The new -pqm- command for parametric quantile models

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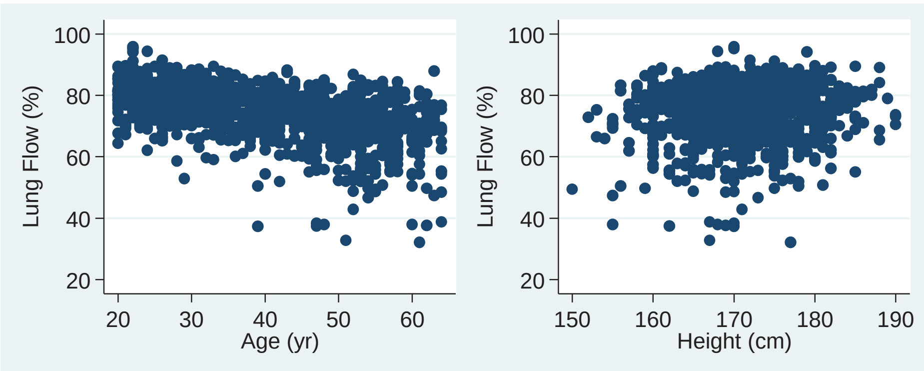
Acknowledgments

Frumento P, Bottai M
Parametric modeling of quantile regression coefficient functions
Biometrics, 2016

Frumento P, Bottai M
Parametric modeling of quantile regression coefficient functions with censored and truncated data
Biometrics, 2017

Cilluffo G, Bottai M
Nonlinear parametric quantile models
Doctoral Thesis

Lung flow, age, and height



In subsequent analyses, all variables are standardized.

A quantile model

We consider the following data-generating model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + e$$

The residual e may depend on x.

The quantile function of y given x is

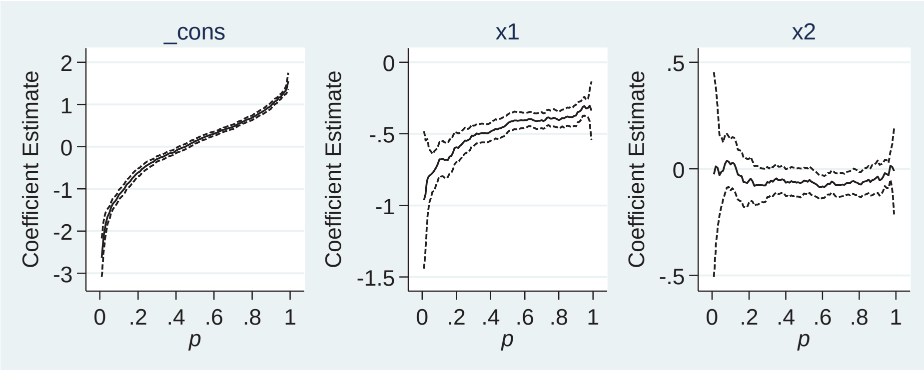
$$Q_y(p) = \beta_0(p) + \beta_1(p) x_1 + \beta_2(p) x_2$$

with $p \in (0,1)$.

The -qreg- command

We define x_1= age and x_2 = height.
We estimate the following model with -qreg-.

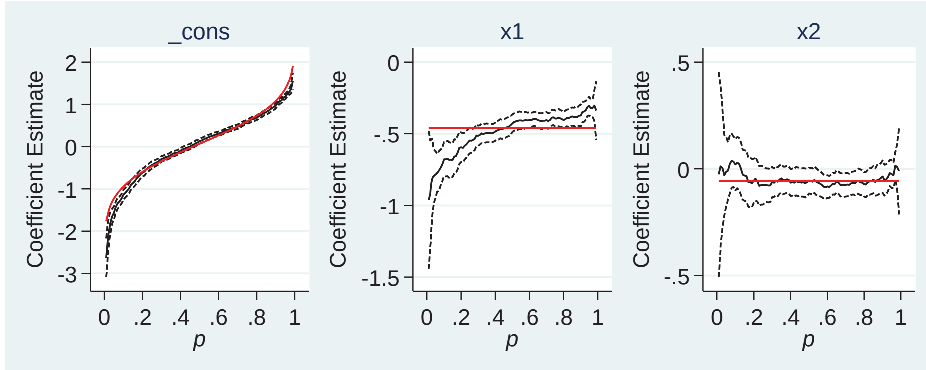
$$Q_y(p) = \beta_0(p) + \beta_1(p)x_1 + \beta_2(p)x_2$$



The -pqm- command: Model 1

We define $z(p)$ as the standard normal quantile function.
We estimate the following model with -pqm-.

