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Easy demand-system estimation with quaids

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Abstract. Previously, to fit an almost-ideal demand system in Stata, one would have to use the `nlsur` command and write a function evaluator program as described in [R] **nlsur** and Poi (2008, *Stata Journal* 8: 554–556). In this article, I introduce the command `quaids`, which obviates the need for any programming by the user. The command fits Deaton and Muellbauer's (1980b, *American Economic Review* 70: 312–326) original almost-ideal demand-system model as well as Banks, Blundell, and Lewbel's (1997, *Review of Economics and Statistics* 79: 527–539) quadratic variant. Demographic variables can also be included in the model. Postestimation tools calculate expenditure and price elasticities.

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1 Introduction

Demand-system estimation is a popular task in Stata. Questions arise regularly on the Statalist email discussion forum, and I frequently receive private requests for assistance from users. Previously, to fit an almost-ideal demand system (AIDS) in Stata, one would have to use the `nlsur` command and write a function evaluator program as described in [R] **nlsur** and Poi (2008). However, many users had difficulty adapting the function evaluator program to fit their specific applications. Moreover, adding demographic variables was difficult, and obtaining price and expenditure elasticities required even more programming.

The `quaids` command solves those shortcomings. `quaids` allows you to fit either the standard AIDS model of Deaton and Muellbauer (1980b) or the quadratic AIDS model of Banks, Blundell, and Lewbel (1997). Demographic variables can be specified and are incorporated using Ray's (1983) method. Postestimation commands allow you to compute expenditure elasticities as well as compensated and uncompensated price elasticities.

The rest of this article is organized as follows. Section 2 outlines the models and elasticity computations. Section 3 describes the `quaids` command and associated postestimation commands. Section 4 provides an example. Section 5 concludes the article.

 st0268

2 Almost-ideal demand systems

In this section, I describe AIDS models and show how demographic variables are incorporated by the `quaids` command. The presentation here is brief; for an in-depth analysis of consumer behavior and demand-system analysis, see the classic monographs by Deaton and Muellbauer (1980a) and Mas-Colell, Whinston, and Green (1995, chap. 3).

2.1 Basics

We consider a consumer's demand for a set of k goods for which the consumer has budgeted m units of currency. For example, the k goods could represent different categories of food, and the amount to be spent on food, m, could be chosen based on a two-stage budgeting process. Alternatively, the k goods could represent broad categories like housing, clothing, food, utilities, and savings; m could represent household income.

The quadratic AIDS model of Banks, Blundell, and Lewbel (1997) is based on the indirect utility function

$$\ln V(\mathbf{p}, m) = \left[\left\{ \frac{\ln m - \ln a(\mathbf{p})}{b(\mathbf{p})} \right\}^{-1} + \lambda(\mathbf{p}) \right]^{-1} \tag{1}$$

where $\ln a(\mathbf{p})$ is the transcendental logarithm function

$$\ln a(\mathbf{p}) = \alpha_0 + \sum_{i=1}^{k} \alpha_i \ln p_i + \frac{1}{2} \sum_{i=1}^{k} \sum_{j=1}^{k} \gamma_{ij} \ln p_i \ln p_k \tag{2}$$

In this function, p_i is the price of good i for $i = 1, \ldots, k$; $b(\mathbf{p})$ is the Cobb–Douglas price aggregator

$$b(\mathbf{p}) = \prod_{i=1}^{k} p_i^{\beta_i}$$

and

$$\lambda(\mathbf{p}) = \sum_{i=1}^{k} \lambda_i \ln p_i$$

Lowercase Greek letters other than α_0 represent parameters to be estimated. In principle, α_0 could be estimated jointly with the other parameters; in practice, it turns out to be rather difficult. The `quaids` command requires the user to specify a value for α_0; Deaton and Muellbauer (1980b), Banks, Blundell, and Lewbel (1997), and most others set α_0 to be slightly less than the lowest value of $\ln m$ observed in the data.

Adding up, homogeneity, and Slutsky symmetry impose the requirements that

$$\sum_{i=1}^{k} \alpha_i = 1, \qquad \sum_{i=1}^{k} \beta_i = 0, \qquad \sum_{j=1}^{k} \gamma_{ij} = 0, \qquad \sum_{i=1}^{k} \lambda_i = 0, \quad \text{and} \quad \gamma_{ij} = \gamma_{ji}$$

The `quaids` command imposes these conditions automatically; the current implementation does not allow the user to fit unrestricted models and test whether these axioms of demand analysis hold.

