

## Problem Set #8

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18.2.a This is a regression of  $Y$  on  $D$  with state fixed effects. So

$$\hat{\theta} = \frac{\sum_{t=0}^T \sum_{i=0}^N (D_{it} - \bar{D}_i)(Y_{it} - \bar{Y})}{\sum_{t=0}^T \sum_{i=0}^N (D_{it} - \bar{D}_i)^2}$$

\* where  $\bar{D}_i$  and  $\bar{Y}_i$  are sample averages over time of  $D_{it}$  and  $Y_{it}$ , respectively.

18.2.b For the untreated sub-sample,  $D_{0t}=0$ , so  $\bar{D}_0=0$  and for the treated sub-sample  $D_{10}=0, D_{11}=1, \bar{D}_1=0.5$

$$\begin{aligned} \hat{\theta} &= \frac{(D_{00} - \bar{D}_0)(Y_{00} - \bar{Y}_0) + (D_{01} - \bar{D}_0)(Y_{01} - \bar{Y}_0) + (D_{10} - \bar{D}_1)(Y_{10} - \bar{Y}_1) + (D_{11} - \bar{D}_1)(Y_{11} - \bar{Y}_1)}{(D_{00} - \bar{D}_0)^2 + (D_{01} - \bar{D}_0)^2 + (D_{10} - \bar{D}_1)^2 + (D_{11} - \bar{D}_1)^2} \\ &= \frac{(D_{10} - \bar{D}_1)(Y_{10} - \bar{Y}_1) + (D_{11} - \bar{D}_1)(Y_{11} - \bar{Y}_1)}{(D_{10} - \bar{D}_1)^2 + (D_{11} - \bar{D}_1)^2} \\ &= \frac{(-0.5)(Y_{10} - \bar{Y}_1) + (0.5)(Y_{11} - \bar{Y}_1)}{(0.25) + (0.25)} \\ &= Y_{11} - Y_{10} \end{aligned}$$

18.2.c. No, since  $\hat{\theta}$  doesn't depend on the untreated sub-sample, this is only a difference estimator.

18.2.d. If there is no time trend, e.g.  $E[Y_{00}] = E[Y_{01}]$ .

18.4. If all dummy variables were included, there would be perfect multicollinearity. One needs to be omitted as a reference group.

18.5. a.

	W1	MN	
Pre	15.23	16.42	1.19
Post	16.72	18.10	1.38
Diff	+1.49	+1.68	= -0.19

18.5. b. -0.19

18.5. c. -1.19

17.1. a.  $E[X^*] = \int x \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x_i - x}{h}\right) dx$

$$= \frac{1}{nh} \int x \sum_{i=1}^n K\left(\frac{x_i - x}{h}\right) dx$$

Let  $y = \left(\frac{x_i - x}{h}\right)$ ,  $h dy = dx$ ,  $x = x_i - hy$

$$= \frac{1}{n} \sum_{i=1}^n \int (x_i - yh) K(y) dy$$

$$= \frac{-h}{n} \sum_{i=1}^n \int y K(y) dy + \frac{1}{n} \sum_{i=1}^n \int x_i K(y) dy$$

$$= \frac{1}{n} \sum_{i=1}^n x_i \int K(y) dy$$

$$= \frac{1}{n} \sum_{i=1}^n x_i$$

$$= \bar{X}_n$$

$$\begin{aligned}
 17.1.b. \quad \text{Var}(X^*) &= E[X^{*2}] - E[X^*]^2 \\
 &= \int x^2 \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x_i - x}{h}\right) dx - \bar{X}_n^2 \\
 &= \frac{1}{nh} \int x^2 \sum_{i=1}^n K\left(\frac{x_i - x}{h}\right) dx - \bar{X}_n^2
 \end{aligned}$$





