

Calibration Theory

Starting point, Let Y (say Income for instance) be a variable of interest and X (some related auxiliary variable)

$$\hat{Y}_a = \sum_{i=1}^n a_{is} y_i$$

a_{is} are the non-response adjusted weights.

Consider the following distance function

$$f(w_{is}, a_{is}) = \sum_s (a_{is} - w_{is})^2 / 2a_{is}q_{is}$$

Where w_{is} will be the Calibrated weights.

Minimize $f(w_{is}, a_{is})$ under:

$$\sum_s w_{is} x_i = X = \sum_{i=1}^N x_i$$

To find the optimum form the lagrangian L :

$$L = \sum_s a_{is} \left(\frac{w_{is}}{a_{is}} - 1 \right)^2 \frac{1}{2q_{is}} + \lambda \left(X - \sum_s w_{is} x_{is} \right)$$

Where q_{is} is an independant parameter to be specified. It follows that

$$\frac{\partial L}{\partial w_{is}} = \sum_s \left(\frac{w_{is}}{a_{is}} - 1 \right) \frac{1}{q_{is}} - \lambda x_{is} \text{ and that } w_{is} = a_{is} + \lambda x_{is} a_{is} q_{is}$$

$$\text{Then } \lambda = \frac{\left(X - \sum_s a_{is} x_{is} \right)}{\sum_s a_{is} x_{is}^2 q_{is}} \text{ and } w_{is} = a_{is} \left(1 + \left(\frac{x - \hat{x}}{\sum_s a_{is} x_{is}^2 q_{is}} \right) x_{is} q_{is} \right)$$

$$w_{is} = a_{is} \left(1 + \left(\frac{x - \hat{x}}{\sum_s a_{is} x_{is}^2 q_{is}} \right) x_{is} q_{is} \right) = a_{is} * g_{is}$$



We can easily generalize to many X variables

$$\hat{Y}_w = \sum_{i=1}^N w_{is} y_i$$

- w_{is} is the calibrated weight

$$w_{is} = g_{is} a_{is}$$

- Now consider an auxiliary vector

$$x_i = (x_{i1}, \dots, x_{ip}) \text{ (} p \text{ variables)}$$

Minimize

$$\sum_{i=1}^n f(w_{is}, a_{is})$$

Under

$$\begin{aligned} \sum_{i=1}^n w_{is} x_{i1} &= \sum_{i=1}^N x_{i1} \\ &\vdots \\ \sum_{i=1}^n w_{is} x_{ip} &= \sum_{i=1}^N x_{ip} \end{aligned}$$

- $f(w_{is}, a_{is})$ need to be a convex function

- Extensive number of choices

$$\frac{(w_{is} - a_{is})^2}{2a_{is}q_{is}} \quad [\text{regression and ratio}]$$

$$\frac{1}{q_{is}} \left[w_{is} \log \left(\frac{w_{is}}{a_{is}} \right) - w_{is} + a_{is} \right] \quad \ll \text{Raking Ratio} \gg$$

- Could add boundaries i.e) $a \leq w_{is} \leq b$