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A New Set of Consumer Demand Estimates for Ireland

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Abstract: This paper provides a new set of consumer demand estimates for Ireland, incorporating a variety of different consumer demand models. Own-price and expenditure elasticities are presented and tests of the propositions implied by utility-maximisation are carried out, including the use of small-sample corrections. The results obtained show reasonable agreement across the different deterministic models but stochastic and dynamic specification appears to be of crucial importance both for plausibility of estimates obtained and for rejection or non-rejection of the restrictions implied by utility-maximisation.

I INTRODUCTION

This paper looks at some new sets of consumer demand estimates for Ireland. Empirical evidence on consumer behaviour is of interest for a number of reasons. It is essential for analysis of such issues as tax design and reform, the effects of different credit conditions and budgetary policies. It also provides a means of testing some of the most fundamental propositions of microeconomics.

Such a study for Ireland is also timely for a number of reasons. First, it is over ten years since the last published work on consumer demand systems in Ireland (Conniffe and Hegarty, 1980), if one excludes work done on commodity demands and labour supply by Murphy and Thom (1986), and consequently the extra ten observations are welcome from a degrees of

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freedom standpoint. Secondly, the study provides estimates from the CBS[1] system of Keller and Van Driel (1985), the first such for Ireland. Thirdly, it uses a more comprehensive battery of tests of the restrictions implied by utility maximisation than has previously been available for Ireland, including small sample corrections.

The plan of the paper is as follows: the next section outlines the different models of consumer demand estimated here. Section III discusses the own-price and expenditure elasticities estimated. Section IV discusses such issues as dynamic specification and tests for homogeneity, symmetry and negativity. Section V compares the results obtained here with results from other studies of consumer demand systems for Ireland, while Section VI offers some concluding remarks.

II MODELS OF CONSUMER DEMAND

We will be looking at demand estimates from three different models of consumer demand. These are the Almost Ideal Demand System (AIDS) (Deaton and Muellbauer, 1980), the Rotterdam model (Theil, 1975) and the CBS model (Keller and Van Driel,1985). While the latter two models can only be estimated in differenced form, the AIDS model can be estimated in both levels and first differences. Thus overall we will have four different "models" of consumer demand estimates. In this section, we briefly outline these models and, in particular, illustrate the similarities between the AIDS model in differences and the Rotterdam and CBS models.

The estimating equation in the AIDS model is derived from a cost function of the form:

$$\log c(u,p) = a(p) + ub(p) \tag{1}$$

where u represents utility, p represents consumer prices and a and b are functions of prices. The particular functions chosen are:

$$a(p) = \alpha_0 + \Sigma_k \alpha_k \log p_k + (1/2).\Sigma_k \Sigma_l \gamma^*_{kl} \log p_k \log p_l \tag{2}$$

$$b(p) = \beta_0 \Pi p^{\beta k} k \tag{3}$$

Since $w_i = \delta \log c/\delta \log p_i$, where w_i is the share of expenditure on good i in the total budget, it can be shown that:

1. The name "CBS" comes from the fact that the authors were working in The Netherlands Central Bureau of Statistics when they first formulated the model.

$$w_i = \alpha_i + \Sigma_j \gamma_{ij} \log p_j + \beta_i \log(m / P) \tag{4}$$

where m is total expenditure and P is a price index defined by:

$$\log P = \alpha_0 + \Sigma_k \alpha_k \log p_k + (1/2)\Sigma_j \Sigma_k \gamma_{kj} \log p_j \log p_k \tag{5}$$

and the parameters γ are defined by:

$$\gamma_{ij} = 1/2(\gamma^*_{ij} + \gamma^*_{ji}) = \gamma_{ji} \tag{6}$$

Expression (5) makes Equation (4) non-linear, and estimation becomes easier when we approximate P by P^*, defined by:

$$\log P^* = \Sigma_k w_k \log p_k \tag{7}$$

The use of (7) is an empirical approximation and preliminary evidence suggested that its use does not lead to important differences in the results when the prices are collinear (see for example Deaton and Muellbauer (1980a)). However, more recent studies have begun to question this, e.g. Pashardes (1992).[2] For the moment, however, we will continue to use the approximation.

Amongst the attractive features of the AIDS model is the relative ease of imposition and testing of such restrictions as aggregation, homogeneity and symmetry. Engel aggregation implies $\Sigma_i\beta_i=0$, while Cournot aggregation implies $\Sigma_i\gamma_{ij}=0$. These two conditions can easily be imposed by simply dropping an arbitrary equation from the system. Homogeneity implies $\Sigma_j\gamma_{ij}=0$, while symmetry implies $\gamma_{ij}=\gamma_{ji}$. However, the γ_{ij} estimated are not the parameter estimates from the Slutsky matrix, so that negativity cannot be imposed in an AIDS model. The estimated β_i show the sensitivity of the budget shares to total real expenditure and will be negative in the case of necessities and positive in the case of luxuries.

The differenced version of the AIDS model, which we label DAIDS can be easily obtained from (4). If we substitute (7) into (4) and take differences we obtain

$$\Delta w_{it} = \beta_i(\Delta \log m_t - \Sigma_k w^*_{kt}\Delta \log p_{kt}) + \Sigma_j \gamma_{ij}\Delta \log p_{jt} \tag{8}$$

where t is a time subscript, $\Delta x_t = x_t - x_{t-1}$, and $w^*_{kt} = (w_{kt} + w_{k,t-1})/2$. The aggregation, homogeneity and symmetry restrictions are imposed as in the levels case. One obvious difference between the levels and the differenced version of the AIDS is the lack of an intercept term in the latter. In their

2. He shows that use of this approximation can lead to a bias in estimates similar to that introduced by omitted variables. However, he suggests that the bias is more serious for estimates from micro-based data, rather than the aggregate data used here.

original paper in 1980, Deaton and Muellbauer include an intercept term when estimating the differenced version. Where these intercepts are significant they imply time trends in the levels model. Owing to the sensitivity of the estimated models to dynamic specification, we also estimated the AIDS model in levels with a quadratic time trend (TAIDS).

