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Comparing the Empirical Performance of Alternative Demand Systems*

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Abstract

In this paper four versions of differential demand systems are compared empirically: namely, the Rotterdam system, a version of the Almost Ideal Demand (AID) system, the Central Bureau of Statistics (CBS) system, and the NBR system. These systems share common right-hand sides but differ in the non-linear data transformations of the endogenous variable. The variable addition testing method of McAleer (1983) for single equations is extended to vectors of equations in which the dependent variables of competing systems are subject to non-linear data transformations. An appealing feature of the variable addition testing procedure is that it accommodates the adding-up condition in a straightforward manner. Annual data over the period 1921-1981 for The Netherlands for four major groups of consumer expenditure are used in the empirical application. It is found that no single system is dominant in explaining the data. Relatively speaking, the CBS system performs the best and the NBR system the worst, with the other two systems occupying intermediate positions. The specification of the price coefficients of the Rotterdam system appears to be empirically superior to that of the AID system.

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1 Introduction

A demand model is a system of equations which explains how a given amount available for consumption is being spent on various goods and services. The variables that explain this allocation are total expenditure and the prices of the goods and services. The theory of the individual consumer implies certain properties for such a system. Using the construction of the representative consumer, these properties are also frequently incorporated in demand systems using aggregated time series data.

Barten (1977) provides a description of various demand systems, differing primarily in the specification of the functional form. For a particular system, however, the individual equations comprising the system have the same functional form. Since the mid-1970's, several other systems have been developed. Among these, the Almost Ideal Demand (AID) system of Deaton and Muellbauer (1980) is perhaps the most well known.

Demand systems can be compared in various respects, such as the ability to reflect theoretical properties and the possibility of representing interesting preference relations among commodities. A further aspect is the flexibility of a system, i.e. its empirical performance for a *potential* set of observations. In this paper, emphasis is placed on a formal comparison of the empirical performance of alternative non-nested demand systems for a *given* set of data .

There are simply too many alternative systems to seriously consider comparing all of them. Attention is thereby focussed on the comparison of only four recent and related alternatives: namely, a version of the AID system,the Rotterdam system proposed by Theil (1965), the Central Bureau of Statistics (CBS) system of Keller and Van Driel (1985), and the NBR system (see Duarte Neves (1987)). The CBS and NBR systems are non-nested hybrids of the Rotterdam and AID systems. These four systems share the property that the right-hand sides of the equations are linear in the logarithmic changes in the same set of explanatory variables. They differ, however, in the specification of the left-hand side variables, which are various data transformations of the expenditures on individual goods and services.

The four systems considered are not special cases of one another. Comparing their empirical performance is, therefore, an exercise in non-nested hypothesis testing. In contrast to the standard non-nested framework in which the left-hand side variables are identical and the functional forms are different (see e.g. Pesaran and Deaton (1978) and Fisher and McAleer (1981)), here the reverse holds. Nevertheless, the method of artificial nesting can also be applied in this case. The variable addition testing method of McAleer (1983) is adopted by taking into account the non-linear data transformations of the left-hand sides so that the vector-valued functions of the systems can be compared. The approach is flexible and allows for testing one model against one or more non-nested alternatives. In Section 2 the general test procedure, which is of wider applicability than comparing non-nested non-linear demand systems, is described. For example, Bera and McAleer (1989) used a similar method to test univariate linear and log-linear functional forms against each other.

The four systems to be compared are presented and discussed briefly in Section 3. It is shown that the adding-up condition of such allocation systems has some consequences for the testing procedure, and these are explained in Section 4. Annual data for The Netherlands are used for the period 1921-1981, and these are described in Section 5. Section 6 presents and discusses the results of the formal comparison, while some concluding comments are given in Section 7.

It might be useful to emphasize that it is not our purpose to decide once and for all which system is dominant. The focus of the paper is on whether differences in functional forms yield significant differences in the explanatory powers of the respective systems. In the actual selection of a model, the relative empirical performance for a given sample is only one of the criteria that might be used. Other criteria, some of which have already been mentioned, also need to be taken into account.

2 The General Testing Procedure

Consider M non-nested non-linear regression models with different non-linear data transformations of the dependent variable y_t:

$$\begin{aligned}
H_1 &: f_{1t}(y_t) = g_{1t}(x_{1t};\ \beta_1) + u_{1t}, \quad u_{1t} \sim NID(0, \sigma_1^2) \\
H_2 &: f_{2t}(y_t) = g_{2t}(x_{2t};\ \beta_2) + u_{2t}, \quad u_{2t} \sim NID(0, \sigma_2^2) \\
&\vdots \\
H_M &: f_{Mt}(y_t) = g_{Mt}(x_{Mt};\ \beta_M) + u_{Mt}, \quad u_{Mt} \sim NID(0, \sigma_M^2).
\end{aligned}$$

The function $g_{mt}(.)$ is assumed continuous and at least twice differentiable with respect to its parameters, the β_m are vectors of parameters, and $f_{mt}(.)$ is assumed known, for $m = 1, 2, \ldots, M$ and $t = 1, 2, \ldots, T$. It is also assumed that the stochastic processes generating x_{mt} are independent of those generating u_{mt}, for $m = 1, 2, \ldots, M$.