Let  $y = \frac{x_i - x}{h}$ ,  $h dy = dx$ ,  $x = x_i - yh$

$$\begin{aligned}
 &\rightarrow = \frac{1}{n} \sum_{i=1}^n \int (x_i - yh)^2 K(y) dy - \bar{X}_n^2 \\
 &= \frac{1}{n} \sum_{i=1}^n \int (x_i^2 - 2x_i y h + y^2 h^2) K(y) dy - \bar{X}_n^2 \\
 &= \frac{1}{n} \sum_{i=1}^n \int x_i^2 K(y) dy - \frac{2h}{n} \sum_{i=1}^n \int x_i y K(y) dy + \frac{h^2}{n} \sum_{i=1}^n \int y^2 K(y) dy - \bar{X}_n^2 \\
 &= \frac{1}{n} \sum_{i=1}^n x_i^2 + h^2 - \bar{X}_n^2 \\
 &= \hat{\sigma}^2 + h^2
 \end{aligned}$$

17.3 The optimal bandwidth is  $h_o = \left( \frac{R_K}{R(f'')} \right)^{1/5} n^{-1/5}$ .

Since the distribution is uniform,  $f'' = 0$ , so the optimal bandwidth is whatever is the largest feasible.

17.4 Using the same bandwidth will result in a much wider, flatter plot than is appropriate since the scaling changed. The bandwidth should be divided by 1,000,000 to get the same shape density plot.

- 19.3. When  $m(x)$  is increasing and concave  $\rightarrow$  neg. bias.   
 increasing and convex  $\rightarrow$  pos. bias.   
 decreasing and concave  $\rightarrow$  neg. bias   
 decreasing and convex  $\rightarrow$  pos. bias 

This is because you're averaging around the point of interest.

19.4. Bias is:

$$B(x) = \frac{1}{2} m''(x) + m'(x) \frac{f'(x)}{f(x)}$$

$$= \frac{\beta f'(x)}{f(x)}$$

If  $\beta > 0$ , then  $B(x) > 0$  if  $f'(x) > 0$  and  $B(x) < 0$  if  $f'(x) < 0$ .

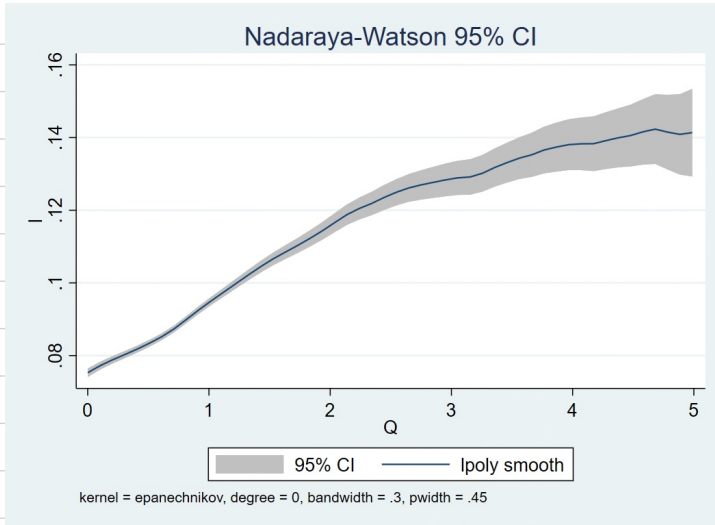
If  $\beta < 0$ , then  $B(x) > 0$  if  $f'(x) < 0$  and  $B(x) < 0$  if  $f'(x) > 0$ .

$f(x)$  is the marginal density of  $x$ . For  $\beta > 0$ , if  $f'(x) > 0$ , then the mass of  $x$  is concentrated to the right of  $x$ , so the bias is positive. If  $f'(x) < 0$ , then the mass of  $x$  is concentrated to the left of  $x$ , so the bias is negative.