Turning next to the Rotterdam model, its estimating equation is (for a detailed account of the Rotterdam model, see Theil (1975)):

$$w_i^* \Delta \log x_i = b_i \Sigma_j w_j^* \Delta \log x_j + \Sigma_j s_{ij} \Delta \log p_j \qquad (9)$$

where x_i refers to the quantity of good i. Using the fact that the first term on the right-hand side of the above equation can also be expressed as $\Delta\log m - \Sigma_j w_j^* \Delta \log p_j$ (from the total differential of the budget share $w_i = x_i p_i / m$), we see that the right-hand side of the estimating equation for the Rotterdam model is the same as that for the differenced AIDS model. The interpretation of the parameters, however, is not the same, owing to the different terms on the left-hand-side of the equation. The b_i are marginal budget shares, while the s_{ij} are the parameters of the Slutsky matrix. Once again, Cournot and Engel aggregation can be imposed by dropping an arbitrary equation. $\Sigma_j s_{ij}=0$ imposes homogeneity, while symmetry implies $s_{ij}=s_{ji}$. Unlike the AIDS models, negativity can be imposed by the condition that the matrix $[s_{ij}]$ be negative semi-definite of rank n–1, where n is the number of commodities.

The final model we will estimate is the CBS model of Keller and Van Driel (1985). Essentially, this model combines the attractive features of the AIDS model (perfect aggregation and non-parallel Engel curves) with the matrix of price coefficients of the Rotterdam model (with its ease of imposing symmetry and negativity). The estimating equation for the CBS model is:

$$w_i^*(\Delta \log x_i - \Sigma_j w_j^* \Delta \log x_j) = \beta_i \Sigma_j w_j^* \Delta \log x_j + \Sigma_j s_{ij} \Delta \log p_j. \qquad (10)$$

Proceeding as with Equation (6), we can see that the CBS estimating equation has the same right-hand side as the Rotterdam and differential AIDS models. The interpretation of the β_i is as in the AIDS models, while the imposition of both types of aggregation, homogeneity, symmetry and negativity is as in the Rotterdam model.

The above models of consumer demand were estimated for Ireland, using annual data, for the period 1958-1988. The data were disaggregated into ten commodities: food, alcohol, tobacco, clothing and footwear, fuel and power, petrol, transport and equipment including travelling within the state, durables, other goods and services. For estimation purposes services was treated as a residual category and equations for the other nine goods were estimated.

III ESTIMATION

Estimation was carried out using the SHAZAM package. The estimation procedure used was Zellner's Seemingly Unrelated Regressions approach. Given that the right hand side variables are the same for all equations, this is equivalent to running separate OLS regressions for each good. The estimates obtained are identical, except when the cross-equation restriction of symmetry is imposed. Given that we have five different models, and three versions of each model (unrestricted, with homogeneity imposed and with symmetry and homogeneity imposed), overall we have fifteen different sets of estimates. The results for own-price elasticities (uncompensated) and expenditure elasticities are presented in Tables 1 and 2. All elasticities are evaluated at their average budget shares over the estimating period.

Dealing firstly with the own-price elasticities, perhaps one of the more striking features of the results is the degree of consistency of estimates across the different models. By and large own-price elasticities for each good tend to be quite stable, barring one or two very strange outliers (e.g., petrol in the unrestricted AIDS in levels model and alcohol in the AIDS in levels model with homogeneity imposed). A substantial majority of the estimates are significantly different from zero at the 95 per cent level, and even those estimates which are not significant tend to be very similar in magnitude to estimates from other models which are significant e.g. in the case of transport and equipment, only estimates from the Rotterdam and CBS models are significant. (Note that when we use the term "significant" we mean that the estimated coefficient from which the elasticity was calculated was significant). Nevertheless, the estimates from the AIDS model in levels, with and without a time trend, and the AIDS in differences model are very close to those in the Rotterdam and CBS models.

The results are also intuitively quite plausible. Generally speaking, the greater the degree of disaggregation of commodities, the higher the values of own-price elasticities one would expect, as there is greater scope for substitution. Within our ten-group classification we can see higher elasticities (in absolute terms) for those goods that intuitively we would regard as "luxuries" or most easily substituted away from, e.g. witness the relatively high elasticities for transport and equipment and services and the relatively low ones for food and fuel and power. Given that food and fuel and power would be regarded as "necessities" while transport and equipment and services might be regarded as "luxuries" this could be viewed as support for the generalisation known as Pigou's Law (Deaton, 1974), i.e., proportionality between own-price and expenditure elasticities. This is of interest, since Pigou's Law is most usually observed in demand systems where preferences

Table 1: *Own-Price Elasticities (at average budget shares)*

Good	*AIDS1*	*AIDS2*	*AIDS3*	*DAIDS1*	*DAIDS2*	*DAIDS3*
Food	–0.891	–0.929	–0.790*	–0.770*	–0.779*	–0.723*
Alcohol	–0.410*	0.281*	–0.123*	–0.274*	–0.253*	–0.61*
Tobacco	–0.662*	–0.678*	–0.338*	–0.685*	–0.628*	–0.586*
Clothing & Footwear	–0.900	–0.667	–0.520*	–1.011	–0.917	–0.655
Fuel & Power	–0.069*	–0.016*	–0.149*	–0.002*	0.027*	–0.247*
Petrol	0.056*	–0.536	–0.437	–0.485*	–0.475*	–0.206*
Transport & Equipment	–1.202	–1.012	–0.918	–0.942	–0.939	–0.940
Durables	–1.500*	–0.778	–1.425	–1.048	–1.037	–0.940
Other Goods	–0.452*	–0.493*	–0.485*	–0.560*	–0.540*	–0.583*
Services	–1.279	–1.237	–1.376	–1.015	–1.023	–0.915
LLF	1,386.49	1,351.27	1,232.91	1,303.56	1,280.45	1,208.4