In artificially nesting all of the M models in a more general alternative for purposes of testing, one of the models, say H_1, is designated as the null hypothesis. Consider then the auxiliary regression model formed as a linear combination of the M non-nested models:

$$(1 - \sum_{m=2,M} \alpha_m)[f_{1t}(y_t) - g_{1t}(x_{1t}; \beta_1)] + \sum_{m=2,M} \alpha_m [f_{mt}(y_t) - g_{mt}(x_{mt}; \beta_m)] = u_t. \quad (1)$$

Clearly, under the null hypothesis $H_1 : \alpha_2 = \alpha_3 = \ldots = \alpha_M = 0, u_t$ in (1) is identical to u_{1t}. Setting $\lambda_m = -\alpha_m/(1 - \sum_{m=2,M} \alpha_m)$ for $m = 2, ..., M$, equation (1) can be rewritten as

$$f_{1t}(y_t) = g_{1t}(x_{1t}; \beta_1) + \sum_{m=2,M} \lambda_m [f_{mt}(y_t) - g_{mt}(x_{mt}; \beta_m)] + v_t \qquad (2)$$

with $v_t = u_t/(1 - \sum_{m=2,M} \alpha_m)$. Under the null hypothesis, $v_t = u_t = u_{1t}$ and $\lambda_m = 0$ for $m = 2, \ldots, M$. The null hypothesis can be tested in (2) by verifying to what extent the λ_m are jointly different from zero.

It is clear from (2) that, apart from $f_{mt}(y_t)$ not being statistically independent of v_t, the parameters λ_m are not identified. In principle, there are several ways of resolving this identification problem, such as Roy's union-intersection principle (see McAleer and Pesaran (1986) for further details). However, these alternative methods would be very difficult for the problem at hand. A far more straightforward method of handling this identification problem has been proposed by McAleer (1983), who tested a null linear regression model against several alternative non-nested non-linear regression models with the same dependent variable. An extension of this method is given as follows. For $m = 2, \ldots, M$, replace y_t in $f_{mt}(y_t)$ with

$$\hat{y}_{1t} \equiv f_{1t}^{-1}[g_{1t}(x_{1t}; \hat{\beta}_1)] \qquad (3)$$

where $\hat{\beta}_1$ is the maximum likelihood (ML) estimator of β_1 under the null hypothesis. Under H_1, $\hat{y}_{1t}$ is asymptotically uncorrelated with u_{1t}, and hence with v_t. Next, for $m = 2, \ldots, M$, estimate the auxiliary regressions

$$f_{mt}(\hat{y}_{1t}) = g_{mt}(x_{mt}; \beta_m) + \eta_{1mt} \qquad (4)$$

by ML. Denote by $\hat{\beta}_{1m}$ the resulting ML estimator for β_m and define the residuals from this regression as

$$\hat{\eta}_{1mt} \equiv f_{mt}(\hat{y}_{1t}) - g_{mt}(x_{mt}; \hat{\beta}_{1m}). \tag{5}$$

Since under the null hypothesis $\hat{y}_{1t}$ is asymptotically uncorrelated with u_{1t} and v_t, $\hat{\eta}_{1mt}$ is also uncorrelated with these disturbances.

The residuals in (5) are used to formulate the following variant of (2), namely

$$f_{1t}(y_t) = g_{1t}(x_{1t}; \beta_1) + \sum_{m=2,M} \lambda_m \hat{\eta}_{1mt} + v_{1t} \tag{6}$$

which can be estimated by ML. The extent to which the $\hat{\eta}_{1mt}$ in (6) contribute significantly to the empirical performance of H_1 can be tested using the likelihood ratio method or one of its asymptotically equivalent counterparts. A test of $H_1 : \lambda_2 = \lambda_3 = \ldots = \lambda_M = 0$ is asymptotically distributed under the null hypothesis as a chi-squared variate with $M - 1$ degrees of freedom.

