SIMULATING DEMAND SYSTEMS*

by

Kenneth W. Clements

and

Dongling Chen

Economic Research Centre
Department of Economics
The University of Western Australia

DISCUSSION PAPER 98.25

DEPARTMENT OF ECONOMICS

THE UNIVERSITY OF WESTERN AUSTRALIA
NEDLANDS, WESTERN AUSTRALIA 6907

ISSN 0811-6067
ISBN 0-86422-878-3

*This research was supported by the ARC. We thank Paul Crompton, Bob Greig, Jan Smith, Ye Qiang and Wana Yang for their help.

TABLE OF CONTENTS

8.1	Introduction	1
8.2	Differential Demand Systems Again	2
8.3	Verifying a Demand System by Simulation	4
8.4	A Generalisation	6
8.5	A Matrix Approach	7
8.6	A Loss Function	13
8.7	Concluding Comments	15
	References	17

LIST OF TABLES

8.1	Simulation Results for Working's Model Under Preference Independence	5
8.2	Simulation of Intercepts, Income Coefficients and Diagonal Slutsky Coefficients	8
8.3	Simulation of Off-Diagonal Slutsky Coefficients	9
8.4	Simulation of the Income Flexibility	10
8.5	MAS Results	11
8.6	Ranks of Models	16

LIST OF FIGURE

8.1	Losses for Four Models	14
-----	------------------------------	----

CHAPTER 8

SIMULATING DEMAND SYSTEMS

8.1 INTRODUCTION

In the previous chapter, simulations were used fairly extensively to assess how econometric procedures perform under idealised conditions. These applications included the evaluation of conventional asymptotic standard errors of maximum likelihood estimators, as well as the extent to which the usual asymptotic test of preference independence gave reliable results. In short, it was found that these procedures left something to be desired, which led to the investigation of the use of alternatives such as bootstrapping and Monte Carlo testing.

Much of this work has its origins in the path-breaking research of Theil and his associates, including that of Laitinen (1978) and Meisner (1979) on testing homogeneity and Slutsky symmetry. A useful overview of that research is contained in Theil (1987). While these developments are in the context of demand systems, Theil argues that their application is much broader. He writes

“...simulation experiments provide an important extension of econometrics. Originally this field consisted of two components: econometric methodology (mainly mathematical statistics) and data analysis. Simulation is now a third component; it shows how econometric methods work under ideal circumstances. This is particularly relevant when theoretical results are confined to large-sample approximations.” (Theil, 1987, pp. 101-102.)

This chapter extends this work by applying a procedure to simulate demand systems in which the “true” model generating the data is unknown. The approach was introduced by Clements *et al.* (1998), who refer to it as the “matrix approach to simulation”, or MAS, as it involves all pairwise comparisons between a number of

true and estimated models which are summarised in the form of a matrix. There is some earlier research related to MAS which includes Kiefer and MacKinnon (1976) and Chen (1995); see Clements *et al.* (1998) for details.

This chapter is structured as follows. In Sections 8.2, we provide a brief, self-contained review of the differential demand systems which are used subsequently. Sections 8.3 and 8.4 deal with verifying a demand system by simulation, a methodology introduced by Theil *et al.* (1983), and its generalisation. This then leads to the matrix approach in Sections 8.5 and 8.6. Concluding comments are contained in Section 8.7.

8.2 DIFFERENTIAL DEMAND SYSTEMS AGAIN

In this chapter, we follow previous chapters in using various differential demand systems in a cross-country context. For convenience, we set out again the key elements of these models.