Let q_i denote the quantity of good i consumed by a household, and define the expenditure share for good i as $w_i = p_i q_i / m$. Applying Roy's identity to (1), we obtain the expenditure share equation for good i:

$$w_i = \alpha_i + \sum_{j=1}^{k} \gamma_{ij} \ln p_j + \beta_i \ln \left\{ \frac{m}{a(\mathbf{p})} \right\} + \frac{\lambda_i}{b(\mathbf{p})} \left[\ln \left\{ \frac{m}{a(\mathbf{p})} \right\} \right]^2, \qquad i = 1, \ldots, k$$

When $\lambda_i = 0$ for all i, the quadratic term in each expenditure share equation drops out, and we are left with Deaton and Muellbauer's (1980b) original AIDS model. Thus testing $H_0\colon \lambda_i = 0 \, \forall \, i$ allows us to choose easily between the original AIDS and the quadratic AIDS models.

Consider the original AIDS model without the quadratic term:

$$w_i = \alpha_i + \sum_{j=1}^{k} \gamma_{ij} \ln p_j + \beta_i \ln \left\{ \frac{m}{a(\mathbf{p})} \right\}, \qquad i = 1, \ldots, k$$

This set of expenditure share equations requires nonlinear estimation techniques because of the price index $\ln a(\mathbf{p})$. Deaton and Muellbauer (1980b, 316) suggest replacing that price index with the approximation $\ln a(\mathbf{p}) \approx \sum_j w_j \ln p_j$,[1] resulting in a set of equations that can be fit by linear estimation techniques. Occasionally, I am asked how to fit those so-called "linearly approximated" AIDS models in Stata. However, given the advances in software in the last 30 years and Stata's `nlsur` command, fitting nonlinear systems nowadays is not much more difficult than fitting linear systems. Therefore, the `quaids` command currently uses the price index defined in (2) and does not offer the option of using alternative price indices.

2.2 Demographics

The `quaids` command incorporates demographics by using the scaling technique introduced by Ray (1983) and extended to the quadratic AIDS model by Poi (2002a). We use $\mathbf{z}$ to represent a vector of s characteristics. In the simplest case, $\mathbf{z}$ could be a scalar representing the number of people in a household. Let $e^R(\mathbf{p}, u)$ denote the expenditure function of a reference household, where a reference household might be one that contains just a single adult.

1. This price index was first introduced by Sir Richard Stone.

Ray's method uses for each household an expenditure function of the form

$$e(\mathbf{p},\mathbf{z},u) = m_0(\mathbf{p},\mathbf{z},u) \times e^R(\mathbf{p},u)$$

The function $m_0(\mathbf{p},\mathbf{z},u)$ scales the expenditure function to account for the household characteristics. Ray further decomposes the scaling function as

$$m_0(\mathbf{p},\mathbf{z},u) = \overline{m}_0(\mathbf{z}) \times \phi(\mathbf{p},\mathbf{z},u)$$

The first term measures the increase in a household's expenditures as a function of $\mathbf{z}$, not controlling for any changes in consumption patterns; a household with four members will have higher expenditures than one with a single member, even ignoring that the composition of goods consumed may change. The second term controls for changes in relative prices and the actual goods consumed; a household with two adults and two infants will consume different goods than one comprising four adults.

Following Ray (1983), `quaids` parameterizes $\overline{m}_0(\mathbf{z})$ as

$$\overline{m}_0(\mathbf{z}) = 1 + \boldsymbol{\rho}'\mathbf{z}$$

where $\boldsymbol{\rho}$ is a vector of parameters to be estimated. As in Poi (2002a), `quaids` parameterizes $\phi(\mathbf{p},\mathbf{z},u)$ as

$$\ln \phi(\mathbf{p},\mathbf{z},u) = \frac{\prod_{j=1}^{k} p_j^{\beta_j} \left(\prod_{j=1}^{k} p_j^{\boldsymbol{\eta}_j'\mathbf{z}} - 1 \right)}{\frac{1}{u} - \sum_{j=1}^{k} \lambda_j \ln p_j}$$