Variations of the test in (6) are possible. For instance, if it were desired to use a paired test of H_1 against only H_2, say, then the test would be based on

$$f_{1t}(y_t) = g_{1t}(x_{1t}; \beta_1) + \lambda_2 \hat{\eta}_{12t} + v_{1t} \tag{7}$$

with $\lambda_2 = -\alpha_2/(1 - \alpha_2)$. The likelihood ratio test of $H_1 : \lambda_2 = 0$ would be asymptotically distributed under the null hypothesis as a chi-squared variate with one degree of freedom. Whether it is more powerful to use a joint test of H_1 against the $M-1$ alternatives (as in (6)) or a paired test of H_1 against only one of the alternatives (as in (7)) depends on the degrees of freedom and non-centrality parameters of the test under a sequence of local alternative hypotheses. Dastoor and McAleer (1989) demonstrate that it is not possible to determine an unambiguous ranking in terms of asymptotic local power of joint versus paired tests of non-nested models.

From expression (7), it might be concluded that if the ML estimate of λ_2 were significantly different from zero, the unexplained part of H_2 reduces the unexplained part of H_1, which might not appear very helpful from the viewpoint of model selection. However, one should return to the artificially nested model, in which $\alpha_2 \neq 0$ means that H_1 and H_2 together are more useful in explaining the data than is H_1 by itself.

Since any of the M alternative models can be cast in the role of null hypothesis, numerous test statistics can be calculated. The empirical applications in Section 6 should clarify the interpretations of the outcomes in such cases.

There is essentially no difference when one interprets f_{mt} and g_{mt} in H_m for $m = 1, \ldots, M$ as vector-valued functions with the same number of elements. Then u_{mt} is also a vector of disturbances specified as $u_{mt} \sim NID(0, \sum_m)$, with $\sum_m$ being the matrix of contemporaneous covariances. Artificial nesting then involves matrix weights rather than scalars. The vector counterpart of (1) is given by

$$(I - \sum_{m=2,M} A_m)[f_{1t}(y_t) - g_{1t}(x_{1t};\beta_1)] \\ + \sum_{m=2,M} A_m[f_{mt}(y_t) - g_{mt}(x_{mt};\beta_m] = u_t \quad (8)$$

and that of (2) by

$$f_{1t}(y_t) = g_{1t}(x_{1t};\beta_1) + \sum_{m=2,M} \Lambda_m[f_{mt}(y_t) - g_{mt}(x_{mt};\beta_m)] + v_t \qquad (9)$$

in which A_m and Λ_m are square matrices with $\Lambda_m = -(I - \sum_{m=2,M} A_m)^{-1} A_m$. Since Λ_m in (9) is not identified, a counterpart to (6) is needed for purposes of implementing the test. Under the null hypothesis H_1, A_m and Λ_m are null matrices. Special cases of A_m and Λ_m are those of diagonal and scalar matrices.

It is perhaps worth noting that an alternative procedure, namely the PE test of MacKinnon et al. (1983), may also be extended to the multivariate case with several non-nested alternative hypotheses. However, the Monte Carlo evidence presented in Godfrey et al. (1988) for a specialization of the problem examined in this paper, namely tests of linear versus log-linear regression models (see also Bera and McAleer (1989)), suggests that both the PE test and the test developed here are very similar in terms of empirical significance levels and powers against fixed alternatives in small samples. Thus, only the approach described in this section will be applied to systems of demand functions, i.e. to vector-valued functions, so that A_m and Λ_m will be treated as general square matrices. An attractive aspect of the variable addition testing procedure is that the adding-up condition may be accommodated in a straightforward manner (see Section 4). First, however, the demand systems to be tested are presented in Section 3.

3 A Class of Differential Demand Systems

A Marshallian demand function can be expressed as

$$q_i = g_i(m, p_1, \ldots, p_n), \qquad i = 1, \ldots, n \qquad (10)$$

where q_i is the (positive) quantity of good i acquired by the consumer, and p_i is the (positive) unit price of good i. In (10), m denotes total expenditure, for which the budget equation holds:

$$\sum_{j=1,n} p_j q_j = m. \tag{11}$$

It is assumed that n is finite and exceeds one. The arguments in the demand function, m and $p_1, \ldots, p_n$, are assumed to be given for the consumer. The theory of the rational individual consumer implies some constraints on (10).

