

# VAM: Regression Discontinuity Design

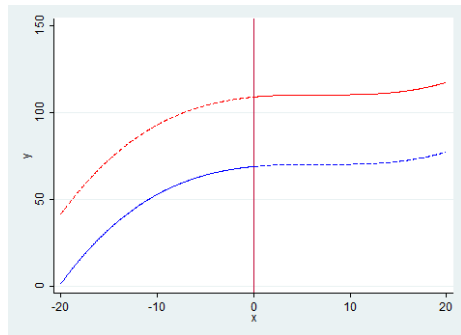
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# RDD Theory

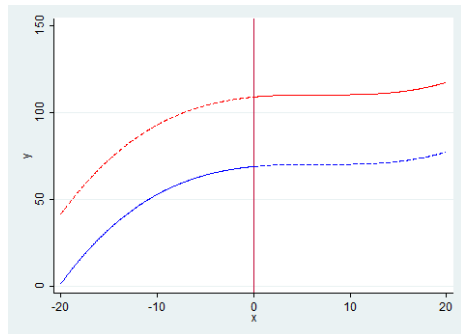
- Regression Discontinuity Design is a quasi-random method with a growing popularity in past ten years.
- The fundamental problem of causal inference: only  $Y_i(1)$  or  $Y_i(0)$  is observed.
- In RD-design treatment status  $T_i$  is determined by forcing variable  $X_i$  E.g. (e.g. test score, vote margin etc.) and a cut-off  $c$ .
- Thus (for sharp RDD) we observe:  
$$Y_i = (1 - T_i) \cdot Y_i(0) + T_i \cdot Y_i(1)$$

$$Y_i = \begin{cases} Y_i(0) & \text{if } X_i < c \\ Y_i(1) & \text{if } X_i \geq c \end{cases}$$



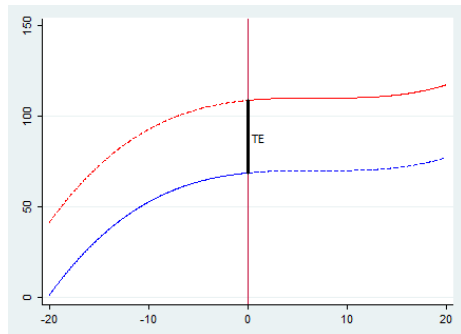
# RDD Theory

- ATE given forcing variable:  
 $\mathbb{E}[Y_i(1)|X_i = x] - \mathbb{E}[Y_i(0)|X_i = x]$
- If functions continuous at  $x = c$ :  
 $\mathbb{E}[Y_i(1) - Y_i(0)|X_i = c] =$   
 $\lim_{x \downarrow c} \mathbb{E}[Y_i|X_i = x] -$   
 $\lim_{x \uparrow c} \mathbb{E}[Y_i|X_i = x] = \tau_{rdd}$



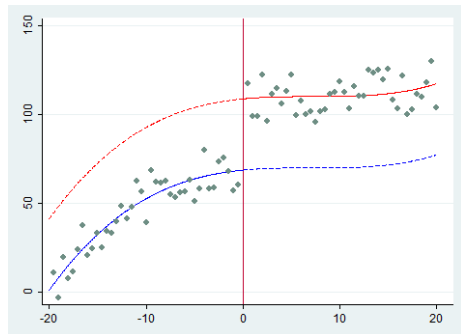
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- Can be interpreted as local average treatment effect for treated.



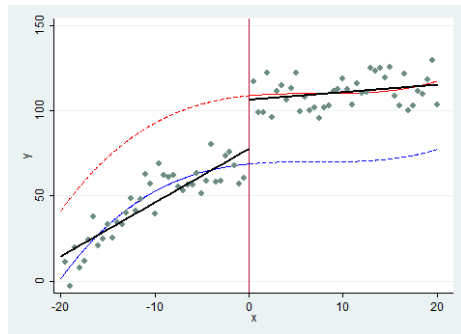
# Bandwidth Choice

- In practice we have to choose how to measure the "jump" at the cut-off.
- In terms of bandwidth choice there is a trade-off between bias and variance.
- A large bandwidth implies less variance but more bias.



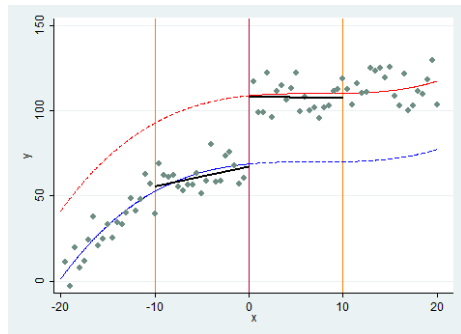
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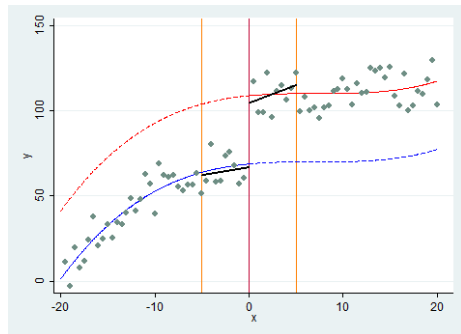
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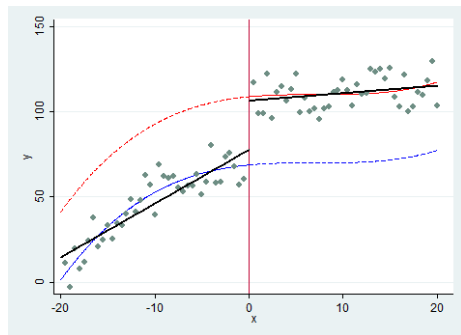
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- In terms of bandwidth choice there is a trade-off between bias and variance.
- A large bandwidth implies less variance but more bias.
- For a small bandwidth it is other way around.
- Current convention is to choose a (theoretically appealing) MSE-optimal (data driven) bandwidth.





# RDD More Choices

- We have to choose also the order of polynomial for the regression functions on both side of the cut-off. In practice one should limit to the low order polynomials (Gelman and Imbens (2017)) i.e. first and second order.
- Triangular weighting within the bandwidth is a common choice in practice.
- However remaining bias, which depends on the curvature of the underlying function, imposes a problem for inference.



# Bias-corrected Robust Inference

- Calonico et al. (2014) provides a robust bias correction method for valid confidence intervals.
- It involves estimating the bias by using a polynomial of order  $p + 1$  and having a new variance formula for the Studentization, which takes bias correction in the account.
- In practice pilotbandwidth can be set equal to the main bandwidth.
- Hyytinen et al. (2018) shows that CCT-method, unlike conventional not bias corrected, recovers lottery estimate of incumbency advantage in Finland.
- CCT can be implemented by rdrobust package, which is available for both R and STATA.

# Plotting Data

- `rdrobust` comes with a companion command: `rdplot`.
- Visualising data important (first) step for rd-analysis.
- Evenly-spaced bins: keeps length of the bin same (for respective sides of the cut-off).
- Quantile-spaced bins: keeps number of observations about the same across bins (across the side of the cut-off), varying in length.
- Data driven methods for number of bins: Mimic Variance and IMSE-optimal.

# Validation/Falsification

- Why we should be concerned on following things?
- Density of the running variable near the cut-off
- Covariate smoothness
- Placebo cut-offs