This functional form may look a bit odd, but it has the distinct advantage of resulting in expenditure share equations that closely mimic their counterparts without demographics. $\boldsymbol{\eta}_j$ represents the jth column of $s \times k$ parameter matrix $\boldsymbol{\eta}$. The expenditure share equations take the form

$$w_i = \alpha_i + \sum_{j=1}^{k} \gamma_{ij} \ln p_j + (\beta_i + \boldsymbol{\eta}_i'\mathbf{z}) \ln \left\{ \frac{m}{\overline{m}_0(\mathbf{z}) a(\mathbf{p})} \right\} + \frac{\lambda_i}{b(\mathbf{p})\, c(\mathbf{p},\mathbf{z})} \left[\ln \left\{ \frac{m}{\overline{m}_0(\mathbf{z}) a(\mathbf{p})} \right\} \right]^2$$

where

$$c(\mathbf{p},\mathbf{z}) = \prod_{j=1}^{k} p_j^{\boldsymbol{\eta}_j'\mathbf{z}}$$

The adding-up condition requires that $\sum_{j=1}^{k} \eta_{rj} = 0$ for $r = 1, \ldots, s$. If we set $\lambda_i = 0$ for all i, we are left with the AIDS model with demographics used by Ray (1983).[2]

2. This is not the only way to incorporate demographics into the quadratic AIDS model using Ray's (1983) method. While writing this article, I became aware of an article by Blacklow, Nicholas, and Ray (2010) that used Ray's (1983) method to incorporate household composition variables in the quadratic AIDS model. Also see Pollak and Wales (1981), who discuss alternative ways of incorporating demographic variables by directly modifying the expenditure share equations.

2.3 Elasticities

We present the formulas for the elasticities for the quadratic AIDS model with demographic variables. The formulas for elasticities for the standard AIDS model and models without demographics are nested within the more general variants.

Tedious but straightforward algebra shows that the uncompensated price elasticity of good i with respect to changes in the price of good j is

$$\epsilon_{ij} = -\delta_{ij} + \frac{1}{w_i}\left(\gamma_{ij} - \left[\beta_i + \boldsymbol{\eta}_i'\mathbf{z} + \frac{2\lambda_i}{b(\mathbf{p})\,c(\mathbf{p},\mathbf{z})}\ln\left\{\frac{m}{\overline{m}_0(\mathbf{z})\,a(\mathbf{p})}\right\}\right] \times \right.$$
$$\left. \left(\alpha_j + \sum_l \gamma_{jl}\ln p_l\right) - \frac{\left(\beta_j + \boldsymbol{\eta}_j'\mathbf{z}\right)\lambda_i}{b(\mathbf{p})\,c(\mathbf{p},\mathbf{z})}\left[\ln\left\{\frac{m}{\overline{m}_0(\mathbf{z})\,a(\mathbf{p})}\right\}\right]^2\right)$$

The expenditure (income) elasticity for good i is

$$\mu_i = 1 + \frac{1}{w_i}\left[\beta_i + \boldsymbol{\eta}_i'\mathbf{z} + \frac{2\lambda_i}{b(\mathbf{p})\,c(\mathbf{p},\mathbf{z})}\ln\left\{\frac{m}{\overline{m}_0(\mathbf{z})\,a(\mathbf{p})}\right\}\right] \tag{3}$$

Compensated price elasticities are obtained from the Slutsky equation: $\epsilon_{ij}^C = \epsilon_{ij} + \mu_i w_j$.

2.4 Estimation

We assume there is an additive zero-mean error term associated with each of the k expenditure share equations. We estimate the parameters by iterated feasible generalized nonlinear least-squares estimation via Stata's `nlsur` command with the `ifgnls` option. To avoid a singular error-covariance matrix, the `quaids` command automatically omits the last equation before calling `nlsur`; the estimator is invariant to which equation is dropped, so there is no option to make `quaids` drop some equation other than the last. The iterated feasible generalized nonlinear least-squares estimator is equivalent to the multivariate normal maximum-likelihood estimator for this class of problems.

The function evaluator program required by `nlsur`, named `nlsur__quaids.ado`, is a wrapper command that calls a Mata routine to compute the predicted expenditure share equations. The elasticity computations are also performed by Mata routines. All of these routines are stored in the `_quaids__utils.mata` file, which accompanies this article.

3 The quaids command suite

Accompanying this article is a complete suite of commands for fitting AIDS models, obtaining forecasts, and calculating elasticities. These programs require Stata 12.1.

