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Abstract

In this paper a set of ten different single-equation models of household energy demand is being analyzed. These simple models are being derived by the imposition of linear parameter restrictions on a fairly general autoregressive distributed lag (ADL) model in log-linear form. Household energy consumption is assumed to be explainable by movements in households' real disposable income, real price of energy, and the temperature variable 'heating degree days'. In the empirical application, Austrian annual data for the period 1970 to 1992 are used. The overall significance level α of the tests is being reduced by applying the closure test principle, introduced by Marcus, Peritz, and Gabriel (1976). The application illustrates nicely how one can, by defining a closed system of hypotheses, reduce the significance level in a relatively unordered search for a suitable specific model. The wide range of estimated elasticities, however, indicates that such estimation results depend heavily on the choice of the model specification.

Zusammenfassung

In dieser Arbeit wird eine Gruppe von zehn verschiedenen Einzelgleichungsmodellen der Haushaltsenergienachfrage untersucht. Diese einfachen Modelle werden durch die Einführung von linearen Parameterrestriktionen in einem relativ allgemeinen ADL-Eingleichungsmodell in log-linearer Form erzeugt. Es wird angenommen, daß der Energieverbrauch der privaten Haushalte durch Veränderungen der Variablen persönlich verfügbares Realeinkommen der Haushalte, Energiepreis, sowie der Temperaturvariablen "Heizgradtage" erklärbar ist. In der empirischen Anwendung werden österreichische Jahresdaten für die Zeitperiode 1970 bis 1992 verwendet. Das Gesamt-Signifikanzniveau α der durchgeführten Testserie wird durch die Anwendung des Abschlußtestprinzips, wie es von Marcus, Peritz und Gabriel (1976) vorgeschlagen wurde, verringert. Die Applikation illustriert anschaulich, wie man durch die Definition eines abgeschlossenen Systems von Hypothesen das Signifikanzniveau bei einer relativ unsystematischen Suche nach einem geeigneten Modell reduzieren kann. Die große Bandbreite der geschätzten Elastizitäten deutet jedoch darauf hin, daß Schätzergebnisse dieser Form sehr stark von der Wahl der Modellspezifikation abhängen.

Keywords
Single-Equation Analysis, Residential Energy Demand, Closure Test, General-to-Specific Modelling

JEL Classification
C12, C22, C52, Q41, R22

Comments
The author greatfully acknowledges fruitful discussions with Raimund Alt.

1 Introduction

In this paper Austrian household energy demand elasticities are being estimated. To this end and based on earlier work by Kouris (1981) and Jones (1993), we analyze ten different types of single-equation models of energy demand. These models are being derived by imposing sets of linear restrictions on a general (or 'benchmark') model. The modelling strategy followed is, in a broad sense, one of 'general-to-specific' modelling.

In general, two approaches are distinguished for the assessment of the empirical performance of non-nested models: information criteria and the conventional, i.e. Neyman-Peirson methodology of hypothesis testing. The former treats the various rival models symmetrically and chooses the one which is expected to outperform the others in terms of a particular loss function. The most popular criteria for model selection are Theil′s $\overline{R}^2$, Akaike′s information criterion, and Schwarz′s Bayesian information criterion (for a discussion, see for example Judge et. al. (1985)). The latter, i.e. the non-nested hypothesis testing, is usually based on some centered log-likelihood statistic (see the seminal papers by Cox (1961, 1962)), the 'comprehensive model approach' (see Atkinson (1970)), or the 'encompassing principle' (popularized recently by Mizon and Richard (1986)).

While the popular hypothesis testing approaches usually put their main focus on the modelling strategy followed and the diagnostic statistics obtained, this paper concentrates on the crucial problem and well-known fact that the overall significance level of a sequence of tests becomes larger than some prespecified significance level α if each single hypothesis is tested at this level α. The reason is that by testing the individual null hypotheses, multiple type I errors may occur. In order to deal with this problem, we have employed the closure test principle, as introduced by Marcus, Peritz, and Gabriel (1976) and discussed in Alt (1991)(for the case of linear regression models), to single-equation analysis in an energy economics context.

The paper is organized as follows: Section 2 presents a brief description of the closure test principle. In Section 3, we discuss the modelling technique and introduce the various models under scrutiny. In Section 4, the main results are reported. Finally, Section 5 contains a summary and some concluding remarks.

2 The Closure Test Principle

The closure test principle has been introduced in the literature by Marcus, Peritz and Gabriel (1976) and further developed by Holm (1979) and Sonnemann (1982). Its major aim is to facilitate the construction of multiple level-α tests, provided a level-α test exists for each single null hypothesis.[1]

Alt (1991) has noted that closed test procedures have not penetrated the econometrics literature yet. As an example, he points to the fact that they have neither been treated by Miller (1981) nor Savin (1984) in their surveys on multiple hypotheses testing, two references still often cited in connection with multiple test procedures. Two of the very few studies in econometrics, in which the closure test principle has been discussed, are Krämer and Sonnberger (1986) and Neusser (1991). In the former the Holm procedure is explained, while in the latter the closure test principle is applied in the context of cointegration analysis.

Applications of the closure test principle have led to the improvement of many classical test procedures. The reason is that 'closure tests', sometimes called 'closed test procedures', are at least as powerful as (and in general more powerful than) their classical counterparts.

In order to better understand the closure test principle, we will first introduce the two concepts 'overall level α' and 'multiple level α'. Let us consider a set of null

[1] A multiple level-α test is a test procedure with the property that the probability of committing any type I error is always less than or equal to the given significance level α, for any combination of true null hypotheses.

hypotheses of interest, H_{0i}, $i = 1, 2, ..., m$. Furthermore, let a multiple test procedure $\Phi = (\varphi_1, \varphi_2, ..., \varphi_m)$ be given, where φ_i is a test for hypothesis H_{0i}.