$$Q_y(p) = [\beta_{00} + \exp(\beta_{01})z(p)] + \beta_{10}x_1 + \beta_{20}x_2$$



The -pqm- command output

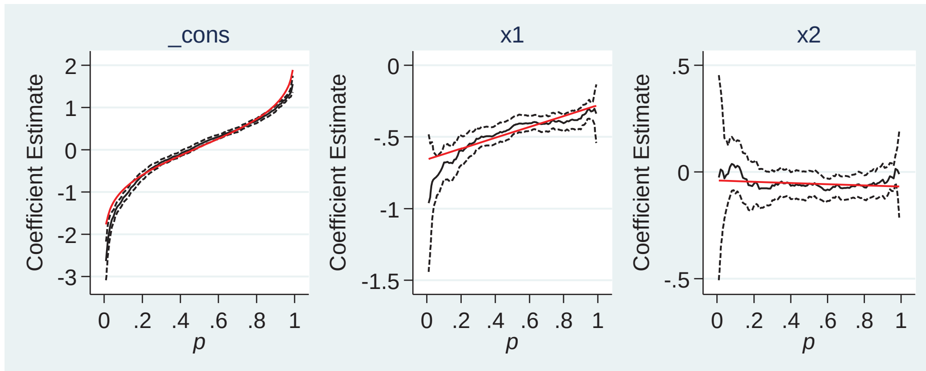
```
. pqm ( {b00} + exp({b01})*invnormal(p) + {b10}*x1 + {b20}*x2 )

Parametric quantile model                         Number of obs     =      1,093
------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
b00          |
       _cons |   .0658915   .0240948     2.73   0.006     .0186666    .1131164
-------------+----------------------------------------------------------------
b01          |
       _cons |  -.2363306   .0277714    -8.51   0.000    -.2907616   -.1818996
-------------+----------------------------------------------------------------
b10          |
       _cons |  -.4610537   .0242314   -19.03   0.000    -.5085464   -.4135609
-------------+----------------------------------------------------------------
b20          |
       _cons |  -.0568619    .029408    -1.93   0.053    -.1145006    .0007768
------------------------------------------------------------------------------
```


The -pqm- command: Model 2

We define $z(p)$ as the standard normal quantile function.
We estimate the following model with -pqm-.

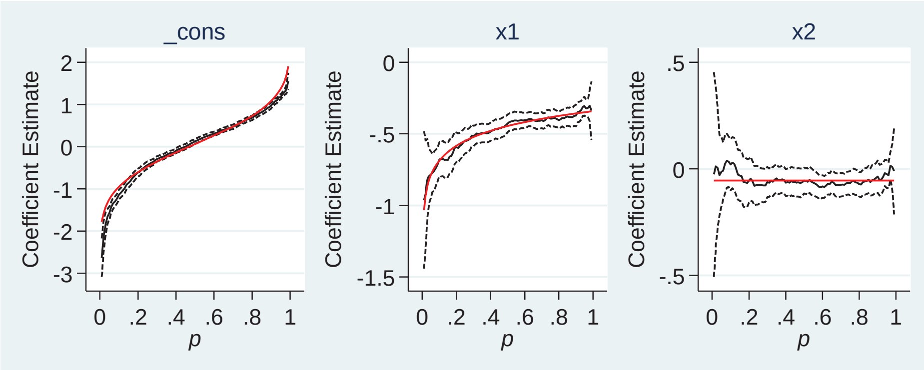
$$Q_y(p) = [\beta_{00} + \exp(\beta_{01})z(p)] + [\beta_{10} + \beta_{11}p]x_1 + [\beta_{20} + \beta_{21}p]x_2$$



The -pqm- command: Model 3

We define $z(p)$ as the standard normal quantile function.
We estimate the following model with -pqm-.

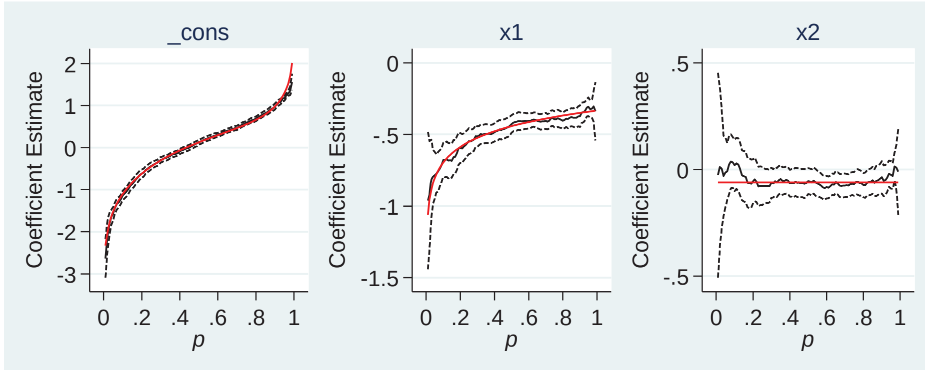
$$Q_y(p) = [\beta_{00} + \exp(\beta_{01}) z(p)] + [\beta_{10} + \beta_{11} \log(p)] x_1 + \beta_{20} x_2$$



The -pqm- command: Model 4

We define $z(p)$ as the standard normal quantile function.
We estimate the following model with -pqm-.

$$Q_y(p) = [\beta_{00} + \exp(\beta_{01}) z(p) + \beta_{02} p^2] + [\beta_{10} + \beta_{11} \log(p)] x_1 + \beta_{20} x_2$$



Summary

Quantile coefficients models

- ✓ Estimate full conditional distributions
- ✓ Can model distributions with no closed-form densities
- ✓ Are statistically efficient
- ✓ Are computationally fast

The -pqm- command

- ✓ Accepts any quantile function
- ✓ Shares the -mlexp- syntax and features
- × Needs optimizing

www.imm.ki.se/biostatistics