# Censored QUAIDS estimation with quaidsce*

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# 1. Introduction

Censoring, or the presence of zero expenditures, in the dependent variables of demand systems has been animportant topic in economics and econometrics for decades (Houthakker, 1953; Deaton,

term as instruments in a two-stage least squares (2SLS) type of estimator for a system of equations (see, e.g., Blundell and Robin, 1999). In the first stage, total expenditure is regressed on the exogenous control variables and the instruments. Then, the residuals from this regression are added to every equation in the system via (2) as additional control variables. Blundell and Robin (1999) show that under the assumption that the error term from (2) can be orthogonally decomposed into the residuals from stage one and a white noise term, the augmented regression estimator is identical to

## 3. The quaidsce command

The quaidsce command syntax for a flexible AIDS model, with or without demographics, censoring and quadratic term, follows:

After estimation, the predict

Macros

| | |
|---|---|
| e(cmd) | quaidsce |
| e(clustvar) | name of cluster variable |
| e(vce) | vcetype specified in vce() |
| e(vcetype) | title used in label Std. Err. |
| e(properties) | b V |
| e( estat_cmd) | program used to implement estat |
| e(predict) | program used to implement predict |
| e(demographics) | demographic variables included |
| e(lhs) | expenditure share variables |
| e(expenditure) | expenditu re variable |
| e(lnexpenditure) | log- expenditure variable |
| e(prices) | price variables |
| e(lnprices) | log- price variables |
| e(quadratic) | noquadratic |
| e(censor) | nocensor |
| e(method) | specified in method() |
| e(properties) | b V |

Matrices

| | |
|---|---|
| e(b) | coefficient vector |
| e(V) | variance- covariance matrix of the estimators |
| e(best) | coefficient vector of estimated parameters |
| e( Vest) | variance- covariance matrix of estimated parameters |
| e(alpha) | alpha vector |
| e(beta) | beta vector |
| e(gamma) | gamma matrix |
| e(lambda) | lambda vector |
| e(eta) | eta matrix |
| e(rho) | rho vector |
| e(delta) | delta vector |

Functions

## 4. Application

We illustrate the use of `quaidsce` and its companion post-estimation commands by estimating a food demand system using expenditures data from a nationally representative survey. We fit a censored QUAIDS model for 17 food-at-home categories with varying censoring rates using data from the Household Budget Survey (EPF, Spanish acronym), collected by the Chilean National Institute of Statistics for the 2016/2017 period (INE, 2020). The data were collected from a sample of households using self-reported diaries of all purchases, including food, over two weeks. Data include monthly income and expenditure values of 15,147 households. Quantity information was requested from INE to calculate quality-adjusted unit values based on the approach of Crawford et al. (2003) and later adapted by Capacci and Mazzocchi (2011), which were used as proxies of prices.

EPF 2016/2017 Descriptive Statistics

| Group | Purchase > 0 | Quantity (gr/day/capita) | Expenditure Shares |
|---|---|---|---|
| 1 Starches | 0.635 | 89.63 | 0.033 |
| 2 Bread | 0.968 | 197.82 | 0.148 |
| 3 Breakfast cereals | 0.264 | 20.25 | 0.009 |
| 4 Unprocessed meat | 0.887 | 146.69 | 0.199 |
| 5 Processed meat | 0.824 | 40.89 | 0.068 |
| 6 Milk and dairy desserts | 0.733 | 164.23 | 0.058 |
| 7 Cheese | 0.707 | 25.79 | 0.043 |
| 8 Fruits | 0.685 | 245.62 | 0.045 |
| 9 Vegetables | 0.891 | 212.15 | 0.121 |
| 10 Legumes & proc. FVs | 0.543 | 24.07 | 0.024 |
| 11 Sweets | 0.587 | 36.81 | 0.032 |
| 12 Snacks | 0.750 | 38.30 | 0.062 |
| 13 Unsweetened beverag | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| delta | | | | | | |
| delta_1 | .0419601 | .0020001 | 20.98 | 0.000 | .03804 | .0458801 |
| delta_2 | .3025808 | .0021382 | 141.51 | 0.000 | .2983901 | .3067715 |

After estimation, we use the estat command to produce expenditure and uncompensated price elasticities. Figures 1 and 2 show the differences between the estimated elasticities with and without correction due to censoring (with 95% confidence intervals). In general, there are important differences in the mean estimated elasticities when censoring is taken into account, changing the interpretation of results dramatically. Overall, we show that ignoring the potential bias of zero expenditures can lead to inaccurate estimates of demand responses to prices and income changes, and therefore affecting inferences in policy analysis.

We recommend using bootstrap methods for standard errors in the censored model estimation due to the nonlinear nature of the model. This is particularly important as it will be used as an input to estimate the standard errors of the predicted elasticities. Similarly, we only recommend making inferences when the models are estimated using the ifgnls method. The method(method_name) is added for experienced users interested in debugging when the model cannot be fitted to their data. Finally, we advise optimizing the processing resources allocated to Stata when using quaids, as computation times increase rapidly with the number of categories and observations (both for the estimated model and post-estimation commands). In practical applications, producing elasticity estimates over a nationally representative sample with bootstrap standard errors can take up to several days using optimized settings on a standard computer.

# 6. References


Amemiya, T. 1974. Multivariate regression and simultaneous equation models when the dependent variables are truncated normal. Econometrica 42(6): 1193-1199.

Banks, J., R. Blundell, and A. Lewbel. 1997. Quadratic Engel curves and consumer demand. The Review of Economics and Statistics 79: 527-539.

Blundell, R., and J.M. Robin. 1999. Estimation in large and disaggregated demand systems: An estimator for conditionally linear systems. Journal of Applied Econometrics 14: 209-232.

Capacci, S., and M. Mazzocchi 2011. Five-a-day, a price to pay: an evaluation of the UK program impact accounting for market forces. Journal of Health Economics 30(1): 87-98.

Crawford, I., Laisney, F., and I. Preston. 2001p.a Fes.