Let $\bar{w}_{ic}^c$, Dq_{ic}^c and Dp_{ic}^c be, respectively, the arithmetic average of the i^{th} budget share, the i^{th} quantity log-change and price log-change for country c ; and $\bar{w}_{ic}$, Dq_{ic} and Dp_{ic} be the corresponding sample means (over time) for country c . We express the demand equation for good i ($i = 1, \dots, n$) in country c ($c = 1, \dots, C$) as

$$(2.1) \quad y_{ic} = \alpha_i + \beta_i DQ_c + \sum_{j=1}^n \pi_{ij} Dp_{jc} + \varepsilon_{ic},$$

where $y_{ic} = \bar{w}_{ic}(Dq_{ic} - DQ_c)$; $DQ_c = \sum_{i=1}^n \bar{w}_{ic} Dq_{ic}$ is the Divisia volume index for country c ; α_i is an intercept; β_i is Working's (1943) income coefficient for good i ; π_{ij} is the $(i, j)^{\text{th}}$ Slutsky coefficient; and ε_{ic} is a disturbance term. Equation (2.1) for $i = 1, \dots, n$ is the unrestricted model.

According to demand homogeneity, when real income is held constant an equi-proportional increase in all prices has no effect on the quantities demanded. In the context of equation (2.1), this implies that

$$(2.2) \quad \sum_{j=1}^n \pi_{ij} = 0, \quad i = 1, \dots, n.$$

Slutsky symmetry states that the compensated cross-price slopes are symmetric, or equivalently

$$(2.3) \quad \pi_{ij} = \pi_{ji}, \quad i, j = 1, \dots, n.$$

Under preference independence (PI), tastes can be characterised by a utility function that is additive in the n goods, $\sum_{i=1}^n u_i(q_i)$, where $u_i(\cdot)$ is the i^{th} sub-utility function. This leads to the following further restrictions on the Slutsky coefficients

$$(2.4) \quad \pi_{ij} = \phi(\beta_i + \bar{w}_{ic})(\delta_{ij} - \beta_j - \bar{w}_{jc}), \quad i, j = 1, \dots, n,$$

where ϕ is the income flexibility (the reciprocal of the income elasticity of the marginal utility of income); and δ_{ij} is the Kronecker delta. Substituting (2.4) into (2.1), we obtain the i^{th} demand equation under PI:

$$(2.5) \quad y_{ic} = \alpha_i + \beta_i DQ_c + \phi(\beta_i + \bar{w}_{ic})(Dp_{ic} - DP'_c) + \varepsilon_{ic},$$

where $DP'_c = \sum_{i=1}^n (\beta_i + \bar{w}_{ic}) Dp_{ic}$ is the Frisch price index.

8.3 VERIFYING A DEMAND SYSTEM BY SIMULATION

Equation (2.5) for $i = 1, \dots, n$ is a demand system which is nonlinear in the coefficients. Most such systems are estimated by maximum likelihood. As ML has only an asymptotic justification, what, if anything, can be said about the small-sample properties of estimators of these types of demand systems? Theil *et al.* (1983) introduced a simulation methodology which can shed light on this question.

The Theil *et al.* procedure has four steps:

1. Estimate the demand system by ML.
2. Generate simulated values of the dependent variables using
 - (i) the data-based estimates of the coefficients;
 - (ii) the observed values of the independent variables; and
 - (iii) simulated values of the disturbances drawn from a $N(0, \hat{\Sigma})$ distribution, where $\hat{\Sigma}$ is the ML estimate of the disturbance covariance matrix.
3. Re-estimate the model with the simulated values of the dependent variables and the observed independent variables. This yields another set of coefficient estimates and their asymptotic standard errors.
4. Repeat steps 2 - 3 a number of times and compute the means and the RMSEs of the estimates, as well as the root-mean-squared asymptotic standard errors (RMSASEs).

This procedure reveals information regarding any biases in the estimated coefficients and the extent to which the asymptotic standard errors are an accurate measure of the precision of the estimates.