To take these constraints into account, Theil (1965) specified (10) as

$$w_i dlnq_i = b_i(dlnm - \sum_j w_j dlnp_j) + \sum_j s_{ij} dlnp_j \tag{12}$$

in which the summation is taken over all n goods. In (12), $w_j = p_j q_j / m$ is the share of good j in the total budget, and the coefficients b_i and s_{ij} are taken to be constant. According to (11), $\sum_j w_j = 1$. The model given in (12), which is commonly known as the *Rotterdam system*, is a double logarithmic differential version of (10) multiplied through by w_i, with the constants satisfying the following conditions:

$\sum_i b_i = 1$ and $\sum_i s_{ij} = 0$	(adding-up)	(13a)
$\sum_j s_{ij} = 0$	(homogeneity)	(13b)
$s_{ij} = s_{ji}$	(Slutsky symmetry)	(13c)
$\sum_i \sum_j x_i s_{ij} x_j < 0$	(negativity)	(13d)

for not all x_i the same.

The differential version of the budget equation (11) can be written as

$$dlnm = \sum_j w_j dlnq_j + \sum_j w_j dlnp_j = dlnQ + dlnP \tag{14}$$

with implicit definitions of $dlnQ$ and $dlnP$. Thus, one can also write (12) as

$$w_i dlnq_i = b_i dlnQ + \sum_j s_{ij} dlnp_j. \tag{15}$$

The s_{ij} are directly related to the substitution effect of price changes. It is clear from (12) that

$$b_i = w_i \frac{\partial lnq_i}{\partial lnm} = p_i \frac{\partial q_i}{\partial m} = \frac{\partial (p_i q_i)}{\partial m}. \tag{16}$$

Thus, b_i is the marginal propensity to spend on good i from the total budget, and is also known as the marginal budget share of good i. Negative values of b_i define inferior goods. It follows from (16) that b_i/w_i is the income or budget elasticity of good i.

The differential form of the budget share w_i can be written as

$$dw_i = w_i dlnq_i + w_i dlnp_i - w_i dlnm.$$

The right-hand sides of (14) and (15) can be used to rewrite dw_i as

$$\begin{aligned} dw_i &= (b_i - w_i) dlnQ + \sum_j (s_{ij} + \delta_{ij} w_j - w_i w_j) dlnp_j \\ &= c_i dlnQ + \sum_j r_{ij} dlnp_j \end{aligned} \tag{17}$$

in which $c_i = b_i - w_i, r_{ij} = s_{ij} + \delta_{ij}w_j - w_iw_j$, and δ_{ij} is the Kronecker delta. With the c_i and r_{ij} as constants, (17) is a simplified version of the *Almost Ideal Demand (AID) system* of Deaton and Muellbauer (1980). Given the properties (13) for the b_i and s_{ij}, it follows that

$\sum_i c_i = 0$ and $\sum_i r_{ij} = 0$	(adding-up)	(18a)
$\sum_j r_{ij} = 0$	(homogeneity)	(18b)
$r_{ij} = r_{ji}$	(symmetry)	(18c)

There is no attractive counterpart for the negativity condition. While (13d) implies that the coefficients s_{ii} are negative, a similar property does not hold for the r_{ii}.

The r_{ij} are not directly related to the substitution effect of price changes. Special preference structures cannot be expressed as special conditions for the r_{ij} in terms of constants, with the s_{ij} being more suitable in this respect. It follows from (18a) that the average value of c_i is zero. The case of $c_i = 0$ corresponds to a budget elasticity of one. For $c_i > 0$, the good is a luxury, and a necessity when $c_i < 0$.

Keller and Van Driel (1985) subtracted $w_i dlnQ$ from both sides of (15) to obtain

$$\begin{aligned} w_i(dlnq_i - dlnQ) &= (b_i - w_i)dlnQ + \sum_j s_{ij}dlnp_j \\ &= c_i dlnQ + \sum_j s_{ij}dlnp_j \end{aligned} \tag{19}$$

with the resulting *CBS system* treating the c_i and s_{ij} as constants. The use of the AID type c_i and the Rotterdam type s_{ij} makes it a hybrid of the two well-known systems.

Treating the Rotterdam type b_i and AID type r_{ij} as constants was proposed by Duarte Neves (1987) to form an alternative hybrid system. This *NBR system* is obtained by adding $w_i dlnQ$ to both sides of (17) to yield

$$dw_i + w_i dlnQ = b_i dlnQ + \sum_j r_{ij} dlnp_j. \tag{20}$$

It should be noted that all four systems have basically the same right-hand sides for their equations. However, differences in data transformations for the left-hand sides imply differences in the interpretation of the coefficients. Note that all systems are equivalent (and trivial) for constant w_i, a patently unrealistic condition.