Good	*ROTT1*	*ROTT2*	*ROTT3*	*CBS1*	*CBS2*	*CBS3*
Food	–0.555*	–0.549*	–0.573*	–0.562*	–0.504*	–0.546*
Alcohol	–0.290	–0.278	–0.648*	–0.235	–0.226	–0.594*
Tobacco	–0.429*	–0.372*	–0.345*	–0.573*	–0.400*	–0.401*
Clothing & Footwear	–1.052*	–0.966*	–0.693*	–1.227*	–0.980	–0.678*
Fuel & Power	0.068	0.086	–0.173	0.057	0.087	–0.175
Petrol	–0.415*	–0.408*	–0.190	–0.489*	–0.448*	–0.225
Transport & Equipment	–1.061*	–1.046*	–1.062*	–1.025*	–1.031*	–1.031*
Durables	–1.095*	–1.092*	–1.054*	–1.413*	–1.013*	–1.013*
Other Goods	–0.651*	–0.648*	–0.686*	–0.582*	–0.728*	–0.728*
Services	–1.094	–1.107	–1.005	–0.724	–1.017	–1.017
LLF	1,304.3	1,286.5	1,212.6	1,308.6	1,291.1	1,210.7

Good	*TAIDS1*	*TAIDS2*	*TAIDS3*
Food	–0.774*	–0.896	–0.785*
Alcohol	–0.562*	–0.649	–0.865
Tobacco	–0.592*	–0.610*	–0.678*
Clothing & Footwear	–1.029	–1.032	–0.873
Fuel & Power	–0.180*	–0.470*	–0.233*
Petrol	–0.238*	–0.122*	+0.062*
Transport & Equipment	–0.709	–0.580	–0.822
Durables	–1.470	–1.210	–0.934
Other Goods	–0.523*	–0.498*	–0.638
Services	–1.124	–1.027	–0.333
LLF	1,464.45	1,418.99	1,293.12

Notes: *indicates significant at 95 per cent confidence level.
LLF — Value of log likelihood function.
Suffixes 1, 2, and 3 refer to unrestricted, homogeneity imposed, and homogeneity and symmetry imposed respectively.

Table 2: *Expenditure Elasticities (at average budget shares)*

Good	*AIDS1*	*AIDS2*	*AIDS3*	*DAIDS1*	*DAIDS2*	*DAIDS3*
Food	0.402*	0.524*	0.524*	0.218*	0.162*	0.476*
Alcohol	0.757*	1.159	1.86	0.343*	0.39*	0.622
Tobacco	–0.048*	–0.086*	0.29*	0.269*	0.35*	0.18*
Clothing & Footwear	1.563*	1.303*	1.253*	1.788*	1.905*	1.705*
Fuel & Power	0.725*	0.822*	0.965	0.213*	0.171*	0.334*
Petrol	2.247*	1.141	1.128	1.04	1.02	0.964
Transport & Equipment	0.75	1.004	0.997	2.322*	2.187*	2.14*
Durables	1.729	1.062	1.278	2.067*	2.217*	1.824*
Other Goods	1.941*	1.873*	1.772*	1.924*	1.947*	2.019*
Services	0.875	0.839	1.592	1.876	1.869	1.136

Good	*ROTT1*	*ROTT2*	*ROTT3*	*CBS1*	*CBS2*	*CBS3*
Food	0.234*	0.182	0.498*	0.231*	0.18*	0.506*
Alcohol	0.378	0.415*	0.651*	0.374*	0.423*	0.67
Tobacco	0.157	0.246	0.03	0.211*	0.259*	0.08*
Clothing & Footwear	1.818*	1.939*	1.737*	1.851*	1.963*	1.761*
Fuel & Power	0.116	0.092	0.287	0.086*	0.053*	0.281*
Petrol	0.978*	0.966*	1.101*	0.851	0.837	0.968
Transport & Equipment	2.483*	2.329*	2.311*	2.341*	2.222*	2.262*
Durables	2.136*	2.257*	1.945*	2.118*	2.262*	1.894*
Other Goods	1.928*	1.932*	2.033*	1.918*	1.942*	2.002*
Services	1.785	1.773	0.902	1.878	1.867	0.939

Good	*TAIDS1*	*TAIDS2*	*TAIDS3*
Food	0.097*	0.117*	0.488*
Alcohol	0.524*	0.492*	0.723
Tobacco	0.140*	0.144*	–0.207*
Clothing & Footwear	2.020*	1.994*	1.932*
Fuel & Power	0.377*	0.406*	0.538*
Petrol	0.688	0.724	1.466
Transport & Equipment	2.540*	2.622*	2.042
Durables	1.740*	1.699*	1.024*
Other Goods	2.010*	1.992*	2.006*
Services	1.850	1.809	1.192

Notes: *means significant at 95 per cent confidence level.
Suffixes 1, 2, and 3 refer to unrestricted, homogeneity imposed, and homogeneity and symmetry imposed respectively.

are additive (indeed for relatively large numbers of goods, i.e., in excess of around ten it is a direct implication of additivity) whereas here we are observing it in cases where additivity of preferences is not imposed.

Turning now to expenditure elasticities, we once again see reasonable consistency across the different models and we also see that a substantial percentage of the estimates are significant at 95 per cent. (This is a very typical result for expenditure elasticities which tend to be better determined than price elasticities.) We also observe some "rogue" estimates, including the two mentioned above in the own-price elasticities case. Overall, there appears to be somewhat less consistency than in the case of own-price elasticities, e.g., observe the case of services which ranges from 0.839 to 1.88 and also those of durables and transport and equipment although in the latter two cases the outlying estimates are not significant. The lesser degree of correspondence between expenditure elasticities is inconsistent with previous findings of O'Riordan (1976), which we discuss in more detail below.

Summarising the expenditure elasticities results we can identify food, alcohol, tobacco and fuel and power as "necessities" in the sense of having expenditure elasticities less than one. There do not seem to be any readily identifiable inferior goods, although three of the expenditure elasticities for tobacco are just negative. Even though these estimates are significant, given the other estimates for tobacco, it seems more reasonable to regard it as a good with a low, but positive, expenditure elasticity. Petrol appears to have an expenditure elasticity of around one, while clothing and footwear, transport and equipment, durables, other goods and services are definite "luxuries", with expenditure elasticity estimates consistently in excess of one.