The previous chapter used data pertaining to 42 countries to estimate by ML equation (2.5) for $i = 1, \dots, 8$ goods. Section 7.10 employed the above simulation methodology to evaluate the quality of these estimates. Table 8.1 reproduces the results obtained with 1,000 trials. As all the means are close to the corresponding true values, the estimates are unbiased. Column 6 reveals that the RMSASEs of the

TABLE 8.1
SIMULATION RESULTS FOR WORKING'S MODEL
UNDER PREFERENCE INDEPENDENCE

Commodity (1)	True value (2)	Mean (3)	RMSE (4)	RMSASE (5)	(5)/(4) (6)
<u>Intercepts α_i</u>					
Food	-.216	-.217	.090	.083	.922
Clothing	-.126	-.126	.055	.051	.927
Housing	.266	.264	.058	.056	.966
Durables	-.168	-.168	.042	.041	.976
Medicine	.067	.067	.034	.032	.941
Transport	.130	.132	.059	.055	.932
Recreation	.016	.017	.038	.036	.947
Other	.032	.031	.053	.050	.943
<u>Income coefficients β_i</u>					
Food	-8.076	-8.029	2.620	2.375	.906
Clothing	2.179	2.174	1.463	1.344	.919
Housing	-6.830	-6.812	1.686	1.618	.960
Durables	5.779	5.776	1.097	1.104	1.006
Medicine	.419	.424	1.042	.954	.916
Transport	2.747	2.670	1.741	1.597	.917
Recreation	2.265	2.249	1.110	1.037	.934
Other	1.518	1.548	1.657	1.556	.939
Income flexibility ϕ	-42.429	-42.531	6.070	4.785	.788

Note: Except for column 6, all entries are to be divided by 100.

Source: Table 7.17.

intercepts and most of the income coefficients are lower than the corresponding RMSEs, which shows that the ASEs give an overly optimistic picture of the sampling variability of these estimates. Looking at the last entry in column 6, we see that the RMSASE : RMSE ratio for the income flexibility indicates that its ASEs are about 20

percent too small on average. For further details and results (including the use of the bootstrap to generate the disturbances), see Section 7.10.

8.4 A GENERALISATION

In the above simulation, the model that is estimated coincides with the model that generated the data, or the “true” model. It should, however, be acknowledged that it is only in the idealised simulation world that the true model is known with certainty. While the analyst may have some priors or preferences regarding the model to be used, in practice the true model is unknown. In this sense then, the simulation gives the benefit of the doubt to the model. In this section, we develop a generalisation in which the true and estimated models do not necessarily coincide.

Suppose that the true model is (2.1) for $i = 1, \dots, n$ with the Slutsky coefficients satisfying homogeneity and symmetry, (2.2) and (2.3), while the model actually estimated is (2.5) for $i = 1, \dots, n$, the preference independence version of (2.1). As there is no reason for the π_{ij} of (2.1) to satisfy exactly the PI constraint (2.4), we thus make a specification error in this situation. One way of assessing the seriousness of this error is, of course, to test the PI hypothesis against symmetry, as was done in Sections 7.7 - 7.9. We shall, however, pursue a simulation approach to this problem by an amendment to the approach set out in the previous section.

The amended procedure is as follows:

1. Estimate the homogeneity- and symmetry-constrained model (the true model).
2. Generate simulated values of the dependent variables using
 - (i) the data-based estimates of the coefficients;
 - (ii) the observed values of the independent variables; and
 - (iii) simulated values of the disturbances drawn from a $N(0, \hat{\Sigma})$ distribution, where $\hat{\Sigma}$ is the ML estimate of the disturbance covariance matrix.
 (This step is the same as before.)

3. Estimate the model under PI (the estimated model) with the simulated values of the dependent variables and the observed independent variables. Use the estimated coefficients and the means of the observed budget shares in equation (2.4) to generate the estimated Slutsky coefficients and their asymptotic standard errors.
4. Repeat steps 2 - 3 a number of times and compute the means and the RMSEs of the estimates, as well as the RMSASEs. (This step is also the same.)