For actual applications, all differentials are replaced by finite first differences and the w_i by the moving averages, $\bar{w}_{it} = (w_{it} + w_{it-1})/2$. Addition of an intercept may be interpreted as representing factors such as changes in tastes over time. An additive disturbance term is typically used to complete the specification. Thus, a typical equation of the Rotterdam system looks like

$$\bar{w}_{it} \Delta lnq_{it} = a_i + b_i \Delta lnQ_t + \sum_j s_{ij} \Delta lnp_{jt} + u_{it} \tag{21}$$

in which u_{it} is a disturbance term and

$$\Delta lnQ_t = \sum_j \bar{w}_{jt} \Delta lnq_{jt}. \tag{22}$$

Note the two additional adding-up conditions:

$$\sum_i a_i = 0 \tag{23a}$$

and

$$\sum_i u_{it} = 0. \tag{23b}$$

The condition in (23b) has several consequences. Let u_t be the n-vector of the u_{it} and let the contemporaneous covariance matrix be $\sum = E(u_t u_t')$. It follows from (23b) that $\sum$ is singular. Without special measures, one cannot estimate the n equations in (21) jointly, which is required both for reasons of efficiency and use of the symmetry condition. A solution is to delete one equation from the system and to estimate simultaneously the remaining $n-1$ equations. As shown in Barten (1969), the method of estimation is invariant to the choice of the deleted equation. The coefficients of the deleted equation can be estimated indirectly by using the adding-up conditions and the residuals of the full system will sum to zero for each observation.

The preceding remarks also apply to the other three systems. In the next section, we discuss some implications of the adding-up condition for the test procedure presented in Section 2.

4 Implications of the Adding-up Condition for the Testing Procedure

An appealing feature of the variable addition testing procedure developed in Section 2 is that the adding-up condition may be accommodated straightforwardly as follows. The vector equation (9) can be rewritten as

$$f_{1t}(y_t) = g(x_t;\beta_1) + \sum_{m=2,M} \Lambda_m[f_{mt}(y_t) - g(x_t;\beta_m)] + v_t \tag{24}$$

which differs from (9) by having replaced $g_{jt}(x_{jt};\beta_j)$ by the common functional form $g(x_t;\beta_j)$. In the case of the Rotterdam system, the function is given by

$$g(x_t;\beta_j) = b\Delta lnQ_t + S\Delta lnp_t$$

in which b is the vector of b_i coefficients, S the matrix of s_{ij} coefficients, and Δlnp_t the vector of Δlnp_{jt} variables. The vector $f_{1t}(y_t)$ has for elements the left-hand side of equation (21).

Let ι denote the vector of unit elements. The adding-up condition implies

$$\iota' f_{jt}(y_t) = \iota' g(x_t;\beta_j), \qquad j = 1,\ldots,M \tag{25}$$

$$\iota' v_t = 0 \tag{26}$$

and

$$\iota'\Lambda_m[f_{mt}(y_t) - g(x_t;\beta_m)] = 0, \qquad m = 2,\ldots,M. \tag{27}$$

To satisfy both (25) and (27), $\iota'\Lambda_m$ must be proportional to ι', which limits the choice of Λ_m matrices. A scalar matrix, $\Lambda_m = \lambda_m I$, is obviously permitted, but a non-scalar diagonal Λ_m matrix is not permitted.

This finding is similar to the one of Berndt and Savin (1975) for the specification of vector autoregressive processes for disturbances of allocation systems.

A consequence of the adding-up condition is the singularity of the contemporaneous covariance matrix of (24), with similar problems as mentioned at the end of the preceding section. There is also a similar solution, namely the deletion of one equation from the vector of equations.

It follows from (26) that the vector counterpart of the residuals (5) adds to zero. Including the residual vectors of all n equations in the estimation of the system is impossible because of perfect collinearity. A simple solution, therefore, is to delete one vector of residuals from the auxiliary regression.

In the empirical application, we delete for each observation the last equation from (24) and the last residual. The truncated version of (24) may then be rewritten as

$$f_{1t}^{*}(y_t) = g^{*}(x_t;\beta_1) + \sum_{m=2,M} \Lambda_m^{**}[f_{mt}^{*}(y_t) - g^{*}(x_t;\beta_m)] + v_t^{*} \qquad (28)$$

where x^{*} indicates that the last element of a vector x is deleted and Λ_m^{**} that the last row and last column of Λ_m are omitted.

As is clear from the discussion, λ_{mij}^{**} should not be interpreted as the marginal contribution of residual j from H_m to the explanation of the i−th dependent variable of H_1. The adding-up condition and the fact that (28) is simply an auxiliary equation for purposes of testing H_1 distort such interpretations.

It should also be noted that (28) cannot be interpreted as a demand system because properties such as symmetry of the substitution effect of price changes are lost. A scalar specification for Λ_m^{**} could, however, correspond to a more general system meeting all the conditions of consumer theory (Barten (1989)). Here, however, our first purpose is empirical comparison of the four demand systems.