The *overall level* α property is a common requirement for a multiple test procedure. It means that the probability of rejecting at least one of the null hypotheses, provided that all null hypotheses are true, should be less than or equal to some prespecified level α. Examples of overall level-α tests are the Bonferroni and the Scheffe procedure. They are discussed, for example, in Savin (1984) and Alt (1991). Alt (1991) notes, however, that the overall level-α requirement has been more and more replaced by its multiple level-α counterpart.

A test procedure is said to control the *multiple level* α if for each index set I the probability of rejecting at least one of the null hypotheses H_{0i}, $i \in I$, given that all null hypotheses H_{0i} are true, is less than or equal to some prespecified level α.

Obviously, the multiple level α concept is much stronger than the overall level α concept, because it requires that the probability of committing any type I error should be less than or equal to α *for each combination* of true null hypotheses. In particular, a multiple level-α test also controls the overall level α (note that in general the converse is not true).

The closure test principle employs the multiple level α property. It ensures that the probability of making *no* type I error is at least (1 - α). This is accomplished by widening the existing set of hypotheses by all subhypotheses in such a way that the new set of hypotheses is closed under intersection (note that in our analysis we understand that the empty set ('∅') as the intersection of two hypotheses is also an admissible null hypothesis in a set of hypotheses that is closed under intersection). A specific hypothesis is being rejected if all its subhypotheses are rejected at some *fixed and prespecified* significance level α.

In other words, the above formulation describes the construction of a multiple level-α test that is based on two assumptions. First, the set $\{H_{01}, ..., H_{0m}\}$ should be closed under intersection (i.e. any intersection of hypotheses from this set should either be the empty set or a hypothesis contained in it).[2] Secondly, for each single hypothesis H_{0i} there should exist a level α test.

3 Introduction of the Modelling Technique and the Models

In the modelling procedure that follows, let the growth in energy demand of private households, ΔQ_t, be a function of the growth in private households' real disposable income, ΔY_t, the real price of energy, P_t, the sum of annual heating degree days, H_t, and the lagged values of all these variables, i.e.

$$\Delta Q_t = f(\Delta Q_{t-i}, \Delta Y_t, \Delta Y_{t-i}, P_t, P_{t-i}, H_t, H_{t-i}); \quad i = 1, 2, \ldots, \mathrm{k}; \quad t = 1, 2, \ldots, \mathrm{T}; \quad (3)$$

where all variables are in logs and k denotes the maximum lag length.

As the modelling vehicle that serves as our general or benchmark model, we have chosen an ADL model in log-linear form, which contains, to simplify matters, just one lag of each variable (i.e. an ADL(1) model, i = 1). In other words, we may express our initial general model in log-linear form as:

$$\begin{aligned} \Delta Q_t = {} & a_1 + a_2 \Delta Q_{t-1} + a_3 \Delta Y_t + a_4 \Delta Y_{t-1} + a_5 P_t + \\ & + a_6 P_{t-1} + a_7 H_t + a_8 H_{t-1} + \varepsilon_t . \end{aligned} \quad (4)$$

Note that, due to the log-linear specification, a_3 can directly be interpreted as the short-run income elasticity (i.e. how responsive energy demand growth is to income growth), a_5 as the short-run price elasticity (i.e. how responsive energy demand growth is to the energy price level), and a_7 as the short-run 'temperature' elasticity (i.e.

[2] It should be noted at this point that the assumption that $\{H_{01}, \ldots, H_{0m}\}$ is closed under intersection is actually not a restriction. If $\{H_{01}, \ldots, H_{0m}\}$ is not closed under intersection, it is always possible to add 'auxiliary hypotheses', constructed by forming intersections of the hypotheses considered, in order to get a closed set of null hypotheses. The crucial point is merely to find suitable level-α tests for the additional hypotheses.

how responsive growth in energy demand is to temperature); ε_t is a Gaussian error term.

Obviously, one could, by imposing parameter restrictions, formulate a large number of specific models even with this simple general model described by Eq. (4). In the following analysis, however, we will restrict ourselves to the investigation of only ten deliberately chosen specific models. Moreover, we will try to find a systematic way of developing and assessing a selected group of restricted models in order to avoid the worst features of data mining.[3]

The econometric methodology traditionally followed is one that starts with a relatively simple (and rarely justified) specification, which is subsequently extended in order to end up with 'reasonable' estimates, i.e. statistically significant parameter estimates with correct signs. This methodology is commonly referred to as 'specific-to-general modelling'. By contrast, the modelling technique followed here is one that is closer related to 'general-to-specific' modelling, an approach that has been advocated particularly by David Hendry and Grayham Mizon, among others (see Hendry (1995), Mizon (1994), Hendry (1993), and Hendry and Mizon (1990) for details; a nice introduction may be found in Charemza and Deadman (1992)). The basic idea behind the general-to-specific approach is that one starts modelling with a deliberately overparameterized initial general model that ideally includes all effects likely to be relevant. It should contain sufficient lags to avoid serial autocorrelation and has to be tested for its validity.[4] Once all that has been established, further model testing may proceed in order to systematically find one or more satisfying simpler model(s) that outperform(s) the general model.

Arguments that have been put up in favor of a general-to-specific modelling strategy include: (1) application of directed instead of directionless strategies; (2) valid interpretation of intermediate test outcomes by avoiding later potential

[3] Data mining may be defined as a procedure or strategy, respectively, to select one model out of many alternative models. On the issue of data mining see the excellent paper by Lovell (1983); for a more recent discussion see Charemza and Deadman (1992), among others.
[4] Due to the lack of observations and for illustrative purposes we will confine ourselves in the empirical application to one lag on each of the variables.

contradictions; (3) escape of the 'non-sequitur' of accepting the alternative hypothesis when a test rejects the null; (4) determination of the baseline innovation error process on the available information; and (5) circumvention of the drawbacks of correcting manifest flaws when such appear as against starting from a congruent model (for a recent and comprehensive discussion of these arguments see Hendry and Doornik (1994)).