To implement this procedure, we again use the cross-country data with 1,000 trials. The results are contained in Tables 8.2 - 8.4. (Here and subsequently, we only report results for the $n - 1 = 7$ independent commodity coefficients.) As can be seen, in contrast to the previous results, some of the estimates now have substantial biases, which is not too surprising given that we have deliberately committed a specification error. Additionally, the RMSASE:RMSE ratios are now all much lower than before. Averaging over commodities, this ratio is .35 for the diagonal Slutsky coefficients and .16 for the off-diagonals.

8.5 A MATRIX APPROACH

The above results represent the symmetry/PI comparison. But as there is also the unrestricted model and the homogeneity-constrained model, there is no reason why we should confine ourselves to just the one pairwise comparison. If i and j denote the true and estimated models and if k is the number of models, then the pairs of indices $i, j = 1, \dots, k$ identify the k^2 cells of a comparison matrix. Clements *et al.* (1998) call this procedure the “matrix approach” to simulating (MAS) demand equations. In this section we illustrate MAS with the estimated coefficients (by contrast, Clements *et al.* apply the methodology to the estimated elasticities).

We implement MAS with the cross-country data by using in Step 1 of the previous section the relevant true model and the relevant estimated model in Step 3. We use $k = 6$ models -- the unrestricted model, homogeneity-constrained,

TABLE 8.2

SIMULATION OF INTERCEPTS, INCOME COEFFICIENTS
AND DIAGONAL SLUTSKY COEFFICIENTSTrue model = Symmetry
Estimated model = Preference independence

Commodity	True value	Bias	RMSE	RMSASE	(5)/(4)
(1)	(2)	(3)	(4)	(5)	(6)
<u>Intercepts α_i</u>					
1. Food	-.146	-.066	.116	.089	.764
2. Clothing	-.094	-.021	.060	.054	.905
3. Housing	.131	.122	.140	.062	.445
4. Durables	-.123	-.038	.061	.049	.795
5. Medicine	.091	-.029	.045	.034	.740
6. Transport	.140	-.013	.069	.063	.920
7. Recreation	-.009	.023	.044	.037	.853
Mean		.045	.076	.055	.725
<u>Income coefficients β_i</u>					
1. Food	-9.899	1.694	3.259	2.548	.782
2. Clothing	1.771	.277	1.516	1.441	.950
3. Housing	-2.987	-3.569	4.079	1.796	.440
4. Durables	4.006	1.810	2.174	1.307	.601
5. Medicine	.182	.291	1.123	1.005	.894
6. Transport	2.271	.487	2.059	1.853	.900
7. Recreation	3.231	-.909	1.424	1.082	.760
Mean		1.291	2.233	1.576	.706
<u>Diagonal Slutsky coefficients π_{ii}</u>					
1. Food	-9.243	1.876	2.548	1.109	.435
2. Clothing	-3.629	-.094	.910	.641	.704
3. Housing	1.811	-4.551	4.595	.564	.123
4. Durables	-6.038	1.747	2.004	.720	.359
5. Medicine	-1.814	.004	.521	.411	.790
6. Transport	-5.790	1.437	1.763	.796	.451
7. Recreation	-4.027	.908	1.163	.531	.456
Mean		1.517	1.929	.682	.353

Notes: 1. Except for column 6, all entries are to be divided by 100.