5 Description of the Data

The data used are annual observations of consumer expenditure and corresponding prices for The Netherlands over the period 1921-1981. The original data for 16 groups of goods and services have been aggregated into four major groups, namely Food, Pleasure Goods (i.e. confectionery, tobacco, drinks), Durables and Remainder.

The full set of observations consists of four subsets: (i) 1921-1939, for which the original source is Barten (1966a), although Barten (1966b) contains the major results; (ii) 1948-1951, which is an unpublished up-date of the data given in Barten (1966a) for that period; (iii) 1951-1977, which is based on data constructed by the Netherlands Central Bureau of Statistics (CBS) and given in CBS (1982); and (iv) 1977-1981, which originates from the CBS and is available in Van Driel and Hundepool (1984).

No attempt is made to combine the three post-World War II data subsets into a single set. For the purpose at hand, this is not strictly necessary because the models are expressed in terms of first differences of the variables and the three post 1948 subperiods overlap by one observation. The data are pooled, however, with estimated dummy variables absorbing the 1939-1948 transition and the 1951 and 1977 shifts. Altogether, 54 observations in first differences are available.

Over the period considered, the population has more than doubled from almost 7 million to 14.2 million. To take this into account, per capita expenditures are used. Real income per capita more than trebled from 1921 to 1981, including a 7 per cent reduction over the period 1938-1948. Inflation has been considerable in the post-World War II period. In general, prices of Durables have increased less than the average and prices of Remainder, which includes services, have increased more than the average. These changes are reflected in variations in the budget shares: for Food, the budget share declined from 34 per cent in 1921 to 13 per cent in 1981; for

Remainder, it increased from 33 per cent in 1921 to 58 per cent 60 years later; for Pleasure Goods and Durables, the budget shares varied within a small range over the 60 year period.

If there is hardly any change in the data, it will be difficult to discriminate between the various functional forms since any functional form can be made to fit the data reasonably well as a local approximation. At first sight there appears to be substantial movements in the data for purposes of testing the alternative models. The next section will determine whether the movement is sufficient to draw strong inferences concering the comparative empirical performances of the four demand systems.

6 Test Results

In this section are reported the outcomes from applying the test procedure of Section 2 to the four demand systems presented in Section 3 using the data of Section 5.

The four systems are denoted as ROT, AID, CBS and NBR, with obvious shorthand notation for Rotterdam. These models are formulated in such a way that estimation satisfies the adding-up conditions identically. For strict comparability, all systems are estimated with the same set of conditions, namely, with the homogeneity and symmetry conditions imposed. Since the focus of the paper is on the empirical comparison of the four systems, the empirical validity of these conditions is not tested. Estimation results for ROT and CBS show that the negativity condition is supported.

All four models are estimated under the assumption of serially uncorrelated disturbances. An inspection of the estimated residuals does not reveal any evidence to the contrary, which is not altogether surprising since the models are basically expressed in terms of first differences of the variables.

For purposes of estimation, the ML procedure is used along the lines of Barten and Geyskens (1975), employing the DEMMOD computer package.

Table A of the Appendix gives, for each of the four systems, the implied estimated demand elasticities with respect to the budget and the own price substitution elasticities. None of the systems estimates these elasticities as constants, but the elasticities can be evaluated for a given set of budget shares w_i. Evaluated at the sample mean budget shares, the elasticities appear to be very similar. As is to be expected, given the underlying specifications, the budget elasticities are pairwise similar for (ROT, NBR) and (CBS, AID), while the own price substitution elasticities are pairwise similar for (ROT, CBS) and (AID, NBR).

A brief discussion of the simulation method might be helpful. Recall that the fitted values $\hat{y}_{1t}$ of the various systems are needed, as in (3). In this paper, y_t is taken to be the change in expenditure from one period to the next. To retrieve this from the estimated system is straightforward in the case of the AID system, but requires an iterative solution in the other three cases. Using the observed values of expenditures of the preceding year, the expenditures of the current year are calculated and used subsequently to calculate the simulated dependent variables of the various systems, as in (3). As a check, the systems are reestimated using the simulated dependent variables. Due to rounding errors, the fits are not perfect but it is evident that the residual variations are not substantially different.

It might also be helpful to reiterate the various steps needed to test, say, ROT as the null against the other three alternative models in the paired and joint cases.

1. Estimate ROT and retain the maximized log-likelihood value. For purposes of testing ROT pairwise or jointly, this is interpreted as the restricted log-likelihood value.

2. Simulate expenditures for the four goods, as in (3), over the sample

period from the estimated version of ROT.

3. Calculate the dependent variables of CBS, AID and NBR for each of the four goods using the simulated expenditures and appropriate data transformations, estimate these systems, as in (4), and retain the residuals from the auxiliary regressions.