Our modelling strategy is much less rigorous than the one just briefly outlined, as we merely aim to demonstrate the empirical applicability of the closure test principle in an energy economics context. Nonetheless, we have tried to implement some of the most important features of general-to-specific modelling. In particular, we start with a general model (Eq. (4)) and successively test individual parameter restrictions in order to end up with ten (prespecified) restricted models.

Table 1 below depicts a list of the ten specific models of interest, followed by Table 2 which shows the thirteen additional sets of restrictions (and models!) that are required for closure of the system.[5]

[5] A major part of the models discussed here can be found in the recent and very detailed 'typology of linear demand equations' by Hendry (1995), Ch. 7.

Table 1: *The Specific Models 1 to 10*

No.	Model Description	Restrictions Imposed (Null Hypothesis)
1.	Static regression model $\Delta Q_t = a_1 + a_3 \Delta Y_t + a_5 P_t + a_7 H_t + \varepsilon_t$	$a_2 = a_4 = a_6 = a_8 = 0$
2.	Model in terms of changes $(\Delta Q_t - \Delta Q_{t-1}) = a_1 + a_3(\Delta Y_t - \Delta Y_{t-1}) +$ $+a_5(P_t - P_{t-1}) +$ $+a_7(H_t - H_{t-1}) + \varepsilon_t$	$a_2 = 1; a_4 = -a_3;$ $a_6 = -a_5; a_8 = -a_7$
3.	Static regression model, with dependent variable defined as energy demand per unit of income $(\Delta Q_t - \Delta Y_t) = a_1 + a_5 P_t + a_7 H_t + \varepsilon_t$	$a_2 = a_4 = a_6 = a_8 = 0;$ $a_3 = 1$
4.	Variation of 3; uses lagged price instead of current price $(\Delta Q_t - \Delta Y_t) = a_1 + a_6 P_{t-1} + a_7 H_t + \varepsilon_t$	$a_2 = a_4 = a_5 = a_8 = 0;$ $a_3 = 1$
5.	'Dynamized' model to allow for an assessment of long-term reactions to price and income changes $\Delta Q_t = a_1 + a_2 \Delta Q_{t-1} + a_3 \Delta Y_t +$ $+a_5 P_t + a_7(H_t - H_{t-1}) + \varepsilon_t$	$a_4 = a_6 = 0; a_8 = -a_7$
6.	Variation of 5 (allows an assessment of reactions to price changes only) $\Delta Q_t = a_1 + a_2 \Delta Q_{t-1} + a_3(\Delta Y_t - \Delta Y_{t-1}) +$ $+a_5 P_t + a_7(H_t - H_{t-1}) + \varepsilon_t$	$a_4 = -a_3; a_6 = 0; a_8 = -a_7$
7.	Autoregressive model of order one (AR(1)) $\Delta Q_t = a_1 + a_2 \Delta Q_{t-1} + \varepsilon_t$	$a_3 = a_4 = a_5 = a_6 =$ $= a_7 = a_8 = 0$
8.	First-order finite distributed lag equation $\Delta Q_t = a_1 + a_3 \Delta Y_t + a_4 \Delta Y_{t-1} + a_5 P_t + a_6 P_{t-1} +$ $+a_7 H_t + a_8 H_{t-1} + \varepsilon_t$	$a_2 = 0$
9.	'Leading indicator' model $\Delta Q_t = a_1 + a_4 \Delta Y_{t-1} + a_6 P_{t-1} + a_8 H_{t-1} + \varepsilon_t$	$a_2 = a_3 = a_5 = a_7 = 0$
10.	'Dead start' model (lagged information only) $\Delta Q_t = a_1 + a_2 \Delta Q_{t-1} + a_4 \Delta Y_{t-1} +$ $+a_6 P_{t-1} + a_8 H_{t-1} + \varepsilon_t$	$a_3 = a_5 = a_7 = 0$

Table 2: *Additional Models for Closure of the System*

No. Model	Restriction Set
11. $(\Delta Q_t - \Delta Y_t) = a_1 + a_7 H_t + \varepsilon_t$	$a_2 = a_4 = a_5 = a_6 = a_8 = 0;\ a_3 = 1$
12. $\Delta Q_t = a_1 + a_3 \Delta Y_t + a_5 P_t + \varepsilon_t$	$a_2 = a_4 = a_6 = a_7 = a_8 = 0$
13. $\Delta Q_t = a_1 + a_5 P_t + \varepsilon_t$	$a_2 = a_3 = a_4 = a_6 = a_7 = a_8 = 0$
14. $\Delta Q_t = a_1 + \varepsilon_t$	$a_2 = a_3 = a_4 = a_5 = a_6 = a_7 = a_8 = 0$
15. $(\Delta Q_t - \Delta Q_{t-1}) = a_1 + a_7(H_t - H_{t-1}) + \varepsilon_t$	$a_2 = 1;\ a_3 = a_4 = a_5 = a_6 = 0;\ a_8 = -a_7$
16. $(\Delta Q_t - \Delta Q_{t-1}) = a_1 + a_3(\Delta Y_t - \Delta Y_{t-1}) + {}$ $+ a_7(H_t - H_{t-1}) + \varepsilon_t$	$a_2 = 1;\ a_4 = -a_3;\ a_5 = a_6 = 0;\ a_8 = -a_7$
17. $(\Delta Q_t - \Delta Q_{t-1}) = a_1 + \varepsilon_t$	$a_2 = 1;\ a_3 = a_4 = a_5 = a_6 = a_7 = a_8 = 0$
18. $(\Delta Q_t - \Delta Y_t) = a_1 + a_5 P_t + \varepsilon_t$	$a_2 = a_4 = a_6 = a_7 = a_8 = 0;\ a_3 = 1$
19. $(\Delta Q_t - \Delta Y_t) = a_1 + \varepsilon_t$	$a_2 = a_4 = a_5 = a_6 = a_7 = a_8 = 0;\ a_3 = 1$
20. $\Delta Q_t = a_1 + a_2 \Delta Q_{t-1} + a_5 P_t + {}$ $+ a_7(H_t - H_{t-1}) + \varepsilon_t$	$a_3 = a_4 = a_6 = 0;\ a_8 = -a_7$
21. $\Delta Q_t = a_1 + a_3 \Delta Y_t + a_5 P_t + {}$ $+ a_7(H_t - H_{t-1}) + \varepsilon_t$	$a_2 = a_4 = a_6 = 0;\ a_8 = -a_7$
22. $\Delta Q_t = a_1 + a_3(\Delta Y_t - \Delta Y_{t-1}) + a_5 P_t + {}$ $+ a_7(H_t - H_{t-1}) + \varepsilon_t$	$a_2 = a_6 = 0;\ a_4 = -a_3;\ a_8 = -a_7$
23. $\Delta Q_t = a_1 + a_5 P_t + a_7(H_t - H_{t-1}) + \varepsilon_t$	$a_2 = a_3 = a_4 = a_6 = 0;\ a_8 = -a_7$