Comparison of cross-price elasticities will be limited owing to the very large number of estimates that could be compared. However, one comment can be made straightaway. The AIDS model when estimated in levels produced a number of cross-price elasticities that were extremely large in magnitude, particularly in the case of terms involving petrol, services and alcohol. For example, the cross-price elasticity between petrol and alcohol in the unrestricted AIDS model was estimated as 1.992. When homogeneity was imposed this increased to 3.266. Both elasticities were significant. Similarly, the cross-price elasticity between services and alcohol was –1.338 in the unrestricted case and –2.456 when homogeneity was imposed. These values do not appear to be intuitively plausible. Curiously, in both cases the further imposition of symmetry caused these elasticities to fall quite dramatically in magnitude to –0.464 and –0.064 respectively. When we examine the corresponding cross-price elasticities for the AIDS model in differences or with a quadratic time trend these intuitively implausible cross-elasticities disappear. This finding is important for research on tax reform as it was the very high substitutability between petrol and alcohol which caused alcohol to have a very low marginal social cost of taxation in an earlier study (see Madden, 1992).

The above results also raise the question of how sensitive are estimated parameters to whether a model is estimated in levels or differences. Harvey (1980) has suggested that the relative merits of the different formulations should be assessed on statistical grounds, in the absence of any a priori guidelines. For our purposes, this question only arises for the AIDS model as the Rotterdam and CBS models can only be estimated in differences. Harvey rejects direct comparison of the likelihood functions of the two models (AIDS in levels and AIDS in first differences) since one model involves a hypothesis about the distribution of n levels while the other involves the distribution of n-1 first differences. He proposes instead the adoption of a criterion which he labels δ^*. This is defined as:

$$\delta^* = (SSE_0 / SSE_1) \exp[(T-1)^{-1} \ln T]$$

where SSE_0 refers to the sum of squared residuals for the regression run in levels, while SSE_1 refers to the sum of squared residuals for the regression run in first differences and T is the number of observations. The levels formulation is to be preferred if $\delta^*<1$. Application of this criterion to the systems of equations we estimated does not produce very conclusive results. The values of δ^* are shown in Table 3 for the comparison between the AIDS model in levels and in first differences, where the model in first differences was estimated both with and without an intercept. δ^* is calculated for the unrestricted model and with homogeneity only and homogeneity and symmetry imposed. It can be seen that the levels model is to be preferred for

Table 3: *Comparison of AIDS Models in Levels and First Differences*

	Unrestricted		*Homogeneity*		*Homog. + Symm.*	
Good	δ^*_1	δ^*_2	δ^*_1	δ^*_2	δ^*_1	δ^*_2
Food	1.40	1.40	1.28	1.00	1.15	1.13
Alcohol	1.78	1.55	2.75	2.46	2.35	2.18
Tobacco	0.92	0.89	0.82	0.81	2.10	1.97
Clothing & Footwear	0.58	0.57	0.61	0.57	0.57	0.57
Fuel & Power	0.96	0.92	0.95	0.71	1.12	0.90
Petrol	1.44	1.84	2.66	2.66	4.26	4.18
Transport & Equipment	1.75	1.44	1.65	1.48	1.52	1.37
Durables	0.52	0.52	0.90	0.75	1.11	0.98
Other Goods	0.78	0.78	0.79	0.78	0.81	0.81
Average	1.13	1.10	1.38	1.25	1.67	1.56

Note: δ^*_1 refers to differenced model estimated with intercept, while δ^*_2 refers to model estimated without intercept. If $\delta^*_i<1$, levels model is preferred; $\delta^*_i>1$, differenced model preferred.

tobacco, clothing and footwear, fuel and power, durables and other goods, with the model in first differences preferred for the other goods. Harvey does not present a formula for δ^* for systems of equations, but a rough measure can be obtained by taking the arithmetic mean of the values. This tends to come down in favour of the model in first differences. This measure may be biased, however, since it has a lower bound of zero and an infinite upper bound. It is interesting to note that for those goods whose cross-elasticities when estimated under levels are implausibly large in magnitude, the value of δ^* is above 1, suggesting that the differenced model is to be preferred.

The sensitivity of the estimates to whether the model is estimated in levels or first differences and whether a time trend is included suggests that dynamic specification is an important issue. This is discussed in the next section along with tests for the restrictions implied by utility maximisation.

IV TESTING RESTRICTIONS

(a) *Homogeneity and Dynamic Specification*

As can be seen from Section II restrictions such as homogeneity and symmetry can be easily tested for the models estimated. Tests of these restrictions have traditionally involved first of all testing for homogeneity, and then testing for symmetry, given the homogeneity restriction. Symmetry is a cross-equation restriction, while homogeneity is a restriction which can, in principle, be tested equation by equation. In their seminal AIDS paper Deaton and Muellbauer test for homogeneity equation by equation. However, this may not be the most appropriate procedure. Intuitively, homogeneity states that if all prices and income are doubled, then demands will be unchanged. This suggests that homogeneity is a restriction which should be tested on a *system* of equations rather than equation by equation. For example, if homogeneity holds for n–1 goods then it must hold for good n. While it is theoretically possible that homogeneity might hold for some goods and not for others, i.e., overspending on good i offset by underspending on good j, it still seems to make more sense to test it for the system.[3] For the sake of comparability with Deaton and Muellbauer's results we test for homogeneity on both an equation by equation and system basis.

Table 4 gives the results for both the system tests and the equation by equation test of homogeneity for the four different models. We can see straightaway that the system tests indicate a firm rejection of the restriction. Two different types of system test are reported here, the Wald chi-square

3. It should also be recognised that system wide tests for homogeneity may have their flaws. This point is discussed in more detail below.

Table 4: *Tests of Homogeneity and Symmetry*

Good	*AIDS*	*TAIDS*	*DAIDS*	*ROTT*	*CBS*
Food	0.058	0.013	0.026	0.106	0.031
Alcohol	0.003	0.060	0.395	0.487	0.368
Tobacco	0.770	0.837	0.154	0.048	0.390
Clothing & Footwear	0.048	0.114	0.090	0.080	0.116
Fuel & Power	0.304	0.007	0.275	0.539	0.376
Petrol	0.009	0.236	0.867	0.903	0.891
Transport & Equipment	0.473	0.059	0.219	0.155	0.271
Durables	0.000	0.069	0.092	0.177	0.112
Other Goods	0.561	0.101	0.667	0.937	0.641
SYS	270.84	559.12	110.05	68.65	65.85
SYSNC			69.6	49.84	91.085
SYMM	202.64	211.52	154.7	151.48	169.66
SYMMH	162.67	n.a.	106.73	109.26	113.92
LRTH	70.44	91.32	46.22	35.72	34.84
LRTS	236.72	251.74	144.14	147.7	160.9
LRTSI	149.22	158.69	89.1	91.3	99.45

Notes: Figures for individual goods give probabilities from F tests, i.e., probability of incorrectly rejecting null hypothesis. Thus, $p<0.05$ indicates that null hypothesis of homogeneity can be rejected at 95 per cent confidence level.

