Online Appendix

A. Quantile regression basics

Suppose Y is the response variable, and X is the p-dimensional predictor. Let $F_Y(y|\mathbf{X} = x) = P(Y \leq y|\mathbf{X} = x)$ be the conditional cumulative distribution function (CDF) of Y given $\mathbf{X} = x$. Then the τ th conditional quantile of Y is defined as the inverse of the CDF or mathematically,

$$Q_{\tau}(Y|\mathbf{X}=x) = \inf\{y: F(y) \ge \tau\}$$

This can be extended to the General Linear quantile regression model:

$$Q_{\tau}(Y|\mathbf{X}=x) = \mathbf{X}^T \boldsymbol{\beta}(\tau), \quad 0 < \tau < 1,$$

where $\boldsymbol{\beta}(\tau) = (\beta_1(\tau), \dots, \beta_p(\tau))^T$ is the quantile coefficient that may depend on τ and represents the marginal change in the τ th quantile due to the marginal change in x.

Whereas the linear regression coefficients are solved by minimising least squares,

$$\hat{\beta} = \arg\min_{\beta \in \mathbf{R}^p} \sum_{i=1}^n (y_i - \mathbf{x}_i^T \beta)^2$$

the τ th regression quantile of the linear conditional quantile function $Q_{\tau}(Y|\mathbf{X} = x)$ is estimated by minimizing a weighted sum of the absolute deviations,

$$\hat{\beta}(\tau) = \arg\min_{\beta \in \mathbf{R}^p} \sum_{i=1}^n \rho_{\tau}(y_i - \mathbf{x}_i^T \beta)$$

for any quantile $\tau \in (0, 1)$. For example the case $\tau = 0.5$ corresponds to median regression.





Figure A1: Data fitted with several quantile regressions for females and males, separately. In grey: the 10th to 90th percentiles in increments of 10%. In black: the 94th, 95th, 96th, 97th, 98th and 99th percentiles. Each dot represents one individual.





Figure A2: Proportion of each birth cohort (1870-1904) in Denmark attaining age 100.



Figure A3: Hypothetical sample sizes of size 10000 and 15000 with bootstrapped regression coefficients and 95% confidence intervals.