4 Closure Test and Estimation Results[6]

In this section, we will first present the results of the closure test. Secondly, we will present the estimation results of the general-to-specific modelling and a brief discussion of the performance of each of the models analyzed. Finally, we will conclude with the suggestion of a superior model that outperforms the others.

[6] Most of the empirical results reported have been obtained through the use of the econometrics computer package PcGive (version 8.0), developed by David Hendry and Jurgen Doornik.

Under the closure test principle, a particular hypothesis is being rejected if the hypothesis itself and all its subhypotheses are rejected at the fixed and prespecified significance level α (in our case 5% and 1%, respectively).

Table 3 below shows the F-test results of testing the null hypotheses 1 to 10 and, in three cases, the test outcomes of all the nested hypotheses of that particular hypothesis (viz. H_{02}, H_{09}, and H_{010}), tested against the general model. Note that because the hypotheses H_{01} and H_{03} to H_{08} on their own cannot be rejected at the 5% significance level, they are also not rejectable under the closure test principle. Hence none of their subhypotheses has been reported.

Table 3: *Model Reduction Test Results I (Closure Test Results)*

	F-statistic	p-value
H_{01}: $a_2 = a_4 = a_6 = a_8 = 0$	**1.0138**	**[0.44]**
H_{02}: $a_2 = 1;\ a_4 = -a_3;\ a_6 = -a_5;\ a_8 = -a_7$	**4.3201**	**[0.02]**
H_{015}: $a_2 = 1;\ a_3 = a_4 = a_5 = a_6 = 0;\ a_8 = -a_7$	6.1620	[0.003]
H_{016}: $a_2 = 1;\ a_4 = -a_3;\ a_5 = a_6 = 0;\ a_8 = -a_7$	3.5847	[0.03]
H_{017}: $a_2 = 1;\ a_3 = a_4 = a_5 = a_6 = a_7 = a_8 = 0$	7.1537	[0.001]
H_{03}: $a_2 = a_4 = a_6 = a_8 = 0,\ a_3 = 1$	**0.8182**	**[0.56]**
H_{04}: $a_2 = a_4 = a_5 = a_8 = 0;\ a_3 = 1$	**0.8311**	**[0.55]**
H_{05}: $a_4 = a_6 = 0;\ a_8 = -a_7$	**1.6428**	**[0.23]**
H_{06}: $a_4 = -a_3;\ a_6 = 0;\ a_8 = -a_7$	**0.3688**	**[0.78]**
H_{07}: $a_3 = a_4 = a_5 = a_6 = a_7 = a_8 = 0$	**2.3937**	**[0.09]**
H_{08}: $a_2 = 0$	**0.2107**	**[0.65]**
H_{09}: $a_2 = a_3 = a_5 = a_7 = 0$	**3.3072**	**[0.04]**
H_{03}: $a_2 = a_4 = a_5 = a_8 = 0;\ a_3 = 1$	0.8182	[0.56]
H_{014}: $a_2 = a_3 = a_4 = a_5 = a_6 = a_7 = a_8 = 0$	2.1370	[0.11]
H_{010}: $a_3 = a_5 = a_7 = 0$	**4.3815**	**[0.02]**
H_{07}: $a_3 = a_4 = a_5 = a_6 = a_7 = a_8 = 0$	2.3937	[0.09]
H_{09}: $a_2 = a_3 = a_5 = a_7 = 0$	3.3072	[0.04]
H_{014}: $a_2 = a_3 = a_4 = a_5 = a_6 = a_7 = a_8 = 0$	2.1370	[0.11]
H_{017}: $a_2 = 1;\ a_3 = a_4 = a_5 = a_6 = a_7 = a_8 = 0$	7.1537	[0.001]

As can be seen from the test results presented in Table 3, the closure test only rejects hypothesis H_{02} at the 5% (but *not* at 1%!) level of significance, whereas all the other models cannot be rejected at this level (note, however, that the closure test principle is valid only asymptotically!). By contrast, as many as three hypotheses (H_{02}, H_{09}, and H_{010}) would be rejected under 'conventional' multiple hypotheses testing at the 5% level of significance, and the rather conservative Bonferroni procedure, for instance, would reject none of the ten hypotheses (for a description of the Bonferroni procedure see Savin, 1984).[7]

Discussion of the Models and the Estimation Results

Table 4 below depicts the estimation results for the general model. It performs quite well in terms of the mis-specification tests reported, consistent with the idea that the model is indeed congruent.