SYS: Wald Chi-square statistic for test of homogeneity (critical value at 95 per cent = 16.919).

SYSNC Wald Chi-square for test of homogeneity when intercept is suppressed (critical value at 95 per cent = 16.919).

SYMM: Wald Chi-square for test of symmetry given homogeneity (critical value at 95 per cent = 16.919).

SYMMH: Wald-Chi-square for test of symmetry given homogeneity (critical value at 95 per cent = c.49).

LRTH: Value of likelihood ratio statistic for test of homogeneity (critical value at 95 per cent = 16.919).

LRTS: Value of likelihood ratio statistic for test of symmetry given homogeneity (critical value at 95 per cent = c.49).

LRTSI: Value of likelihood ratio statistic for test of symmetry given homogeneity with Italianer correction factor applied (critical value at 95 per cent = c.49).

statistic and the likelihood ratio test statistic.[4] However, given that both tests are in agreement in all the hypotheses tested here, we can be reasonably confident of the results they give, subject to some caveats discussed below. The results all indicate a firm rejection of homogeneity but it is interesting to compare the value of the Wald statistic for the different systems. The critical value for the statistic at 95 per cent confidence is 16.919. While all the systems have Wald statistics well outside this figure, both the Rotterdam and CBS models have considerably lower statistics than does the differenced AIDS model, which in turn is well below that of the AIDS model in levels,

4. For a discussion of the relative merits of these and other similar test statistics see Harvey (1981) and Bera and Ullah (1991). I am grateful to an anonymous referee for the latter reference.

with and without the time trend.

Alternatively, we can test for homogeneity on an equation by equation basis. Here we can see a disimilarity between the different AIDS models. When estimated in levels, homogeneity is rejected in four cases and is borderline in a fifth (food). When estimated in differenced form, homogeneity is rejected only for food, and is borderline in two other cases. This is consistent with findings of Deaton and Muellbauer and we will return to this below. We note that the equation by equation results for the AIDS model in difference form are very similar to those for the Rotterdam and CBS models. Homogeneity for food is rejected at the 95 per cent level for both the AIDS in differences and CBS models, and is only barely not rejected in the Rotterdam model.

We now return to possible explanations of the discrepancy between the two different versions of the AIDS model. In their original paper in 1980 and in their well known textbook Deaton and Muellbauer (1980a, 1980b) report that for those goods for which homogeneity was rejected, its imposition led to a sharp drop in the Durbin-Watson statistic, implying positive serial correlation in the residuals. They interpreted this as suggesting that the converse might also be true, i.e., the rejection of homogeneity might be due to an inadequate dynamic specification of the model; and they note that when the model is estimated in first differences, with an intercept, their F statistics for homogeneity are much reduced. But this is entirely consistent with the finding we reported above concerning the different results obtained when testing for homogeneity in the different AIDS models! A check back on the Durbin-Watson statistics for the AIDS in levels equations also revealed the same pattern.

In another attempt to examine the sensitivity of tests for homogeneity to dynamic specification, we tested for homogeneity on an equation by equation basis in the TAIDS model, i.e., the AIDS model in levels but with a quadratic time trend also included. Once again we see less rejection of homogeneity than in the case of the simple model in levels, with outright rejection only for food and fuel and power. Overall, on an equation by equation basis, we could regard the model in levels with a time trend as being intermediate between the simple model in levels and the differenced models in terms of acceptance and rejection of homogeneity. Curiously on a *system* test, homogeneity is most decisively rejected for the levels model with a time trend.

The link between dynamic specification of a model and rejection of homogeneity has also been made by Anderson and Blundell (1983) in their dynamic version of an AIDS model. However, factors other than dynamic specification may be at the root of rejection of homogeneity. In his survey article, Blundell (1988) tests for homogeneity on an AIDS model using pooled cross-sectional and time-series data for the UK. This data set enabled him to include demographic and locational factors as additional explanatory variables. He found that homogeneity was acceptable across all goods. This was consistent with the findings of Stoker (1986) who demonstrated the statistical equivalence between static models which accomodated individual characteristics and simple dynamic models with first-order autocorrelation. Thus, the less decisive rejection of homogeneity in differenced models may actually reflect omitted variables in a static model. For example, Blundell, Pashardes and Weber (1989) discover that in the UK such simple demographic variables as the number of adults in a household or the presence of a market-working wife exhibit time trends and are also significantly correlated with prices and total expenditure. This can cause problems in identifying price and income effects from aggregate data. Unfortunately, the absence of pooled cross-sectional and time-series data for Ireland precludes any testing for the presence of this phenomenon.[5]

The inclusion or non-inclusion of an intercept term in a differenced model is also a potential area of debate. Intuitively, a significant constant term implies the existence of a time trend. Only three goods had significant constant terms in the difference models estimated: alcohol (positive) and transport and equipment (negative) were significant in all three models while fuel and power (positive) just about was significant in the Rotterdam and CBS models. This implies that there were independent influences other than income and relative prices explaining the budget shares of these goods. A further conundrum concerns the system wide tests for homogeneity when the intercept term is suppressed. For the AIDS in differences and Rotterdam models it causes a sharp drop in the Wald statistic, while in the CBS model it causes a sharp rise!

A further indication of the sensitivity of homogeneity tests to the inclusion or non-inclusion of an intercept term can be obtained by testing for homogeneity on an equation by equation basis without an intercept and comparing the results to tests with an intercept. Once again, this procedure throws little new light on the matter. Testing for homogeneity without an intercept causes a firmer rejection of homogeneity for food, clothing and footwear, fuel and power and durables. Those goods for which homogeneity is "less non-rejected" following the exclusion of an intercept are alcohol and transport and equipment, while the p-values for the other goods (tobacco, petrol and other goods) are relatively unchanged. There appears to be little pattern between the

5. The foregoing discussion is essentially concerned with the problem of the "representative agent" model underlying the use of aggregate data to estimate parameters describing individual behaviour. Kirman (1992) provides a recent theoretical discussion of this problem, while Gilbert (1989) discusses the interpretation of tests for individual behaviour using aggregate data.

results from the various tests for homogeneity across the different models and those goods for which it is rejected and accepted and the inclusion or non-inclusion of an intercept.