2. Absolute values are used in computing the means.

TABLE 8.3

SIMULATION OF OFF-DIAGONAL SLUTSKY COEFFICIENTS

True model = Symmetry
Estimated model = Preference independence

Commodity subscripts		True value	Bias	RMSE	RMSASE	(5)/(4)
i	j	(3)	(4)	(5)	(6)	(7)
(1)	(2)					
1	2	3.509	-2.327	2.349	.269	.114
1	3	1.036	-.197	.292	.331	1.133
1	4	-.108	1.507	1.554	.297	.191
1	5	.001	.538	.565	.183	.323
1	6	1.160	.258	.446	.345	.774
1	7	1.957	-.988	1.021	.220	.216
2	3	-.799	1.143	1.147	.129	.113
2	4	.868	-.293	.334	.072	.214
2	5	1.114	-.893	.896	.042	.047
2	6	1.360	-.772	.791	.097	.122
2	7	-1.288	1.688	1.692	.061	.036
3	4	.123	.283	.300	.130	.434
3	5	-.223	.381	.384	.089	.230
3	6	1.282	-.869	.875	.160	.183
3	7	-.322	.606	.611	.105	.172
4	5	.808	-.548	.554	.037	.067
4	6	.374	.315	.364	.084	.230
4	7	2.827	-2.357	2.361	.053	.022
5	6	-.128	.394	.404	.055	.137
5	7	.522	-.343	.347	.030	.087
6	7	-.537	1.015	1.024	.071	.069
Mean			.844	.872	.136	.156

See notes to Table 8.2.

symmetry-constrained, preference independence, no substitution ($\pi_{ij} = 0$, $i, j = 1, \dots, 8$) and no substitution plus homotheticity ($\pi_{ij} = 0$, $i, j = 1, \dots, 8$; $\beta_i = 0$, $i = 1, \dots, 8$). The results, obtained with 1,000 trials, are summarised in Table 8.5 in terms of the biases and RMSEs. The shaded entries indicate the biases and RMSEs when the true and estimated models coincide. As in this situation there is no specification error, we should expect these biases to be the minima of the relevant columns and rows. This is

TABLE 8.4
SIMULATION OF THE INCOME FLEXIBILITY

True model = Symmetry
Estimated model = Preference independence

Mean	-.365
RMSE around mean	.077
RMSASE	.050
RMSASE/RMSE	.649

true for the vast majority of cases. We can eliminate the role of the true model by averaging over the six alternatives, as in the last rows of the upper and lower panels of Table 8.5. The boxes in the last row of the upper panel indicate that the biases are minimised with the unrestricted model.

The picture emerging from the lower panel of the table for the RMSEs is a little different. Averaging over the six true models, we find that the models with the lowest RMSEs are as follows:

Coefficients	Model
Intercepts α_i	No substitution
Income coefficients β_i	Symmetry
Diagonal Slutsky coefficients π_{ii}	Preference independence
Off-diagonal Slutsky coefficients π_{ij}	Preference independence
All coefficients	No substitution and homotheticity

We may wish to rule out the (i) no substitution and (ii) no substitution and homothetic models for consideration on the basis that these are considerably different from the others as prices play no role. In this case, the model under symmetry has the lowest RMSEs for the intercepts, and preference independence has the lowest for all