3.1 Estimation command

The `quaids` command fits an AIDS model, with or without the quadratic expenditure term and with or without demographic variables.

`quaids` $varlist_{expshares}$ [*if*] [*in*], `anot(`#`)`
{`prices(`$varlist_{prices}$`)` | `lnprices(`$varlist_{lnprices}$`)`}
{`expenditure(`$varname_{exp}$`)` | `lnexpenditure(`$varname_{lnexp}$`)`}
[`demographics(`$varlist_{demo}$`)` `noquadratic` `nolog` `vce(`*vcetype*`)` `level(`#`)`]

$varlist_{expshares}$ represents the variables containing the expenditure shares. To fit a system with k goods, specify k variable names. Do not omit one of the goods to avoid a singular error-covariance matrix during estimation; the `quaids` command handles that automatically. The expenditure share variables should sum to 1 for each observation; `quaids` exits with an error message if that is not true of the data.

Specify k price variables, $varlist_{prices}$, in the `prices()` option or specify k variables containing the natural logarithms of the prices of the k goods, $varlist_{lnprices}$, in the `lnprices()` option. Specify one or the other but not both. The price variables must appear in the same order as the expenditure share variables; `quaids` has no way to verify this, but results will be meaningless if the ordering is not preserved.

Specify the total expenditure variable, $varname_{exp}$, in the option `expenditure()` or specify the variable containing the natural logarithm of expenditure, $varname_{lnexp}$, in the option `lnexpenditure()`. Specify one or the other but not both. The expenditure variable should represent total expenditures on the goods that this demand system represents such that $\sum_j p_j q_j = m$ for each observation in the dataset.

Specify the value for α_0 in option `anot()`. Specify optional demographic variables, $varlist_{demo}$, in option `demographics()`. Option `noquadratic` instructs `quaids` to omit the quadratic term. Option `nolog` suppresses the iteration log. Option `level(`#`)` sets the confidence level for confidence intervals.

`vce(`*vcetype*`)` controls the type of variance–covariance matrix calculated. *vcetype* may be `gnr` (the default), `robust`, `cluster` *clustvar* (where *clustvar* is the name of a clustering variable), `bootstrap`, or `jackknife`. This option works just as it does for `nlsur`; see [R] **nlsur**.

3.2 Prediction

After fitting an AIDS model, use the `predict` command to obtain predicted values of the expenditure shares.

`predict` [*type*] {*stub*`*` | $newvar_1$, ..., $newvar_k$} [*if*] [*in*]

Specify *stub* immediately followed by an asterisk (`*`), or specify k new variable names, where k is the number of goods in the demand system. If the user specifies, say, `what*`, then the new variables created will be named `what1`, ..., `what`k. By default, the predictions are computed for all observations in the dataset; specify `if e(sample)` to restrict computations to only those observations used during estimation.

3.3 Elasticities

One is often more interested in the expenditure and price elasticities rather than in the parameters of the expenditure share equations per se. However, I suspect that many Stata users attempting to fit demand systems give up before computing the elasticities. There are at least two reasons. First, some users have had significant difficulty writing the requisite function evaluator program for use with `nlsur`, so writing a program to compute the elasticities or using the `nlcom` command to do so may be out of reach. Second, I often receive email questions asking for help fitting an AIDS model, but remarkably, few of those users ask about obtaining elasticities.

The `quaids` command includes three postestimation utilities for computing expenditure elasticities as well as compensated and uncompensated price elasticities. These commands allow you to compute the elasticities at the means of all the variables in the model or to compute the elasticities for each observation in the current dataset. You can compute elasticities for various subsets of the data by creating an artificial dataset containing the appropriate variable means. The example in the next section illustrates how to compute elasticities for "average" rural and urban households. The current implementation does not compute standard errors for the elasticity estimates.

All three of the `estat` commands accompanying this article will compute elasticities for each observation in the dataset and place the results in new variables. Alternatively, you may specify `atmeans` to have the commands first compute the means of the price, expenditure, and demographic variables, and then compute the elasticities at the means of those variables; with this option, the elasticities are returned as a vector or matrix. In both cases, by default, the `estat` commands compute the statistics for all the observations in the dataset unless you use the `if` or `in` modifiers to restrict the sample.