Table 4: *OLS Estimates, Unrestricted Model, 1972-92*

Variable	Coefficient	Std.Error	t-value	t-prob.	Partial R^2
Constant	-0.16542	2.40780	-0.069	0.9463	0.0004
ΔQ_{t-1}	0.10546	0.22976	0.459	0.6538	0.0159
ΔY_t	0.86782	0.66107	1.313	0.2120	0.1170
ΔY_{t-1}	-1.22620	0.67985	-1.804	0.0945	0.2001
P_t	-0.27632	0.24116	-1.146	0.2725	0.0917
P_{t-1}	0.09748	0.20502	0.475	0.6424	0.0171
H_t	0.43111	0.17294	2.493	0.0269	0.3234
H_{t-1}	-0.30575	0.19202	-1.592	0.1353	0.1632

DIAGNOSTIC STATISTICS:
$R^2 = 0.53503$
$F(7,13) = 2.137$ [0.11]
$\sigma = 0.0398459$
DW = 1.99
RSS = 0.02064

MISSPECIFICATION TESTS:
AR 1-2 $F(2,11) = 0.29486$ [0.75]
ARCH 1 $F(1,11) = 0.06708$ [0.80]
Normality $\chi^2(2) = 1.39360$ [0.50]
Reset $F(1,12) = 0.00012$ [0.99]

The tests reported constitute residual tests for a variety of null hypotheses of interest, viz. AR, a Lagrange multiplier test statistic for first order serial correlation in the

[7] Under 'conservative' we understand in this context that the probability of rejecting at least one of the true null hypotheses is, in general, small compared to the given significance level α.

residuals; ARCH, an LM statistic of testing first-order autocorrelated squared residuals with the null of no autoregressive conditional heteroscedasticity (see Engle, 1982); a normality χ^2 test with two degrees of freedom (Prob ($\chi^2 \geq 1.3936$) = 0.50); and finally 'Reset', the regression specification test due to Ramsey (1969), which tests the null of correct specification against the alternative that the residuals are correlated.

The P_t, H_t and ΔY_t coefficients have the correct sign and, compared with other studies in this field, are of a reasonable magnitude. Note, however, that most parameters are insignificant in this equation and thus should be treated with caution. Moreover, the DW statistic is upward biased due to the inclusion of the lagged dependent variable ΔQ_{t-1}.

The solved static long-run equation is (standard errors in parentheses):

$$\Delta Q_t = \underset{(2.68)}{-\,0.185} \underset{(0.14)}{-\,0.20 P_t} \underset{(0.30)}{+\,0.14 H_t} \underset{(1.11)}{-\,0.40 \Delta Y_t} \qquad (5)$$

In what follows, we will on the one hand present the OLS estimates of the restricted models and, on the other hand, discuss their main features and performance. (Note that we have omitted the constants in reporting the estimation results.)

Model 1: *(static regression model)*

Variable	Coefficient	Std.Error	t-value	t-prob.	Partial R^2
ΔY_t	1.09760	0.51991	2.111	0.0499	0.2077
P_t	-0.04371	0.08541	-0.512	0.6154	0.0152
H_t	0.43014	0.15509	2.773	0.0130	0.3115

DIAGNOSTIC STATISTICS:	MISSPECIFICATION TESTS:	
R^2 = 0.389982	AR 1-2	F(2,15) = 0.41596 [0.67]
F(3,17) = 3.6227 [0.03]	ARCH 1	F(1,15) = 0.13654 [0.72]
σ = 0.0399108	Normality	$\chi^2(2)$ = 0.92350 [0.63]
DW = 1.70	Xi^2	F(6,10) = 2.57800 [0.09]
RSS = 0.02708	Xi*Xj	F(9, 7) = 1.61570 [0.27]
	Reset	F(1,16) = 0.12986 [0.72]

Model 1 represents the simple static version of the general regression model. In contrast to the P_t coefficient, both the H_t and the ΔY_t coefficient show significant t-values; all coefficients show rather reasonable values with the correct signs, although the estimated price elasticity of -0.04 seems to be too low. The mis-specification tests do not show any problems with the specification of the model either. Of course, the usual deficiency of such a simple static model remains: it does not allow for any long-term analysis.

Model 2: *(model in terms of changes; dependent variable ΔQ_t-ΔQ_{t-1}; sample: 1973-92)*

Variable	Coefficient	Std.Error	t-value	t-prob.	Partial R^2
ΔP_t	-0.12622	0.21005	-0.601	0.5558	0.0208
ΔH_t	0.49208	0.14144	3.479	0.0029	0.4159
$\Delta\Delta Y_t$	1.5676	0.51419	3.049	0.0073	0.3535

DIAGNOSTIC STATISTICS:	MISSPECIFICATION TESTS:	
R^2 = 0.519939	AR 1-2	F(2,15) = 0.89217 [0.43]
F(3,17) = 6.1374 [0.01]	ARCH 1	F(1,15) = 0.46661 [0.51]
σ = 0.053179	Normality	$\chi^2(2)$ = 2.91370 [0.23]
DW = 2.14	Xi^2	F(6,10) = 2.51020 [0.10]
RSS = 0.04808	Xi*Xj	F(9, 7) = 1.34800 [0.35]
[Note: 'ΔΔ' denotes second differences]	Reset	F(1,16) = 3.74240 [0.07]

The specification of Model 2 purports to lessen multicollinearity. When a model is specified in terms of changes, the statistical biases arising both from serial correlation and collinearity between the independent variables are supposed to be restricted at the same time. The important drawback of such a specification is that the explanatory power of the model is drastically reduced, because by differencing low-frequency variations of the data are being removed. The problem is aggravated by the fact that we have already chosen ΔQ_t and ΔY_t in first differences as our initial variables, so that they appear as second differences in the regression equation. The coefficients of primary interest, i.e. $\Delta\Delta Y_t$, ΔP_t, and ΔH_t, show the correct sign. The income elasticity seems to be unreasonably high. Again, the mis-specification tests do not exhibit any major specification deficiencies.