TABLE 8.5

MAS RESULTS

True model	Estimated model	Unrestricted					Homogeneity					Symmetry				
		α_i	β_i	π_{ii}	π_{ij}	Mean	α_i	β_i	π_{ii}	π_{ij}	Mean	α_i	β_i	π_{ii}	π_{ij}	Mean
Unrestricted		.002	.048	.037	.052	.035	.017	.158	.127	.139	.110	.038	.445	1.156	1.222	.715
Homogeneity		.002	.047	.038	.051	.035	.002	.045	.036	.050	.033	.027	.359	1.128	1.192	.676
Symmetry		.002	.051	.039	.052	.036	.002	.048	.037	.051	.034	.002	.037	.047	.030	.029
Preference independence		.007	.170	.429	.219	.206	.006	.154	.438	.225	.206	.009	.177	.437	.137	.190
No substitution		.002	.056	.049	.051	.040	.002	.052	.045	.049	.037	.002	.043	.051	.035	.033
No substitution and homotheticity		.003	.061	.047	.055	.041	.002	.057	.044	.052	.039	.002	.046	.053	.037	.035
Mean		.003	.072	.107	.080	.065	.005	.086	.121	.094	.077	.013	.184	.479	.442	.280
Mean absolute biases																
Unrestricted		.079	1.784	1.920	1.821	1.401	.078	1.780	1.916	1.820	1.399	.079	1.784	2.248	1.828	1.485
Homogeneity		.079	1.781	1.914	1.819	1.398	.075	1.766	1.901	1.809	1.388	.074	1.757	2.232	1.813	1.469
Symmetry		.080	1.806	1.942	1.842	1.417	.076	1.791	1.929	1.831	1.407	.066	1.700	1.765	1.159	1.173
Preference independence		.077	1.751	1.942	1.799	1.392	.074	1.735	1.929	1.790	1.382	.065	1.653	1.798	1.143	1.165
No substitution		.085	1.926	2.081	1.967	1.515	.081	1.910	2.067	1.957	1.504	.070	1.818	1.844	1.242	1.243
No substitution and homotheticity		.089	2.016	2.188	2.053	1.586	.085	1.999	2.173	2.042	1.575	.073	1.902	1.971	1.312	1.314
Mean		.082	1.844	1.998	1.883	1.452	.078	1.830	1.986	1.875	1.442	.071	1.769	1.976	1.416	1.308
Mean RMSEs																
Unrestricted		.079	1.784	1.920	1.821	1.401	.078	1.780	1.916	1.820	1.399	.079	1.784	2.248	1.828	1.485
Homogeneity		.079	1.781	1.914	1.819	1.398	.075	1.766	1.901	1.809	1.388	.074	1.757	2.232	1.813	1.469
Symmetry		.080	1.806	1.942	1.842	1.417	.076	1.791	1.929	1.831	1.407	.066	1.700	1.765	1.159	1.173
Preference independence		.077	1.751	1.942	1.799	1.392	.074	1.735	1.929	1.790	1.382	.065	1.653	1.798	1.143	1.165
No substitution		.085	1.926	2.081	1.967	1.515	.081	1.910	2.067	1.957	1.504	.070	1.818	1.844	1.242	1.243
No substitution and homotheticity		.089	2.016	2.188	2.053	1.586	.085	1.999	2.173	2.042	1.575	.073	1.902	1.971	1.312	1.314
Mean		.082	1.844	1.998	1.883	1.452	.078	1.830	1.986	1.875	1.442	.071	1.769	1.976	1.416	1.308

Notes: 1. All entries are to be divided by 100.

2. The shaded entries correspond to the true and estimated models coinciding.

3. The entries in boxes represent the minimum average bias (over the various estimated models) for the respective coefficients.

(Continued on next page)

TABLE 8.5 (continued)

MAS RESULTS

True model	Estimated model	Preference independence					No substitution					No substitution and homotheticity				
		α_i (16)	β_i (17)	π_{ii} (18)	π_{ij} (19)	Mean (20)	α_i (21)	β_i (22)	π_{ii} (23)	π_{ij} (24)	Mean (25)	α_i (26)	β_i (27)	π_{ii} (28)	π_{ij} (29)	Mean (30)
<u>Mean absolute biases</u>																
Unrestricted Homogeneity		.065	1.683	1.755	1.521	1.256	.031	.829	-	-	.430	.090	-	-	-	.090
Symmetry		.062	1.630	1.701	1.541	1.233	.038	.931	-	-	.485	.103	-	-	-	.103
Preference independence		.045	1.291	1.517	.844	.924	.031	.636	-	-	.333	.131	-	-	-	.131
No substitution		.001	.024	.010	.003	.009	.034	.546	-	-	.290	.145	-	-	-	.145
No substitution and homotheticity		.001	.033	.027	.004	.016	.001	.037	-	-	.019	.108	-	-	-	.108
Mean		.001	.038	.029	.004	.018	.001	.042	-	-	.022	.001	-	-	-	.001
		.029	.783	.840	.653	.576	.023	.503	-	-	.263	.096	-	-	-	.096
<u>Mean RMSEs</u>																
Unrestricted Homogeneity		.096	2.511	2.127	1.542	1.569	.068	1.927	-	-	.997	.096	-	-	-	.096
Symmetry		.090	2.453	2.073	1.563	1.545	.071	1.947	-	-	1.009	.108	-	-	-	.108
Preference independence		.076	2.233	1.929	.872	1.278	.067	1.851	-	-	.959	.133	-	-	-	.133
No substitution		.052	1.497	.777	1.40	.616	.068	1.709	-	-	.888	.148	-	-	-	.148
No substitution and homotheticity		.061	1.767	.705	.105	.659	.061	1.756	-	-	.908	.112	-	-	-	.112
Mean		.064	1.854	.737	.111	.691	.063	1.839	-	-	.951	.023	-	-	-	.023
		.073	2.053	1.391	.722	1.060	.066	1.838	-	-	.952	.103	-	-	-	.103