To compute the expenditure elasticities for individual observations in the dataset, you type

`estat` `expenditure` [*type*] {*stub*`*` | *newvar*$_1$, ..., *newvar*$_k$} [*if*] [*in*]

Similarly to the `predict` command discussed above, you may specify either a variable *stub* or k new variable names. The jth new variable will contain the expenditure elasticity for the jth good.

To compute the expenditure elasticities at the means of all the variables and have the result returned in a $1 \times k$ vector, type

`estat expenditure` [*if*] [*in*]`, atmeans`

With this syntax, `estat expenditure` computes the means of all the price, expenditure, and demographic variables of your model and computes the expenditure elasticities for the k goods at those means.

To compute the uncompensated price elasticities for individual observations in the dataset, type

`estat uncompensated` [*type*] {*stub*`*` | *newvar*$_1$`,` ...`,` *newvar*$_{k^2}$} [*if*] [*in*]

Specify a *stub* or specify k^2 new variables. Variables are created in the order $v_{1,1}, \ldots,$ $v_{1,k}$, $v_{2,1}, \ldots, v_{2,k}, \ldots, v_{k,1}, \ldots, v_{k,k}$, where $v_{i,j}$ represents the elasticity of good i with respect to changes in the price of good j. To avoid confusion, we strongly recommend specifying a new variable *stub* rather than specifying k^2 new variables. `estat uncompensated` adds variable labels to the new variables to aid in interpretation.

To compute the uncompensated price elasticities at the means of all the variables and have the results returned in a $k \times k$ matrix, type

`estat uncompensated` [*if*] [*in*]`, atmeans`

With this syntax, `estat uncompensated` computes a $k \times k$ matrix. The entry in row i, column j contains the elasticity of good i with respect to the price of good j.

Compensated price elasticities are obtained similarly to uncompensated price elasticities. To obtain observation-specific compensated price elasticities, type

`estat compensated` [*type*] {*stub*`*` | *newvar*$_1$`,` ...`,` *newvar*$_{k^2}$} [*if*] [*in*]

To compute the compensated price elasticities at the means of all the variables, type

`estat compensated` [*if*] [*in*]`, atmeans`

3.4 Saved results

`quaids` saves the following in `e()`:

Scalars	
`e(N)`	number of observations
`e(ll)`	log likelihood
`e(N_clust)`	number of clusters
`e(ndemos)`	number of demographics
`e(anot)`	value of α_0
`e(ngoods)`	number of goods
Macros	
`e(cmd)`	`quaids`
`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)`	expenditure variable
`e(lnexpenditure)`	log-expenditure variable
`e(prices)`	price variables
`e(lnprices)`	log-price variables
`e(quadratic)`	`noquadratic`
Matrices	
`e(b)`	coefficient vector
`e(V)`	variance–covariance matrix of the estimators
`e(alpha)`	estimated $\boldsymbol{\alpha}$ vector
`e(beta)`	estimated $\boldsymbol{\beta}$ vector
`e(gamma)`	estimated $\boldsymbol{\gamma}$ matrix
`e(lambda)`	estimated $\boldsymbol{\lambda}$ vector (if applicable)
`e(eta)`	estimated $\boldsymbol{\eta}$ matrix (if applicable)
`e(rho)`	estimated $\boldsymbol{\rho}$ vector (if applicable)
Functions	
`e(sample)`	marks estimation sample

`estat expenditure, atmeans` saves `r(expelas)`, the vector of expenditure elasticities.

`estat uncompensated, atmeans` saves `r(uncompelas)`, the matrix of uncompensated price elasticities. The i, j entry is the elasticity of good i with regard to price j.

`estat compensated, atmeans` saves `r(compelas)`, the matrix of compensated price elasticities. The i, j entry is the elasticity of good i with regard to price j.