Model 3: *(static regression model with dependent variable ΔQ_t-ΔY_t)*

Variable	Coefficient	Std.Error	t-value	t-prob.	Partial R^2
P_t	-0.04983	0.07681	-0.649	0.5247	0.0228
H_t	0.42319	0.14652	2.888	0.0098	0.3167

DIAGNOSTIC STATISTICS:	MISSPECIFICATION TESTS:	
$R^2 = 0.31681$	AR 1-2	F(2,16) = 0.41064 [0.67]
F(2,18) = 4.1735 [0.03]	ARCH 1	F(1,16) = 0.18187 [0.68]
$\sigma = 0.0388265$	Normality $\chi^2(2)$ =	0.98176 [0.61]
DW = 1.76	Xi^2	F(4,13) = 5.06120 [0.01]*
RSS = 0.02713	Xi*Xj	F(5,12) = 3.82870 [0.03]*
	Reset	F(1,17) = 4.85590 [0.04]*

Model 3 takes account of the usual assumption that what matters most is not energy consumption per se, but energy consumption per unit of household income. Thus the energy/income ratio becomes the dependent variable in the regression. However, we do have some specification problems as can be seen from the Xi^2, the Xi*Xj, and the Reset test. As usual, the H_t coefficient, by contrast to the P_t coefficient, is significant. Both show correct signs from the economic point of view. Note that in this model we have restricted the income elasticity to be unity, which artificially lowers the explanatory power of the model. Obviously, such a transformation absorbs quite a big portion of the dependent variables' variability, leaving less to be explained by the remaining price variables.

Model 4: *(variation of 3; uses lagged price instead of current price)*

Variable	Coefficient	Std.Error	t-value	t-prob.	Partial R^2
P_{t-1}	-0.04616	0.07790	- 0.593	0.5608	0.0191
H_t	0.42998	0.15030	2.861	0.0104	0.3126

DIAGNOSTIC STATISTICS:	MISSPECIFICATION TESTS:	
$R^2 = 0.314219$	AR 1-2	F(2,16) = 0.47299 [0.63]
F(2,18) = 4.1237 [0.03]	ARCH 1	F(1,16) = 0.12006 [0.73]
$\sigma = 0.0389$	Normality $\chi^2(2)$	= 0.94486 [0.62]
DW = 1.78	Xi^2	F(4,13) = 5.47020 [0.01]**
RSS = 0.02724	Xi*Xj	F(5,12) = 4.13000 [0.02]*
	Reset	F(1,17) = 5.09070 [0.04]*

Model 4 only differs from Model 3 in that it takes lagged price instead of current price. However, this modification does not gain any significant advantage, as compared to the results of model 3. What has been said on model 3 about the income effect applies to model 4 analogously.

Model 5: *('dynamized model'; allows an assessment of long-term reactions to price and income)*

Variable	Coefficient	Std.Error	t-value	t-prob.	Partial R^2
ΔQ_{t-1}	0.05454	0.23142	0.236	0.8167	0.0035
ΔY_t	0.91761	0.58044	1.581	0.1335	0.1351
P_t	- 0.03766	0.09549	- 0.394	0.6985	0.0096
ΔH_t	0.27754	0.11433	2.427	0.0274	0.2691

DIAGNOSTIC STATISTICS:
$R^2 = 0.358754$
$F(4,16) = 2.2379$ [0.11]
$\sigma = 0.0421789$
DW = 2.02
RSS = 0.02846

MISSPECIFICATION TESTS:
AR 1- 2 $F(2,14) = 0.55123$ [0.59]
ARCH 1 $F(1,14) = 0.51964$ [0.48]
Normality $\chi^2(2) = 0.43185$ [0.81]
Xi² $F(8, 7) = 1.47240$ [0.31]
Reset $F(1,15) = 0.41046$ [0.53]

The specification of model 5 includes some dynamics of the relationships to enable an improved assessment of the long-term reactions. Such a specification is desirable when either assuming habit persistence or some stock adjustment process. The mis-specification test results exhibit no problem of mis-specification. The coefficients of interest show reasonable values of the expected signs. Note that again the Durbin-Watson statistic is upward biased due to the included lagged dependent variable ΔQ_{t-1}.

Model 6: *(variation of 5; allows an assessment of reactions to price changes only)*

Variable	Coefficient	Std.Error	t-value	t-prob.	Partial R^2
ΔQ_{t-1}	0.15712	0.20922	0.751	0.4636	0.0340
$\Delta\Delta Y_t$	1.10020	0.40141	2.741	0.0145	0.3195
P_t	- 0.14932	0.07580	- 1.970	0.0664	0.1952
ΔH_t	0.36788	0.10940	3.363	0.0040	0.4141

DIAGNOSTIC STATISTICS:
$R^2 = 0.495457$
$F(4,16) = 3.928$ [0.02]
$\sigma = 0.0374138$
DW = 1.95
RSS = 0.02240

MISSPECIFICATION TESTS:
AR 1- 2 $F(2,14) = 0.30901$ [0.74]
ARCH 1 $F(1,14) = 0.60391$ [0.45]
Normality $\chi^2(2) = 0.05003$ [0.98]
Xi² $F(8, 7) = 3.23870$ [0.07]
Reset $F(1,15) = 0.02949$ [0.87]

Model 6 is a similar way to the specification chosen for model 5 in that it also tries to capture some long-term reactions that might still exist (despite the fact that Q_t and Y_t already entered the unrestricted model in first differences). The specification assumes that there is a long-term reaction to price, but not to income changes. The implicit assumption in model 6 is that income has only a short-term effect, while price changes have both a short- and a long-term impact on energy consumption. The coefficients are of reasonable magnitude and have the expected signs. Note also that the price elasticity for the first time is almost significant, and that all other t-values are higher than in the preceding regressions.

