality is, at least, questionable.

V. Mechanism

The challenge imposed by large bandwidths on causal inference is not limited to the NW study discussed in previous sections. To further articulate this issue, let's consider an illustrative regression discontinuity design depicted in Figure 5, where the solid a, b, and c lines stand for the true relationship of the vertical outcome variable and the horizontal running variable. Since there is no discontinuity in b at the cutoff, the real causal effect in Figure 5 is zero.

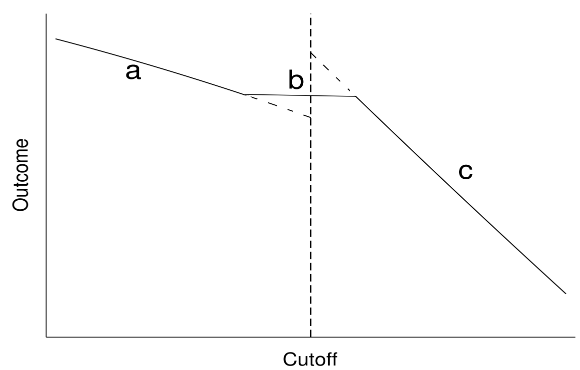


Figure 5: Discontinuity due to large bandwidths

Notes: The solid a, b, and c represent the true relationship of the vertical outcome variable and the horizontal running variable. The dashed a and c lines illustrate the fitted regression lines when large bandwidths are adopted for regression discontinuity analysis.

When arbitrarily large bandwidths are adopted, however, data points that lie around a and c will likely dominate the fewer ones around b. This will force the fitted regression lines (dashed) to exhibit discontinuity at the cutoff. Consequently, we may encounter the seemingly significant causal effect, which should not be taken at its face value.

To evaluate the mechanism depicted in Figure 5, we conduct a simulation experiment. In the data generation process, we use the NW data for the calibration of the lines a, b, and c, and repeatedly draw random samples of the same size. Using the simulated data, we then conduct the quadratic polynomial estimation as NW do for their main result. Figure 6 reports the frequency that we get significantly positive causal effects (i.e., t-statistic $>$ 1.96) as a function of the adopted bandwidth, while the real causal effect is zero in the data generation process.

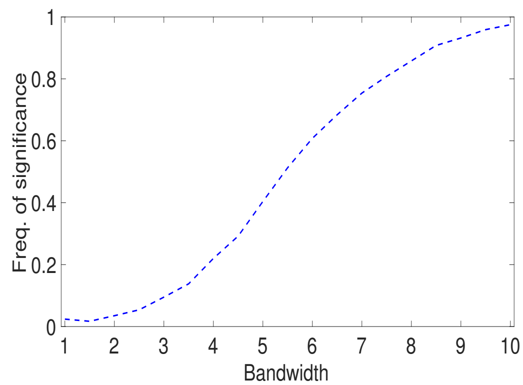


Figure 6: Frequency of false positive significance as a function of the bandwidth

Notes: This figure reports the simulated frequency that the t-statistic on the causal effect exceeds 1.96 in the quadratic polynomial estimation, while the real causal effect is zero in the data generation process. The running variable x is drawn from the uniform distribution between -10 and 10, and its cutoff is normalized to 0. The outcome variable $y = -0.05005 - 0.0004 \cdot x + \epsilon$ for $x \leq 0.75$; $y = -0.046 + 0.005 \cdot x + \epsilon$ for $-0.75 < x < 0.75$; $y = -0.04075 - 0.002 \cdot x + \epsilon$ for $x \geq 0.75$. $\epsilon \sim N(0, 0.3)$. The sample size is 1,187,476. The number of Monte Carlo replications is 1,000.

Consistent with our expectations, Figure 6 shows that as the bandwidth becomes large, we are more likely to get the false positive result in the quadratic regression. In particular, if 10 is the adopted bandwidth, then the chance that we get the false positive significance is almost 100%. These findings therefore cast doubt on causal inference using regression discontinuity analysis with arbitrarily large bandwidths.[2]

[2]In the Appendix, we further use the local linear regression with the triangular kernel for estimation, and find that the simulation outcome is similar to Figure 6. Thus, giving more weight to the observations near the cutoff does not fully resolve the false positive problem caused by large bandwidths.

VI. Conclusion

NW find the positive wage effect of unemployment insurance by using a regression discontinuity design. Yet this comment reveals that NW's finding is driven by the data distant from the cutoff of the regression discontinuity design due to the use of unnecessarily large bandwidths, while the data near the cutoff do not show strong support for the positive wage effect. Given the importance of the topic studied in NW and the fact that NW's estimated wage effect has been taken for economic policy analysis (see, for example, Lawson 2017, page 308), we feel that future researchers deserve to know the findings documented in this comment.