12

coefficients. In what follows, we exclude the two models which have no Slutsky coefficients and consider only the remaining four.

8.6 A LOSS FUNCTION

Next, following Clements *et al.* (1998), we use a loss function to combine the biases and the RMSEs. Let B be the bias and $S^2 = \text{RMSE}^2 - B^2$ be the variance. The loss function we use is a weighted average of the squared bias and the variance:

$$(6.1) \quad \sqrt{\alpha B^2 + (1 - \alpha)S^2},$$

where $0 \leq \alpha \leq 1$. This has the attraction of involving only one unknown parameter, α , and takes the following values:

α	Loss
0	S
1/2	$(1/\sqrt{2})\text{RMSE}$
1	B

For a given set of coefficients (the intercepts, income coefficients, etc.) and for a given value of α , we evaluate the loss function (6.1) for each true and estimated model and then average the loss over the four true models. Figure 8.1 presents the results. As can be seen, the losses generally decline as α rises, indicating that the biases ($\alpha = 1$) tend to be smaller than the standard errors ($\alpha = 0$). For the intercepts and the income coefficients (Panels A and B), there is not much difference between the losses for the various models for a given value of α . However, for the diagonal Slutsky coefficients (Panel C), the preference independence model performs best for all values of α up to and including .75. This same pattern also occurs with the off-diagonal coefficients (Panel D). Finally, averaging the losses over all sets of coefficients, we see from Panel E of the figure that PI again performs best for most

FIGURE 8.1
LOSSES FOR FOUR MODELS
($\times 100$)

Note: U = unrestricted model; H = homogeneity-restricted model; S = symmetry-restricted model; and PI = preference-independent restricted model.

values of α . Interestingly, the losses for the Slutsky coefficients (both diagonal and off-diagonal) under PI tend to be less dependent on α than those for the other models.

Table 8.6 summarises the results in an alternative way by using the information in Figure 8.1 to rank the four models for alternative values of α . As can be seen from column 7, on the basis of the mode the PI model performs either best or equal best for each set of coefficients, as well as for all coefficients combined. The only exception to this rule is for the income coefficients where PI performs the worst. However, this is not such a serious indictment of PI as Panel B of Figure 8.1 shows that the losses do not vary all that much across different models.

8.7 CONCLUDING COMMENTS

Choosing between different demand models is a problem of considerable practical importance. This paper applies MAS (the matrix approach to simulation) to this problem. This methodology involves using one model (known as the "true model") to generate artificial data and then using these data to estimate another model (the "estimated" model); all pairs of the true and estimated models then form a comparison matrix which can be used to assess the various alternatives.

Using international data pertaining to 42 countries, we find that:

- There is little to discriminate between models on the basis of the intercepts (which, given the first-difference formulation of the models, play the role of trend-like changes in tastes) and the income coefficients.
- There is considerable evidence in favour of the preference independence (PI) version of the demand equations. This finding contradicts older findings against PI (see, e.g., Barten, 1977, and Deaton, 1974), but is consistent with the more recent work of Clements *et al.* (1997) and Selvanathan (1993).