Model 7: *(AR(1) model)*

Variable	Coefficient	Std.Error	t-value	t-prob.	Partial R^2
ΔQ_{t-1}	- 0.14846	0.23062	- 0.644	0.5274	0.0213

DIAGNOSTIC STATISTICS:

$R^2 = 0.0213468$
$F(1,19) = 0.41444$ [0.53]
$\sigma = 0.0478168$
DW = 2.05
RSS = 0.04344

MISSPECIFICATION TESTS:

AR 1- 2	F(2,17) = 0.99259 [0.39]	
ARCH 1	F(1,17) = 0.30996 [0.59]	
Normality	$\chi^2(2)$ = 0.17539 [0.92]	
Xi^2	F(2,16) = 1.06260 [0.37]	
Xi*Xj	F(2,16) = 1.06260 [0.37]	
Reset	F(1,18) = 3.31110 [0.09]	

Model 7 is the simple autoregressive version of order one of the unrestricted general model. Clearly, no elasticities can be derived from this model. The coefficient of the lagged dependent variable is insignificant (p > 0.52). The DW statistic is reported merely for completeness; as in the general model and in models 5 to 7, it is substantially upward biased and therefore not reliable.

Model 8: *(first-order finite distributed lag model)*

Variable	Coefficient	Std.Error	t-value	t-prob.	Partial R^2
ΔY_t	0.78447	0.61745	1.270	0.2246	0.1034
ΔY_{t-1}	-1.14800	0.63932	- 1.796	0.0942	0.1872
P_t	- 0.28058	0.23409	- 1.199	0.2506	0.0931
P_{t-1}	0.09696	0.19915	0.487	0.6339	0.0166
H_t	0.42409	0.16733	2.534	0.0238	0.3145
H_{t-1}	- 0.27395	0.17397	- 1.575	0.1376	0.1505

DIAGNOSTIC STATISTICS:
R^2 = 0.527495
F(6,14) = 2.6049 [0.07]
σ = 0.0387064
DW = 1.91
RSS = 0.02097

MISSPECIFICATION TESTS:
AR 1- 2 F(2,12) = 0.26920 [0.77]
ARCH 1 F(1,12) = 0.14965 [0.71]
Normality $\chi^2(2)$ = 2.40060 [0.30]
Reset F(1,13) = 0.00489 [0.95]

Model 8, the first-order finite distributed lag equation of the general model, shows no specification problems and a Durbin-Watson coefficient close to two. The coefficients of interest have the proper sign, although only the H_t-coefficient is significant.

Model 9: *('leading indicator model', lagged information only, no lagged ΔQ_t)*

Variable	Coefficient	Std.Error	t-value	t-prob.	Partial R^2
ΔY_{t-1}	-0.27959	0.69976	-0.400	0.6945	0.0093
P_{t-1}	-0.027153	0.11499	-0.236	0.8162	0.0033
H_{t-1}	-0.20000	0.19172	-1.043	0.3115	0.0602

DIAGNOSTIC STATISTICS:
R^2 = 0.0618792
F(3,17) = 0.37378 [0.77]
σ = 0.0494935
DW = 1.99
RSS = 0.04164

MISSPECIFICATION TESTS:
AR 1- 2 F(2,15) = 1.36550 [0.29]
ARCH 1 F(1,15) = 0.35067 [0.56]
Normality $\chi^2(2)$ = 0.26884 [0.87]
Xi^2 F(6,10) = 2.99240 [0.06]
Xi*Xj F(9, 7) = 2.03070 [0.18]
Reset F(1,16) = 1.77910 [0.20]

The 'leading indicator' model exhibits insignificant coefficients of doubtable magnitudes and signs. Note also the high probability of the F-test for deleting all three variables.

However, there are no significant test results with regard to mis-specification, and also the DW-value is very close to two. This may be a result of the fact that the explanatory variables are not strongly exogenous with respect to ΔQ_t. As a consequence, again the DW-statistic is unreliable.

Model 10: *('dead start' model, lagged information only)*

Variable	Coefficient	Std.Error	t-value	t-prob.	Partial R^2
ΔQ_{t-1}	-0.063111	0.27810	-0.227	0.8234	0.0032
ΔY_{t-1}	-0.23861	0.74243	-0.321	0.7521	0.0064
P_{t-1}	-0.029410	0.11876	-0.248	0.8076	0.0038
H_{t-1}	-0.17926	0.21745	-0.824	0.4218	0.0407

DIAGNOSTIC STATISTICS:
$R^2 = 0.064889$
$F(4,16) = 0.27757$ [0.89]
$\sigma = 0.0509348$
DW = 1.96
RSS = 0.04151

MISSPECIFICATION TESTS:
AR 1- 2 $F(2,14) = 1.92300$ [0.18]
ARCH 1 $F(1,14) = 0.11821$ [0.74]
Normality $\chi^2(2) = 0.25700$ [0.88]
Xi^2 $F(8, 7) = 1.85590$ [0.22]
Reset $F(1,15) = 2.98620$ [0.10]

Model 10, the 'dead start' model, also includes the lagged dependent variable ΔQ_{t-1}. The performance, in terms of significance and expected signs of the coefficients, is extremely poor.

Table 5 depicts a summary of the short- and long-run elasticities that have been estimated. Table 6 concludes the report of the results. It shows the F-test outcomes of the nested hypotheses tested against the other restricted models. Only two model reductions are rejected, viz. the reduction from model 6 to model 7, and the reduction from model 8 to model 9. This is not too surprising, given the poor explanatory performance of both the AR(1) (model 7) and the 'leading indicator' model (model 9).

All in all, Model 6 seems to be the clear winner of our investigation: The estimates of its regression coefficients depict high t-values, show the expected signs and are of a reasonable magnitude. Also, the mis-specification tests do not show any specification problems.