4. In testing ROT as the null pairwise against the CBS alternative, include the residuals from step 3 above for the first three goods of CBS as additional explanatory variables in the estimation of ROT, and retain the log-likelihood value from this expanded model. Repeat this, in turn, for the residuals of AID and NBR in testing ROT pairwise against AID and NBR, respectively. Repeat this procedure jointly for the residuals of CBS and AID, CBS and NBR, and AID and NBR, in turn, in testing ROT as the null jointly against three combinations of two non-nested alternatives. Finally, repeat the procedure jointly for the residuals of the three other systems in testing ROT as the null jointly against three non-nested alternatives. This step produces seven maximized log-likelihood values, each of which is to be compared with the restricted log-likelihood value obtained in step 1 above.

Steps 1-4 above are repeated three times, with each of the CBS, AID and NBR models being treated, in turn, as the null hypothesis. Note that, in step 4 above, 9 extra coefficients are estimated in the paired case when only one other system is considered as the alternative. This number is doubled for pairs of other systems, while in the final joint testing case 27 extra coefficients are estimated.

Twice the difference of the log-likelihood values obtained in steps 4 and

1 is asymptotically distributed under the null as χ^2, with degrees of freedom equal to the number of additional coefficients estimated in step 4. Table 1 presents values of the likelihood ratio test (LRT) statistics for the case of paired tests, that is, tests of the designated null against only one alternative at a time.

Table 1: LRT Values for Paired Tests

Null Model	Alternative Model ROT	CBS	AID	NBR
ROT	-	44.4	35.9	27.3
CBS	29.6	-	26.5	16.9
AID	41.8	37.1	-	30.2
NBR	40.6	50.1	42.9	-

For 9 degrees of freedom, the 5 and 1 per cent critical values for the χ^2 distribution are 16.9 and 21.7, respectively. Note that all entries except one in Table 1 are larger than the asymptotic critical values, indicating rejections of the designated null hypotheses. This may reflect, in part, the property of the LRT that its finite sample distribution has empirical rejection frequencies that are greater than those predicted by asymptotic theory, especially in the case of multivariate models with estimated covariance matrices. Italianer (1985) has provided an approximate small sample correction factor for the LRT in such circumstances. For the entries of Table 1, this correction factor is 0.806, application of which yields the results in Table 2.

Table 2: Corrected LRT Values for Paired Tests

Null Model	Alternative Model ROT	CBS	AID	NBR
ROT	-	35.8	28.9	22.0
CBS	23.8	-	21.3	13.7
AID	33.7	29.9	-	24.3
NBR	32.7	40.4	34.6	-

The general picture has not changed appreciably. Each model is rejected by at least one alternative at the 1 per cent level of significance, which means that no single model is adequate to explain the variation present in the data. It is worth noting that ROT and CBS each rejects the other three systems, which is not so for AID and NBR.

The results of Table 2 can also be used in a relative sense. The entries for CBS as the null are the smallest per column, whereas those for NBR as the null are among the largest. Thus, it would appear that CBS needs the information contained in the other three models the least, whereas NBR needs the information the most. There is a slight domination of ROT over AID in this respect, since AID rejects ROT less strongly than ROT rejects AID. CBS in its role as the alternative appears to contribute most to NBR as the null, followed by AID and ROT. As the alternative, NBR is clearly the weakest. Therefore, from Table 2 an ordering in quality of performance is CBS, ROT, AID and NBR.

It is useful to examine possible causes behind this ordering. CBS has AID type income coefficients and ROT type price coefficients. The superior performance of both CBS and ROT points towards the superiority of the ROT price coefficient specification. However, the superiority of CBS over ROT might suggest the superiority of the AID income coefficient specification over that of ROT. Nevertheless, the strong performance of ROT as the only alternative which rejects CBS as the null indicates that the ROT income coefficient formulation has explanatory power which could be usefully combined with that of CBS.

Table 3 presents the corrected LRT values for joint tests against two non-nested alternatives. The Italianer correction factor of 0.778 has been used in constructing the table of results.

Table 3: Corrected LRT Values for Joint Tests Against Two Alternatives

Null Model	ROT + CBS	ROT + AID	ROT + NBR	CBS + AID	CBS + NBR	AID + NBR
	Joint Alternative Models					
ROT	-	-	-	51.3	49.0	39.7
CBS	-	35.9	34.7	-	-	31.3
AID	44.3	-	40.1	-	40.9	-
NBR	55.5	59.3	-	52.1	-	-

The 5 and 1 per cent critical values are 28.9 and 34.8, respectively. CBS is the only system not being rejected by all of the joint tests at the 1 per cent level.