4 Example

Here we illustrate the `quaids` command using the same dataset used in Poi (2002b), Poi (2008), and [R] **nlsur**. We first create a random integer representing the number of children in each household and a random binary variable representing rural versus urban households so that we can demonstrate a model that includes demographics. We then fit a quadratic AIDS model using $\alpha_0 = 10$. To save space, we use the `nolog` option to suppress the iteration log.

```
. webuse food
. set seed 1
. generate nkids = int(runiform()*4)
. generate rural = (runiform() > 0.7)
. quaids w1-w4, anot(10) prices(p1-p4) expenditure(expfd)
> demographics(nkids rural) nolog
(obs = 4048)
Calculating NLS estimates...
Calculating FGNLS estimates...
FGNLS iteration 2...
FGNLS iteration 3...
FGNLS iteration 4...
```

```
Quadratic AIDS model

Number of obs          =      4048
Number of demographics =         2
Alpha_0                =        10
Log-likelihood         =  13098.966
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
alpha						
alpha_1	.910531	.0696028	13.08	0.000	.7741121	1.04695
alpha_2	-.1328957	.0707108	-1.88	0.060	-.2714863	.0056949
alpha_3	.0155448	.0419878	0.37	0.711	-.0667499	.0978394
alpha_4	.2068199	.070847	2.92	0.004	.0679623	.3456775
beta						
beta_1	.2130298	.0294805	7.23	0.000	.1552492	.2708105
beta_2	-.1323188	.0277094	-4.78	0.000	-.1866283	-.0780093
beta_3	-.0347438	.015612	-2.23	0.026	-.0653428	-.0041449
beta_4	-.0459672	.027198	-1.69	0.091	-.0992743	.0073399
gamma						
gamma_1_1	.2800049	.046504	6.02	0.000	.1888587	.3711511
gamma_2_1	-.1508244	.0305337	-4.94	0.000	-.2106693	-.0909794
gamma_3_1	-.0607434	.0133462	-4.55	0.000	-.0869016	-.0345853
gamma_4_1	-.0684371	.0235138	-2.91	0.004	-.1145233	-.022351
gamma_2_2	.1262665	.0263559	4.79	0.000	.0746098	.1779231
gamma_3_2	.0145941	.0075466	1.93	0.053	-.000197	.0293852
gamma_4_2	.0099638	.0118494	0.84	0.400	-.0132605	.0331881
gamma_3_3	.0465848	.0041107	11.33	0.000	.0385279	.0546416
gamma_4_3	-.0004354	.0044489	-0.10	0.922	-.0091552	.0082844
gamma_4_4	.0589087	.0096251	6.12	0.000	.0400439	.0777736
lambda						
lambda_1	.0179386	.0029482	6.08	0.000	.0121603	.0237169
lambda_2	-.0097531	.0026165	-3.73	0.000	-.0148814	-.0046248
lambda_3	-.0032877	.0014164	-2.32	0.020	-.0060638	-.0005117
lambda_4	-.0048978	.0025236	-1.94	0.052	-.0098439	.0000483
eta						
eta_nkids_1	.0002252	.000316	0.71	0.476	-.0003941	.0008446
eta_nkids_2	-.0004756	.0003542	-1.34	0.179	-.0011699	.0002186
eta_nkids_3	.0000165	.0001179	0.14	0.889	-.0002147	.0002476
eta_nkids_4	.0002339	.0002466	0.95	0.343	-.0002494	.0007173
eta_rural_1	-.0010496	.0007044	-1.49	0.136	-.0024301	.000331
eta_rural_2	.0006118	.0008155	0.75	0.453	-.0009866	.0022102
eta_rural_3	.0000242	.0002797	0.09	0.931	-.0005239	.0005724
eta_rural_4	.0004135	.0005931	0.70	0.486	-.0007489	.001576
rho						
rho_nkids	-.1318313	.0465259	-2.83	0.005	-.2230204	-.0406422
rho_rural	.2314054	.1909003	1.21	0.225	-.1427523	.6055631

The header of the output indicates the type of model fit, the number of observations and demographic variables, the value of α_0 used, and the maximized value of the log-likelihood function assuming multivariate normal errors. The table of estimated parameters is divided into groups representing each vector or matrix that appears in the demand system. Inspection reveals that the estimated parameters satisfy the adding-up and homogeneity conditions.

Commands like `test` and `testnl` can be used to perform Wald tests on the parameters just like any other estimation command. Here we test the null hypothesis that the dummy variable `rural` plays no significant role in determining expenditure patterns. If that null hypothesis is true, then all elements of the row of the $\boldsymbol{\eta}$ matrix corresponding to `rural` must be jointly 0, along with the corresponding element of the $\boldsymbol{\rho}$ vector.