Before concluding our discussion of tests for homogeneity, it is worthwhile considering the arguments of Laitinen (1978). He maintains that the conventional tests for homogeneity are biased towards rejection of the hypothesis, all the more so as the number of commodities in the demand system increases. The standard test statistic is usually reported as being asymptotically distributed as a Chi-square distribution under the null hypothesis.

More generally, given the standard system of equations model in vector terms,

$$y = (I \otimes X)\beta + \varepsilon$$

and a set of linear restrictions $R\beta = 0$, where $R = I \otimes a'$, $\otimes$ refers to Kronecker multiplication and $a=[0,1,..,1]'$, the test statistic for homogeneity can be shown to be:

$$b'R'S^{-1}Rb/a'(X'X)^{-1}a$$

where b is the estimate of β and S is the unbiased estimator of Σ, the matrix of error covariances. This test statistic is equivalent to the Wald statistic widely reported in standard econometric packages.

Using a result from Andersen (1958), Laitinen shows that this statistic is also distributed as Hotelling's T^2, which is distributed as a multiple of an F distribution. He maintains that this statistic is more suitable for small samples and shows that using this statistic, the probability of incorrectly rejecting homogeneity is considerably lower than when using the conventional statistic. (For parameter specifications that were deliberately set up to satisfy homogeneity, he found that the number of rejections out of 100, at the 95 per cent level, for the conventional statistic was 53, while for the small sample statistic it was 5. This was for the case of n=11 and N=31.) Laitinen does not specify what exactly he means by "small" in the context of a small sample, but it can be inferred from his article that N=30, 31 (the case for our estimation) would be considered small.

In a further contribution to this debate, Deaton (1986) concurs with Laitinen's findings and says: "In consequence, homogeneity should *always* be tested using exact F or T^2 statistics and *never* using asymptotic test statistics such as uncorrected Wald, likelihood ratio, or Lagrange multiplier tests. However, my reading of the literature is that rejection of homogeneity in practice tends to be confirmed using exact tests and is not a statistical illusion based on the use of inappropriate asymptotics" (Deaton, 1986, p.1,794). This quote highlights the importance of calculating T^2 statistics, especially given that homogeneity was not so firmly rejected when tested on an equation by equation basis, using exact F statistics. It should be noted that Deaton's comments were made in the context of *static* models of consumer demand and so may not be applicable to such models as those of Anderson and Blundell (1983,1984).

Table 5 shows the result of applying Hotelling's T^2 to our consumer demand systems. It leads to much less firm rejections of homogeneity, and in some cases to homogeneity not being rejected at all. The AIDS model in levels and in differences with a constant term included, and the CBS model without an intercept still reject homogeneity, at both the 95 per cent and 99 per cent levels of confidence. AIDS in differences without a constant fails to reject homogeneity at 99 per cent, which is also the case for the Rotterdam and CBS models with intercepts and the Rotterdam model without an intercept (which almost fails to reject it at 95 per cent). These results still leave unresolved the issue of why tests of homogeneity should be so sensitive to the inclusion or non-inclusion of an intercept term.

Table 5: *Hotelling's T^2 Statistic for Homogeneity*

Model	*T^2 Statistic*	*95 Per Cent Value*	*99 Per Cent Value*
AIDS	270.84	43.4	65.85
TAIDS	559.12	43.4	65.85
DAIDS	110.05	44.9	71.76
DAIDSNC	69.6	44.9	71.76
ROTT	68.65	44.9	71.76
ROTTNC	49.84	44.9	71.76
CBS	65.85	44.9	71.76
CBSNC	91.09	44.9	71.76

To summarise the results of this section, the majority of the system tests for homogeneity are rejected, with some exceptions when small-sample corrections are applied. We have noted however, that tests for homogeneity can be sensitive to the dynamic specification adopted and that they may also be sensitive to omitted variables, even when the underlying model is static. Unfortunately, lack of adequate data prevents a more rigorous examination of these issues for Ireland.

(b) *Symmetry*

Unlike homogeneity, symmetry is a cross-equation restriction. Once again we can test the restriction using both the likelihood ratio test and the Wald test. A further point to notice that we test both for symmetry, and for symmetry given the imposition of homogeneity. The reason for this is that many demand studies find that homogeneity is the restriction most usually rejected and that, given homogeneity, symmetry is often not rejected. Also, for many of the standard tests the bias towards rejection of symmetry is less when homogeneity is imposed.

Table 4 provides results of Wald tests for symmetry both with and without homogeneity. We can see that it is firmly rejected but that the test statistic is much lower when homogeneity is imposed.

In a similar contribution to that of Laitinen to the debate on testing for the restrictions implied by utility maximisation, Meisner (1979) demonstrates that the standard test for symmetry is biased towards rejection of the null hypothesis. Meisner carried out tests similar to those of Laitinen in generating variables that had symmetric Slutsky matrices by construction. For the case of $n=14$ the null hypothesis was rejected 96 times out of 100 at the 95 per cent confidence level. He concludes that it is the use of S, the estimator of the covariance matrix, Σ which is the cause of the bias. In his simulations, replacement of S by Σ leads to the null hypothesis being rejected 6 times out of 100 at a 95 per cent confidence level (of course in empirical work Σ is unobservable).

In a further contribution to this debate Bera, Byron and Jarque (1981) examined the three most common asymptotic tests for homogeneity and symmetry: the likelihood ratio, Wald and Lagrange Multiplier tests. They point out that if the test statistics are properly size corrected, then the bias towards rejection disappears. However, the appropriate size adjustment for cross-equation restrictions was not available. They also conclude that the bias against rejection was less pronounced for the Lagrange Multiplier test.[6]

The breakthrough in this debate comes from Italianer (1985). He derives a correction factor for the likelihood ratio test for small samples for generalised restrictions. He applies this correction factor to the Rotterdam model to test homogeneity and homogeneity plus symmetry. He shows that when the number of degrees of freedom is small, the correction factor points to a considerable bias towards rejection of the null hypothesis if it were not applied. His results also are consistent with the often observed phenomenon that tests for symmetry in the presence of homogeneity are rejected less conclusively than are tests for homogeneity alone. Calculation of the Italianer correction factor for the models estimated here indicates that it is in the region of 0.63 for the model estimated in levels and 0.62 for the model estimated in first differences. As can be seen from Table 4, however, the application of the Italianer correction factor to our models still leaves symmetry being decisively rejected.