Moreover, the findings presented in this comment also lead us to make three practical suggestions for conducting regression discontinuity analysis: (i) Instead of using some arbitrarily chosen bandwidth, researchers should attach more weight to the bandwidths resulting from data-driven methods; (ii) Instead of reporting estimates for several selected bandwidths, it is helpful to report empirical findings for a sequence of bandwidths which nest those from commonly used data-driven methods; (iii) Instead of relying on data points far from the cutoff, it is important to take a closer look at those near the cutoff.[3] It is apparent that the NW study could have drawn a different conclusion if (i), (ii), and (iii) were accounted for.

[3]These suggestions have been similarly made in several other articles. For example, Cattaneo and Vazquez-Bare (2016) state "Localizing near the cutoff is crucial because empirical findings can be quite sensitive to which observations are included in the analysis" and "Always employ RD optimal data-driven neighborhood (bandwidth or window) selectors, at least as a benchmark or starting point". Lee and Lemieux (2000) also suggest to "Explore the sensitivity of the results to a range of bandwidths".

References

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Appendix

Similar to Figures 3 and 4 presented in the main text, the Appendix revisits some other estimation results of the wage effect in NW to illustrate the bandwidth issue; see Figures 7-11. Figure 12 presents more simulation results.

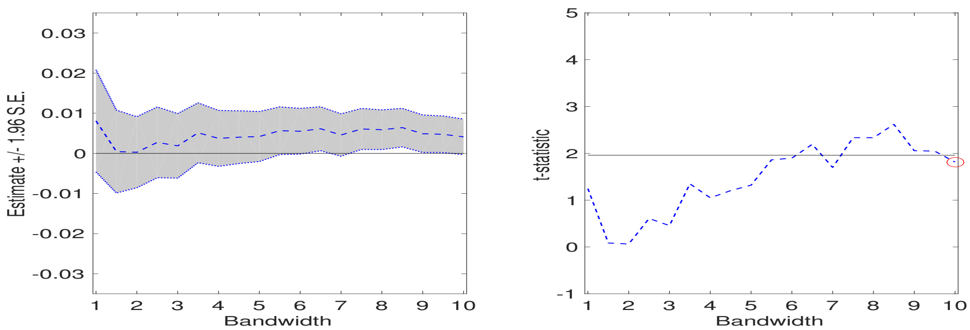

Figure 7: Estimation by using the third-order polynomial

Notes: The left panel presents the point estimate ± 1.96 standard error of the estimated wage effect as a function of the bandwidth. The right panel presents the *t*-statistic (estimate/standard error) as a function of the bandwidth. NW use 10 as the bandwidth (see their Appendix Table A2, Column 2), leading to the *t*-statistic in the red circle.

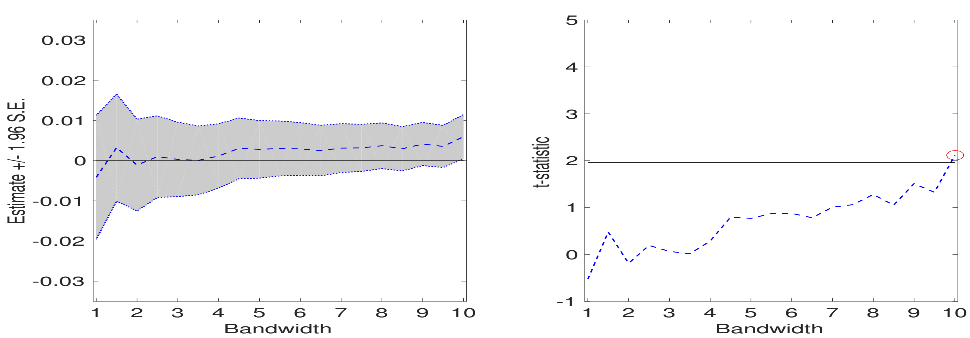

Figure 8: Estimation by using the fourth-order polynomial

Notes: The left panel presents the point estimate ± 1.96 standard error of the estimated wage effect as a function of the bandwidth. The right panel presents the *t*-statistic (estimate/standard error) as a function of the bandwidth. NW use 10 as the bandwidth (see their Appendix Table A2, Column 3), leading to the *t*-statistic in the red circle.