```
. test [eta]_b[eta_rural_1], notest
 ( 1)  [eta]eta_rural_1 = 0
. test [eta]_b[eta_rural_2], notest accumulate
 ( 1)  [eta]eta_rural_1 = 0
 ( 2)  [eta]eta_rural_2 = 0
. test [eta]_b[eta_rural_3], notest accumulate
 ( 1)  [eta]eta_rural_1 = 0
 ( 2)  [eta]eta_rural_2 = 0
 ( 3)  [eta]eta_rural_3 = 0
. test [eta]_b[eta_rural_4], notest accumulate
 ( 1)  [eta]eta_rural_1 = 0
 ( 2)  [eta]eta_rural_2 = 0
 ( 3)  [eta]eta_rural_3 = 0
 ( 4)  [eta]eta_rural_4 = 0
. test [rho]_b[rho_rural], accumulate
 ( 1)  [eta]eta_rural_1 = 0
 ( 2)  [eta]eta_rural_2 = 0
 ( 3)  [eta]eta_rural_3 = 0
 ( 4)  [eta]eta_rural_4 = 0
 ( 5)  [rho]rho_rural = 0
       Constraint 4 dropped
           chi2(  4) =    3.42
         Prob > chi2 =    0.4909
```

The output from `test` indicates that `Constraint 4 dropped`. Recall that the rows of $\boldsymbol{\eta}$ are constrained to sum to 0. If the first three elements of the row corresponding to `rural` are each equal to 0, then the fourth must be 0 as well. Therefore, testing whether all four elements are equal to 0 is equivalent to testing whether the first three are equal to 0. In fact, knowing that, we could have omitted the line

```
. test [eta]_b[eta_rural_4], notest accumulate
```

We would have obtained the same test statistic either way. Given that our `rural` variable was randomly generated, we are not surprised that the test statistic does not allow us to reject the null hypothesis.

We are often more interested in the expenditure and price elasticities rather than in the estimated coefficients per se. Here we compute the expenditure elasticities for each household in the dataset and then summarize them:

```
. estat expenditure e*
. summarize e_1-e_4
    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
         e_1 |      4039    1.966449    1.399172   1.261789   59.43863
         e_2 |      4029   -.0024687    1.061976  -31.56926   .7976551
         e_3 |      3996    .2458694    .9005266  -22.42106   .9050692
         e_4 |      4047     .631619    .8235479  -45.74813   .9296512
```

Recall that (3) includes w_i in the denominator of a fraction. Thus if a household does not consume a particular item ($w_i = 0$), the expenditure elasticity will be infinite (a missing value in Stata parlance). That explains why the number of nonmissing observations for each of our four expenditure elasticities is less than the estimation sample size. Moreover, if w_i is close to 0, then the expenditure elasticity will be very large in magnitude. When computing household-level elasticities, you should therefore be cognizant of extreme values for some households and perhaps use summary statistics such as medians that are not influenced by outliers.

Next we compute the uncompensated price elasticities for "representative" rural and urban households, where we set all variables other than `rural` equal to their group-level means. To do that, we use the `atmeans` option of `estat uncompensated`, and we use an `if` condition to restrict computations to the relevant subsample.

```
. estat uncompensated if rural, atmeans
. matrix uprural = r(uncompelas)
. estat uncompensated if !rural, atmeans
. matrix upurban = r(uncompelas)
. matrix list uprural
uprural[4,4]
            c1          c2          c3          c4
r1  -1.2651808  -.10694767  -.13132521  -.25314115
r2   .32700506  -.74128023   .04191575   .12540763
r3    .0511128  -.03848514  -.55763258   .05041919
r4   .08810754  -.06235336  -.00975406  -.73724268
. matrix list upurban
upurban[4,4]
            c1          c2          c3          c4
r1  -1.3038599   -.0934749   -.1296122  -.25505899
r2   .36542124  -.75058651   .04011097   .12743289
r3   .07559882  -.04814826  -.55976996   .05029575
r4    .1021857  -.06701876  -.01060621  -.74324303
```

The entry in row i, column j of each elasticity matrix represents the percentage change in the quantity of good i consumed for a 1% change in the price of good j. Among rural consumers, a 1% increase in the price of good A raises consumption of good B by 0.33%.

5 Conclusion

Previously, to fit an AIDS model in Stata, a user would have to write his or her own program to be used with `nlsur`; this proved a challenge for beginners. Widely distributed example programs did not allow for demographic variables either. The new `quaids` command removes all programming-related barriers to fitting these models in Stata, and it allows one to include demographic variables.

Even if users were successful in fitting an AIDS model, many probably struggled with computing elasticities; postestimation commands after `quaids` make those tasks easy.

6 References

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