# Censored QUAIDSestimation with quaidsce

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## 1. Introduction

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

term as instruments in a two age least squar (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 dell and Robin (1999) show that under the assumption that the error tefrom (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 syntaxisor a flexible AIDS model, with or without demographics, censoring and quadratic term, follows:

After estimation, the predict

#### Macros e(cmd) quaidsce name of cluster variable e(clustvar) e(vce) vcetype specified in vce() title used in label Std. Err. e(vcetype) b۷ e(properties) 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(Inexpenditure) logexpenditure variable price variables e(prices) e(Inprices) logprice variables noquadratic e(quadratic) 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(eta) eta matrix e(rho) rho vector e(delta) delta vector

#### **Functions**

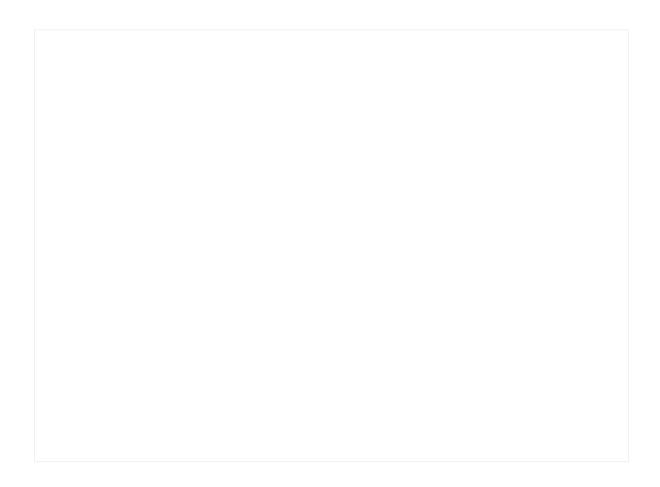
### 4. Application

We illustrate the use of uaidsceand its companion possistimation commands by estimating a food demand system using expenditures data from a nationapility sentative survey. We fit a censored QUAIDS model for 17 food-home categories with varying censoring ratesing 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-ported diaries of all purchases, including food, over two well include monthly income and expenditure values of 15,147 households. Quantity information was requested from INE to calculate quality justed unit values based on the approach of Crawford et al. (2003) and later adapted by Capacci and Mazzocchi (2011) have used as proxies of prices.

EPF 2016/2017 Descriptive Statistics

| Group                     | Purchase > ( | Quantity (grday/capita) | ExpenditureShares |  |  |
|---------------------------|--------------|-------------------------|-------------------|--|--|
| 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 estatommand to produce expenditure and uncompensated price elasticities. Figures 1 and 2 show the differences between the estimate interest with and without correction due to censoring (with 95% confidence intervals). In general, there are important differences in the mean estimated elasticities when censoring in the count, changing the interpretation of results dramatical Overall, we show that ignoring the tential 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 used bootstrapmethods for standard errors in the censored model estimation due to the nonlinear nature of the model. This is particularly important will be used as an input to estituenthe 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 optimized the processing resources allocated to Stata when using quaids can computation times increase rapidly with ruben ber of categories and observations (both for the estimated model and application ommands). In practical applications, producing elasticity estimates over a nationally representative sample with bootstrap standard errors can take up to several dassing optimized settings on a standard computer.

### 6. References

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