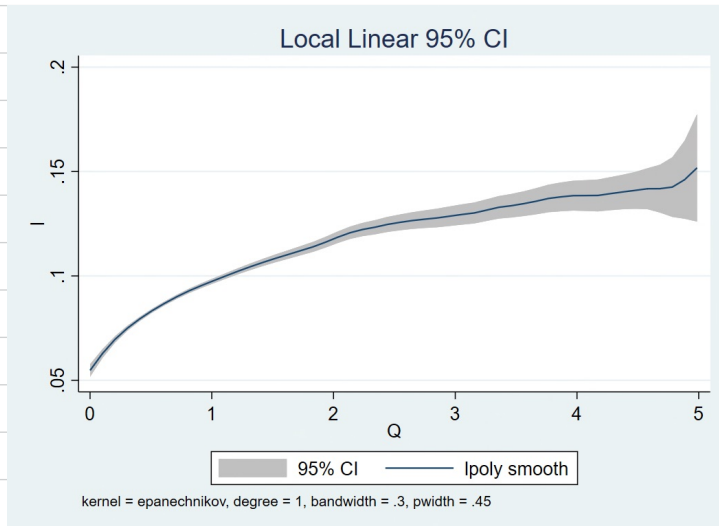
For  $\beta < 0$ , if  $f'(x) > 0$ , then the mass of  $x$  is concentrated to the left of  $x \rightarrow$  negative bias. If  $f'(x) < 0$ , the mass is concentrated to the right  $\rightarrow$  positive bias.

In short, if the mass is to the left of  $x$ , there's negative bias. If the mass is concentrated to the right, there is positive bias.

19.9.a



19.9.b.



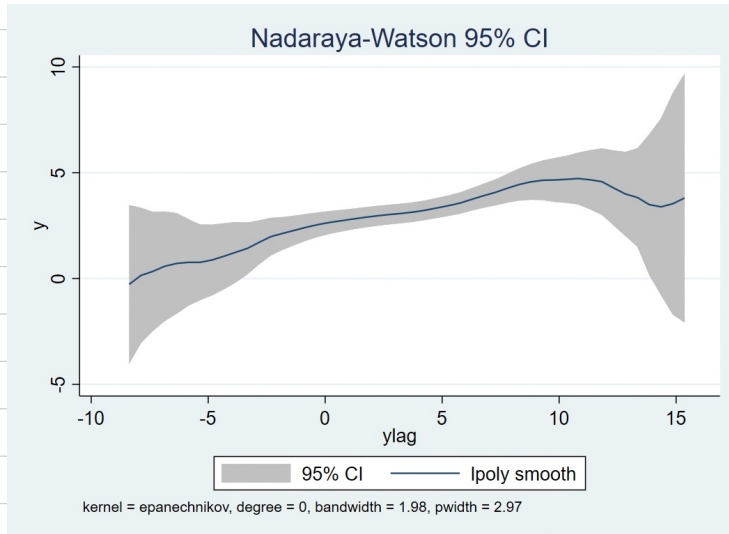
19.9.c.

It appears that there is non-linearity in the relationship.

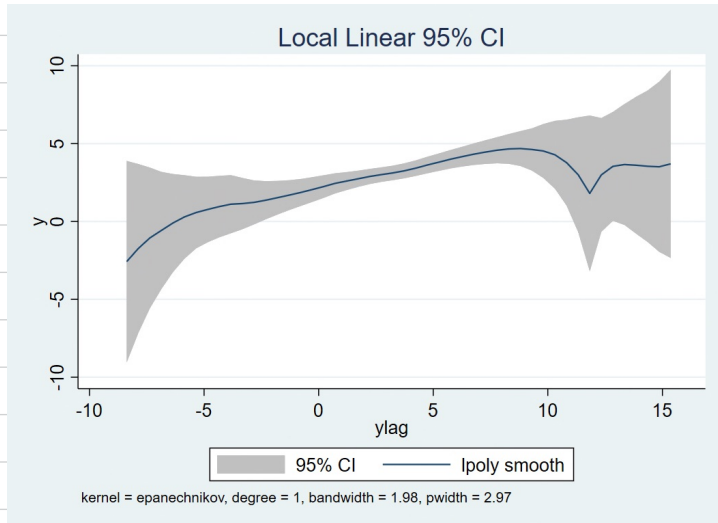
19.11.a.

Done in stata.

19.11.b.



19.11.c.



19.11.d

It appears that there is non-linearity in the relationship.