TABLE 8.6
RANKS OF MODELS

Model (1)	Values of loss function parameter					Mode (7)
	$\alpha = 0$	$\alpha = .25$	$\alpha = .5$	$\alpha = .75$	$\alpha = 1$	
	SE (2)	(3)	(1/ $\sqrt{2}$) RMSE (4)	(5)	BIAS (6)	
A. Intercepts						
1. Unrestricted	4	4	4	3	1	4
2. Homogeneity	3	3	3	2	2	3
3. Symmetry	2	2	1	1	3	1, 2
4. Preference independence	1	1	2	4	4	1, 4
B. Income Coefficients						
1. Unrestricted	4	3	3	3	1	3
2. Homogeneity	3	2	2	2	2	2
3. Symmetry	1	1	1	1	3	1
4. Preference independence	2	4	4	4	4	4
C. Diagonal Slutsky Coefficients						
1. Unrestricted	4	4	4	3	1	4
2. Homogeneity	3	3	3	2	2	3
3. Symmetry	2	2	2	4	3	2
4. Preference independence	1	1	1	1	4	1
D. Off-Diagonal Slutsky Coefficients						
1. Unrestricted	4	4	4	4	1	4
2. Homogeneity	3	3	3	3	2	3
3. Symmetry	2	2	2	2	3	2
4. Preference independence	1	1	1	1	4	1
E. Mean						
1. Unrestricted	4	4	4	4	1	4
2. Homogeneity	3	3	3	3	2	3
3. Symmetry	2	2	2	2	3	2
4. Preference independence	1	1	1	1	4	1

Note: Emboldened cells indicate the top-ranked models.

REFERENCES

- Barten, A. P. (1977). "The Systems of Consumer Demand Functions Approach: A Review." *Econometrica* 45: 23-51.
- Chen, D. L. (1995). "Undersized Samples and Demand Analysis." Chapter 5 in E. A. Selvanathan and K. W. Clements (eds) *Recent Developments in Applied Demand Analysis: Alcohol, Advertising and Global Consumption*. Berlin/Heidelberg: Springer-Verlag. Pp. 191-220.
- Clements, K. W., W. Yang and D. L. Chen (1998). "The Matrix Approach to Evaluating Demand Equations." Discussion Paper 98.10, Department of Economics, The University of Western Australia.
- _____, W. Yang and S. W. Zheng (1997). "Is Utility Additive? The Case of Alcohol." *Applied Economics* 29: 1163-67.
- Deaton, A. S. (1974). "A Reconsideration of the Empirical Implications of Additive Preferences." *Economic Journal* 84: 338-48.
- Kiefer, N. M. and J. G. MacKinnon (1976). "Small-Sample Properties of Demand System Estimates." In S. M. Goldfeld and R. E. Quandt (eds) *Studies in Nonlinear Estimation*. Cambridge, Mass.: Ballinger. Pp. 181-210.
- Laitinen, K. (1978). "Why is Demand Homogeneity So Often Rejected?" *Economics Letters* 1: 187-91.
- Meisner, J. F. (1979). "The Sad Fate of the Asymptotic Slutsky Symmetry Test for Large Systems." *Economics Letters* 2: 231-33.
- Selvanathan, S. (1993). *A System-Wide Analysis of International Consumption Patterns*. Dordrecht, Netherlands: Kluwer Academic.
- Theil, H. (1987). "The Econometrics of Demand Systems." Chapter 3 in H. Theil and K. W. Clements *Applied Demand Analysis: Results from System-Wide Approaches*. Cambridge, Mass.: Ballinger Publishing Co., pp. 101-62.
- _____, R. Finke and M. C. Rosalsky (1983). "Verifying a Demand System by Simulation." *Economics Letters* 13: 15-18.
- Working, H. (1943). "Statistical Laws of Family Expenditure." *Journal of the American Statistical Association* 38: 43-56.