6. For an account of the Lagrange Multiplier test and its relation to the Likelihood Ratio and Wald tests see Harvey and Bera and Ullah (op. cit.)

(c) *Negativity*

The final condition implied by utility maximisation which we wish to test is negativity. Utility maximisation implies that the matrix of Slutsky coefficients be symmetric and negative semi-definite. In particular negativity implies that the consumer's cost function be concave. We have already seen that the symmetry restriction has been decisively rejected. Nevertheless, it is still of interest to test whether negativity holds given the imposition of symmetry.

Owing to the particular expression for the Slutsky coefficients in the AIDS models it is not possible to impose negativity and then test for the restriction using either a likelihood ratio, Wald or Lagrange multiplier test. However, it is still relatively straightforward to test for negativity. A well-known result from linear algebra states that a necessary and sufficient condition for a real symmetric matrix to be negative semi-definite is that all the eigenvalues of that matrix should be less than or equal to zero (see Johnston (1984) p.151). This condition can be visually inspected for our different consumer demand systems. Table 6 shows the eigenvalues for the different systems. In no case are all the eigenvalues negative. Six of the ten eigenvalues are negative for the AIDS in levels model, seven are negative for the AIDS in levels with a time trend, while eight of them are negative for the other models. In most cases those eigenvalues which are positive are quite small in size, suggesting that the matrices may not be that far from being negative semi-definite.[7]

Table 6: *Eigenvalues of Slutsky Matrix, Homog. + Symm. Imposed*

AIDS	*TAIDS*	*DAIDS*	*ROTT*	*CBS*
.0568	.0987	.0379	.0533	.0400
.0371	.0325	.0012	.0025	.0022
.0018	.0055	–.0118	–.0004	–.0101
.0012	–.0090	–.0143	–.0120	–.0134
–.0163	–.0347	–.0197	–.0179	–.0200
–.0383	–.0580	–.0443	–.0238	–.0444
–.0494	–.0828	–.0652	–.0542	–.0628
–.1123	–.1166	–.0862	–.0847	–.0866
–.1861	–.1790	–.1509	–.1328	–.1555
–.2353	–.1968	–.1807	–.1828	–.1753

7. As Gilbert (1989) points out classical rejections on aggregate data cannot necessarily be taken to imply rejection of the theories in question. Whether or not to use estimates from non-concave cost functions is an open issue (for a discussion in the context of tax reform see Madden (1993)).

V COMPARISON WITH OTHER IRISH STUDIES

In this section we will compare our results with those from other Irish studies, bearing in mind that these studies covered shorter estimation periods and that some of the commodity classifications may have differed. The three studies we shall examine, in chronological order, are those of O'Riordan (1976), McCarthy (1977) and Conniffe and Hegarty (1980).

The study most close in spirit to this one is that of O'Riordan (1976) where he estimates own-price and expenditure elasticities from a number of different models: the Linear Expenditure System (LES), the Rotterdam system, Indirect Addilog and the Double Log System. He used an eight good classification from "National Income and Expenditure": Food and non-alcoholic beverages, alcoholic beverages, clothing, footwear and personal equipment, fuel and power, durable household goods, transport equipment, other goods (including tobacco) and other expenditure. His data set ran from 1953 to 1972 and he evaluated his elasticities for 1972.

In Table 7 we show O'Riordan's results for his different models. They are similar to our results in some ways. For example, some of the expenditure elasticities are quite similar in magnitude, e.g., food, transport equipment, durables and clothing and footwear. Others are not so similar, e.g., alcohol, fuel and power and his residual categories of expenditure, i.e., other goods and other expenditure, which we could compare with other goods and services in our study.[8]

Table 7: *O'Riordan's Elasticities*

Good	*LES*	*ROTT*	*IA*	*REG*	*LES*	*ROTT*	*IA*	*REG*
Food	–0.39	–0.43	–0.15	–0.07	0.571	0.581	0.505	0.55
Alcohol	–0.75	–0.48	–0.97	–0.07	1.309	1.153	1.641	1.25
Clothing and Footwear	–0.69	–1.01	–0.55	–0.31	1.267	1.746	1.169	1.56
Fuel & Power	–0.59	0.11	–0.29	0.016	0.982	1.605	0.935	1.36
Durables	–0.83	–0.48	–1.00	–0.40	1.577	1.667	1.676	2.02
Transport and Equipment	–0.98	–1.59	–1.84	–1.51	1.907	2.123	2.548	4.44
Other Goods	–0.51	–0.76	–0.16	–0.43	0.878	0.924	0.711	0.85
Other Expenditure	–0.62	0.43	–0.47	–0.32	1.005	0.696	0.961	0.51

LES: Linear Expenditure System
ROTT: Rotterdam System.
IA: Indirect Addilog System.
REG: Double-log single equation system.

8. The discrepancy between our alcohol estimates and those of the other authors may be partly explained by the distortion in recorded alcohol consumption in the 1980s owing to cross-border trade. I am grateful to an anonymous referee for pointing this out.

O'Riordan's own-price elasticities also show some similarities, e.g., those for food, clothing and footwear, fuel and power, transport equipment and other goods in his Rotterdam model and our own. Overall however, it is probably true to say that his elasticities show greater variability across different systems than do our own. In fairness though, it must be added that the four different models he estimated were more heterogeneous from each other than the four we estimate, e.g., one would expect reasonable correspondence between price elasticities estimated from a Rotterdam model and a CBS model.

In terms of overall goodness of fit O'Riordan finds no one system to be obviously superior to the others, although he finds the double log system to perform considerably worse than the others. He tentatively concludes that "the Rotterdam system is best, but the margin of superiority is small" (O'Riordan, 1976, p.82).