Comparative analysis shows that CBS performs the best and NBR the worst as the null. ROT + CBS (the ROT type price coefficient case) rejects more strongly than does AID + NBR (the AID type price coefficient case), with CBS + AID (the AID type income coefficient case) also rejecting more strongly than ROT + NBR (the ROT type income coefficient case). Therefore, in Table 3 the evidence favours the ROT type price coefficient and AID type income coefficient formulation.

The final set of results pertain to the case where the null is tested jointly against three non-nested alternative models. Table 4 gives the corrected LRT values for this case, with the Italianer correction factor being 0.750.

Table 4: Corrected LRT Values for Joint Tests Against Three Alternatives

Null Model	CBS+AID + NBR	ROT+AID + NBR	ROT+CBS + NBR	ROT+CBS + AID
	Joint Alternative Models			
ROT	62.8	-	-	-
CBS	-	48.2	-	-
AID	-	-	56.8	-
NBR	-	-	-	74.1

The relevant 5 and 1 per cent critical values are 40.1 and 47.0, respectively.

All four models are rejected by the joint test against three alternatives. The alternative models appear to contain useful information in explaining the designated null, with CBS needing this information the least and NBR the most. Relative rankings are now given as CBS, AID, ROT and NBR. The general result is that none of the models is completely satisfactory in the sense that one or more of the other models contributes significantly to explaining the relevant dependent variable.

In general, CBS performs the best, NBR the worst, and AID and ROT hold an intermediate position. The ROT type price coefficient specification performs better than its AID counterpart, but the AID type income coefficient specification performs better than that of ROT.

7 Conclusions

In this paper, we have developed a general procedure, outlined in Section 2, to compare the empirical performance of alternative demand systems. This is an extension of the variable addition procedure for comparing the performance of single non-nested equations subject to different non-linear data transformations of the dependent variable. The adding-up condition required of demand systems causes minor complications, but these can readily be accommodated by simply reconsidering these systems with one equation deleted.

The four systems compared are the Rotterdam (ROT) system, the Almost Ideal Demand (AID) system, the CBS system, and the NBR system. These systems share common right-hand sides but differ in the non-linear data transformations of the endogenous variable. The CBS and NBR systems are hybrids of ROT and AID in the sense that CBS has ROT type price coefficients and AID type income coefficients, whereas NBR has ROT type income coefficients and AID type price coefficients.

Annual data are used for The Netherlands for the period 1921-1981.

As the empirical application shows, there is sufficient variation in the 54 available data points to arrive at significant conclusions.

One of the conclusions is that no single system is dominant empirically, with CBS performing the best, NBR the worst and with ROT and AID occupying roughly equivalent intermediate positions. Examining the results more closely, the ROT price coefficient specification clearly outperforms its AID counterpart. On the other hand, the AID income coefficient specification is superior to its ROT counterpart, but the dominance is less clear than for the case of the price coefficients.

If interest lies primarily in empirical performance and the choice is limited to the use of the four systems considered here, the results suggest that the CBS system is to be preferred.

Matrix linear combinations of demand systems, as implied by the artificial nesting approach, are not in themselves attractive demand systems, unless the weights are scalars. Analysis of the models examined in the paper using scalar weights is a topic for further research.

Another issue that is worthy of further study is the impact of the degree of aggregation on the results. This paper is concerned with 4 major groups of consumer expenditure. It would be interesting to examine the outcomes when 8 or 16 groups are used.

The approach used here is sufficiently flexible to compare the empirical performance of models in terms of first differences, such as those examined in the paper, with those expressed in terms of levels of the variables.

There would appear to be much scope for further research along the lines presented here. An important conclusion is that the method may usefully be employed for comparing the empirical performance of general systems of equations.

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Appendix Table A: Estimated elasticities for the four demand systems

CATEGORY OF FOOD	ROT		CBS		AID		NBR	
	Budget elasticity	Own price substitution elasticity	Budget elasticity	Own price substitution elasticity	Budget elasticity	Own price substitution elasticity	Budget elasticity	Own price substitution elasticity
FOOD (0.251)	0.57	-0.42	0.52	-0.37	0.50	-0.34	0.55	-0.39
PLEASURE GOODS (0.091)	0.76	-0.53	0.71	-0.54	0.72	-0.53	0.77	-0.53
DURABLES (0.254)	2.21	-0.11	2.19	-0.12	2.19	-0.16	2.21	-0.15
REMAINDER (0.404)	0.56	-0.10	0.62	-0.09	0.63	-0.12	0.57	-0.13

Note: Elasticities are evaluated at the sample mean budget shares, which are given in parentheses.

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