Table 5: *Short- and Long-Term Income and Price Elasticities*

Model	price elasticity (short run)	price elasticity (long run)	income elasticity (short run)	income elasticity (long run)	weather elasticity (short run)	weather elasticity (long run)
GM	-0.28 (-1.15)	-0.20	0.87 (1.31)	-0.40	0.43 (2.49)	0.14
1	-0.04 (-0.51)	-	1.10 (2.11)	-	0.43 (2.77)	-
2	-0.13 (-0.60)	-	1.57 (3.05)	-	0.49 (3.48)	-
3	-0.05 (-0.65)	-	-	-	0.42 (2.89)	-
4	-	-	-	-	0.43 (2.86)	-
5	-0.04 (-0.39)	-0.04	0.92 (1.58)	0.97	0.28 (2.43)	0.29
6	-0.15 (-1.97)	-0.18	1.10 (2.74)	1.31	0.37 (3.36)	0.44
7	-	-	-	-	-	-
8	-0.28 (-1.20)	-0.18	0.78 (1.27)	-0.36	0.42 (2.53)	0.15
9	-0.03 (-0.24)	-0.03	-0.28 (-0.40)	-0.28	-0.20 (-1.04)	-0.20
10	-0.03 (-0.25)	-0.03	-0.24 (-0.32)	-0.22	-0.18 (-0.82)	-0.17

[NOTE: t-values in brackets where applicable]

Table 6: *Model Reduction Test Results II (Hypotheses against Other Restricted Models)*

Models	F-statistic	p-value
$1 \rightarrow 3$	0.0352	[0.85]
$5 \rightarrow 7$	2.8063	[0.07]
$6 \rightarrow 7$	5.0116	[0.01]*
$8 \rightarrow 1$	1.3581	[0.30]
$8 \rightarrow 3$	1.0280	[0.43]
$8 \rightarrow 4$	1.0451	[0.42]
$8 \rightarrow 9$	4.5986	[0.02]*
$10 \rightarrow 7$	0.2483	[0.86]
$10 \rightarrow 9$	0.0515	[0.82]

[NOTE: * depicts rejection of the hypothesis at the 5% level of significance]

5 Summary and Conclusions

In this paper, ten deliberately chosen single-equation models of household energy demand have been analyzed. In order to handle the problem of multiple hypotheses, the closure test principle, as suggested by Marcus, Peritz, and Gabriel (1976) has been applied.

The models under scrutiny are derived by the imposition of linear restrictions on the parameters of a single-equation log-linear ADL(1)-model. Residential energy demand has been explained by movements in the logarithmic values of households' real disposable income (in first differences), real energy price faced by households, and a physical temperature variable 'heating degree days', both in levels.

In the empirical analysis, Austrian annual data have been employed, ranging over the period from 1970 to 1992. General-to-specific modelling led to a final restricted model (Model 6) with a short-run price elasticity of -0.15 (-0.18 in the long run), a short-run income elasticity of +1.10 (+1.31 in the long run), and a weather elasticity of +0.37 (+0.44 in the long run), respectively.The results also indicate that the model specification plays a crucial role for the estimation of energy elasticities.

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Appendix: *The Data*

Year	Energy Consumption of "Households and Other" (in Petajoule)	Real Disposable Income of the Household Sector (in bn ATS; price index: 1976 = 100)	Real Energy Price for Households (Index, 1966=100)	Sum of Heating Degree Days (p.a.)
1970	291.809	351.11	95.4	3976
1971	287.967	374.32	95.8	4003
1972	297.139	385.41	94.0	4049
1973	325.729	401.22	93.1	4029
1974	300.751	413.81	103.1	3501
1975	302.864	435.42	106.9	3659
1976	315.794	457.79	106.6	3847
1977	317.761	471.02	104.3	3758
1978	338.770	480.92	102.2	3985
1979	361.156	502.50	105.5	3355
1980	361.259	505.22	118.4	4120
1981	338.917	494.28	132.5	3850
1982	346.828	512.81	134.2	3828
1983	342.902	528.42	127.8	3673
1984	349.415	526.58	129.4	4010
1985	373.495	537.60	130.0	4109
1986	374.811	562.90	114.0	3978
1987	387.051	588.28	106.7	4064
1988	365.426	607.29	101.9	3661
1989	359.703	635.62	101.6	3524
1990	375.540	666.34	102.6	3560
1991	406.391	683.14	99.3	4009
1992	393.690	684.44	98.3	3632

[NOTES: The pre-1977 values of heating degree days have been adjusted by a mark-up of 52% due to a change in measurement technique from 1977 onwards; household energy consumption is assumed to follow essentially the same patterns as consumption of the 'households and other' sector (in Austria called 'Kleinverbrauchersektor'), which also includes trade and commerce as well as private and public services.

DATA SOURCES: Austrian Institute of Economic Research (WIFO)/Austrian Petroleum Administration (ÖMV) (on consumption data); WIFO - GEN database (on income data); Austrian Statistical Office (ÖSTAT) (on price and heating degree days data).

The variable 'heating degree days' was created in order to facilitate assessments of the influence of weather conditions on energy demand. Being only a very crude indicator, it was designed mainly to reflect seasonal temperature variations in the form of sums of heating degree days per time period (usually a year, but if desired, any other period may be used). A heating degree day is being defined as $HDD = \sum_n (BT - T_n)$, where BT denotes a constant ambient temperature of 20°C and T_n the average outdoor air temperature of the day, counted only if it is below or equal to an assumed marginal heating temperature of 12°C (cf. Austrian standard ÖNORM B 8135). The variable 'Sum of Heating Degree Days', as its name implies, is simply the sum of all heating degree days over the period of interest, usually a year. Note that the 'heating degree days' data reported are average values, calculated as a weighted arithmetic mean of the sums of HDD of the nine Austrian provinces, and the weights employed being 1991 census data.]

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