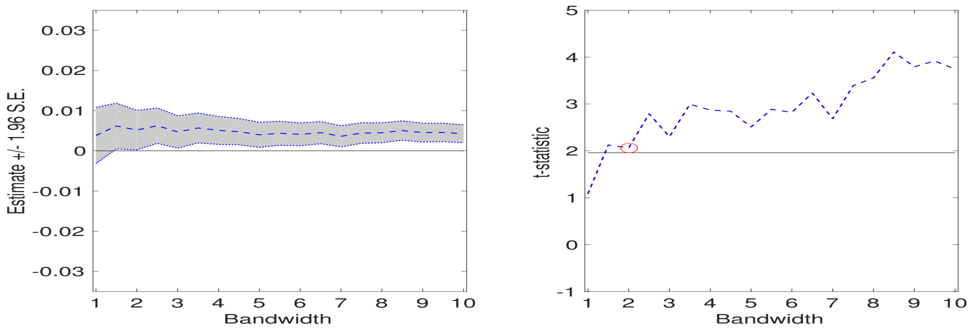

Figure 9: Estimation by using the first-order polynomial

Notes: The left panel presents the point estimate $\pm$ 1.96 standard error of the estimated wage effect as a function of the bandwidth. The right panel presents the t-statistic (estimate/standard error) as a function of the bandwidth. NW use 2 as the bandwidth (see their Appendix Table A2, Column 5), leading to the t-statistic in the red circle.

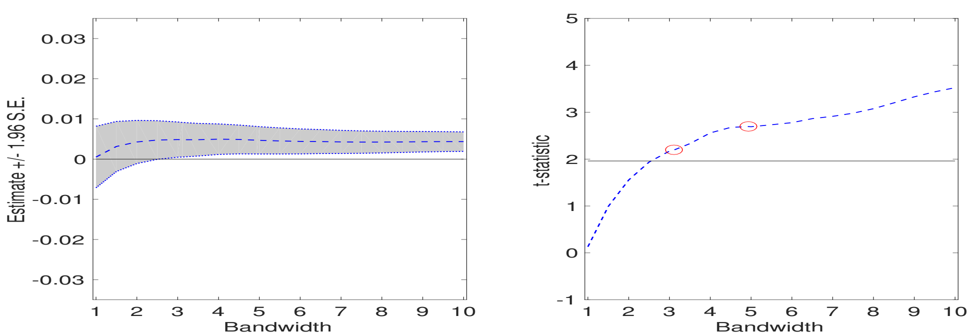

Figure 10: Estimation by local linear regression without bias correction

Notes: The left panel presents the point estimate $\pm$ 1.96 standard error of the estimated wage effect as a function of the bandwidth. The right panel presents the t-statistic (estimate/standard error) as a function of the bandwidth. NW use 3.114 and 4.936 as the bandwidth (see their Appendix Table A2, Columns 6 and 9), leading to the two t-statistics in red circles. The triangular kernel is adopted.

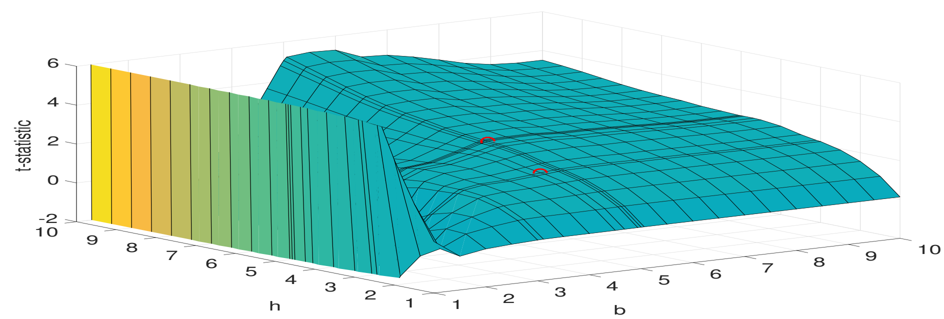

Figure 11: t-statistic on the wage effect based on the local linear regression with bias correction and non-robust standard errors

Notes: h is the bandwidth for the local linear regression. b is the bandwidth used in the quadratic regression for estimating the bias of the linear regression estimator. NW consider two pairs of h and b: $h = 3.114$, $b = 4.681$; $h = 4.936$, $b = 5.06$, leading to the two bias-corrected t-statistics with non-robust standard errors in red circles (see their Appendix Table A2, Columns 7 and 10). The non-robust standard errors ignore the variability due to bias correction. The triangular kernel is used for this figure.

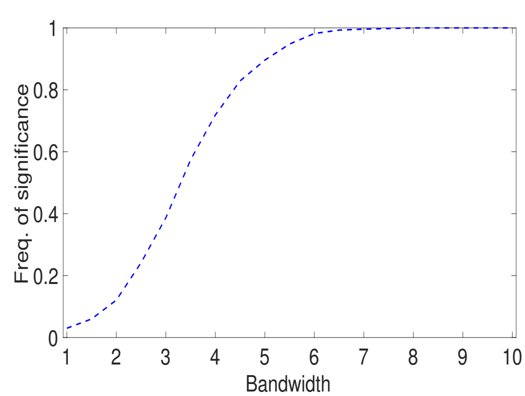

Figure 12: Frequency of false positive significance in local linear regression

Notes: This figure is simulated in the same manner as Figure 6 in the main text, except that the local linear regression with the triangular kernel is used for estimation, instead of the quadratic polynomial.