The second paper whose results can be compared to ours is that of McCarthy (1977). He estimated an LES model for 1953-1974, experimenting with different commodity classifications. The final model he estimated consisted of nine goods and the breakdown is very similar to that used in this paper, the only difference being that he used the single residual category of expenditure "Residual Expenditure", while in this study we have a category "Other Goods" and "Services" acts as a residual. McCarthy's use of the LES makes comparison of his results and ours somewhat inappropriate, since the LES is quite a restrictive system, e.g., it does not permit inferior goods, nor own-price elasticities greater than one in magnitude and its price effects work mainly through the income terms (Deaton and Muellbauer, 1980b) discuss the undesirable features of the LES).

Table 8: *McCarthy's Elasticities*

Good	*Price Elasticity*	*Budget Elasticity*
Food	–0.46	0.65
Alcohol	–0.80	1.24
Tobacco	–0.17	0.15
Clothing	–0.68	1.12
Fuel	–0.57	0.81
Petrol	–0.84	1.40
Durables	–0.81	1.58
Transport Equipment	–0.93	1.82
Residual Expenditure	–0.71	1.09

McCarthy's estimates came from a Linear Expenditure System.

The correspondence between McCarthy's estimates and our estimates is mixed. While the estimated own-price elasticities for clothing and footwear, durables, transport equipment and the residual categories of expenditure are reasonably close (given that LES own-price elasticities cannot exceed one in absolute value), those for alcohol, tobacco, fuel and power and petrol are quite at variance, while the correspondence for food depends upon the particular model chosen. The correspondence between the expenditure elasticities is better. In part this may reflect the fact that there is considerable variation between our expenditure elasticities and so there is a greater chance of finding at least one of our models which corresponds to McCarthy's results. However, this would not fully explain the degree of correspondence for such categories as tobacco, clothing and footwear, petrol, transport and equipment, durables and residual expenditures.

The final study whose results can be compared to ours is Conniffe and Hegarty (1980). While this study confines itself to the Rotterdam System, it does address such issues as homogeneity, symmetry and negativity more explicitly. Conniffe and Hegarty's (henceforth CH) purpose in the paper was to compare estimates from a LES model with those of a Rotterdam model with symmetry and negativity imposed. In the course of this they provide own-price and income elasticities for an eight good system (using the same commodity breakdown as O'Riordan). We have not imposed negativity but, nevertheless, it may be instructive to compare the respective Rotterdam systems, unrestricted and with homogeneity and symmetry imposed. Once again, the correspondence is mixed. Comparing the own-price elasticities on a good by good basis, food shows a reasonable correspondence, but alcohol does not. In particular, our estimates show that the imposition of symmetry caused

Table 9: *Conniffe and Hegarty's Elasticities*

	Own-Price		*Income*	
Good	*Simple*	*Symmetry*	*Simple*	*Symmetry*
Food	–0.40	–0.42	0.55	0.68
Alcohol	–0.55	–0.56	1.25	1.51
Clothing	–0.98	–0.70	1.70	1.37
Fuel	0.16	–0.06	1.79	1.66
Durables	0.47	–0.84	1.81	1.72
Transport	–1.92	–1.02	2.64	3.52
Other Goods	–0.72	–0.35	0.97	0.67
Other Expenditure	0.42	0.65	0.69	0.67

Conniffe and Hegarty's estimates came from a Rotterdam model.

a sharp rise in the price elasticity of alcohol, while this is not the case for the CH estimates. The clothing and footwear estimates show a much closer correspondence. Not only are the actual estimates quite close in magnitude but both studies show the elasticity falling by approximately the same amount following the imposition of symmetry. The fuel and power estimates are also quite close with both studies showing a *positive* own-price elasticity for the unrestricted case which changes to a low negative elasticity when symmetry is imposed. The correspondence for durables and transport and equipment is mixed, the estimates with symmetry imposed comparing quite well. The other goods category also compares quite well in the unrestricted case although this comparison may not be quite valid since "other goods" in the CH classification includes tobacco. Finally, the CH estimates for residual expenditure own-price elasticities are positive and quite large in magnitude, which is completely at variance with the estimates obtained here.

The correspondence for income/expenditure elasticities is slightly worse than that for own-price elasticities. Alcohol and fuel and power are the principal offenders here although there is reasonable correspondence in the cases of clothing and footwear, durables and transport and equipment.

VI SUMMARY AND CONCLUSIONS

This paper has presented new estimates of demand elasticities obtained from a range of different models. It also provides systematic tests of some of the fundamental propositions of consumer demand theory. Compared to earlier studies, the reliability of the estimates obtained is hopefully enhanced by the length of time series covered, the wide range of models estimated and the battery of tests applied. The results obtained can be regarded as encouraging. The own-price and expenditure elasticities obtained showed consistency across models, to the extent that for many broad groups of commodities, we can be reasonably confident of having acceptable estimates of these parameters.

An important issue raised by this study is the question of stochastic and dynamic specification. Even the addition of relatively simple dynamic structures such as the inclusion of a quadratic time trend, or estimation of the model in differenced form, appears to affect the estimates. In particular, it appears to remove from the AIDS model some of its more implausible estimates. While the importance of dynamic specification is stressed it is also noted that omitted variables from a static model can crucially affect the estimates obtained. These findings would suggest that, in the Irish case, the static AIDS model estimated with aggregate data does not perform well.

Dynamic specification also affects tests for homogeneity, symmetry and negativity, although here the results are less clearcut. The addition of a time trend renders homogeneity more acceptable on an equation by equation basis, but not when a system-wide test is applied. Differenced models are less likely to reject homogeneity on both an equation by equation and system-wide basis, and the application of small-sample correction factors actually leads to homogeneity not being rejected for systems of equations in some cases. Symmetry remains decisively rejected, despite the application of correction factors, and while the test for negativity is carried out on a more casual basis, once again dynamic specification matters. In summary, we could say that stochastic and dynamic rather than deterministic specification seems to matter more both for the plausibility of estimates and for the rejection or non-rejection of the restrictions implied by utility maximisation.

The points raised above also suggest directions of future research in this area. More sophisticated dynamics could be introduced along the lines of Anderson and Blundell (1983). The incorporation of micro variables would also be a desirable development but the relative lack of such data for Ireland may be a stumbling block here. Finally, sensitivity to dynamic specification should be carried out in those areas which regularly utilise consumer demand estimates (see, for example, Madden (1993)).

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