Residential energy demand elasticities: what lessons can be learned from bottom-up and top-down methodologies.

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Abstract

In standard MARKAL, substitution between capital and energy is represented by a set of technology options and energy price shifts resulting in an opposite energy consumption movement, while keeping the energy service constant. Standard MARKAL does not count for non-technical solutions such as price driven behavioural changes. MARKAL-ED (Elastic Demand) includes a functionality to account for such behaviour. The energy service demand is then price sensitive. In this article we consider the case of residential fuel consumption and search for empirical evidence to quantify the energy service elasticity.

Keywords: energy demand elasticity, energy service elasticity, MARKAL, TIMES, bottom-up, top-down

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1. Introduction

Techno-economic optimisation models, like Markal, TIMES and Message and which we will further refer to as optimisation models are used worldwide for energy policy analysis and energy scenario development. These models are offered to potential users as a software package, providing facilities for building a national energy system by

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entering technology data, demand scenarios and system parameters. Besides the parameters characterising the technologies implemented in such models; these models need also parameters reflecting more the behaviour of the economic agents, regarding e.g. their reaction to change in the price of energy services.

Energy econometric models are also widely used for energy and GHG scenario and policy analysis, but have a different nature. Technology choices and economic behaviour are reflected in econometrically estimated parameters, such as price and income elasticity of energy demand or technical progress. They however donot give any indication on the energy service price elasticity needed for the energy optimisation models.

In this paper we investigate through an econometric approach if we can provide some guidance in quantifying energy service price elasticities. Answering this question requires first some clarification.

First, energy service price elasticities are difficult to observe econometrically, mainly due to lack of data for energy services demand and energy service prices. The econometric literature as well as our analysis focuses on energy demand elasticities. The difference between the two conceptis elaborated in the following section.

Second, optimisation models, with their presence of the capital stock, are relevant for developing long term scenarios, with a horizon from 10 up to 40-50 years. They need therefore estimated parameters reflecting this focus on the long term. Before the nineties, econometric research mainly focussed on short or medium term, not only because of the Neo-Keynesian nature but also due to lack of a sound theoretical background for quantifying long term effects. The concept of coïntegration and error correction specification presented by Engle and Granger (1987) was a conceptual breakthrough. Nowadays coïntegration analysis is a standard methodology for deriving long term elasticities.

Third, quantifying price reactions is a core business of any economic modelling activity but the way this is implemented in optimisation models and in econometric models is completely different as is illustrated in table 1. One fundamental difference is the ‘historical’ relation, i.e. econometric models rely on past dataand optimisation models on actual and future technology deployment. Technological improvements might explain both energy efficiency improvements and shifts in price reactions. Another important difference is that optimisation models usually assume a perfect competitive market, whereas models estimated on historical observations reflect also past market imperfections.

	Optimisation models	Econometric models
Representation	Price induced technology shifts	Single parameter
Historical relation	Future technology deployment	Historical data
Rationale	Economic reasoning	Historical observations
Market imperfections	Competitive market	Historical market imperfections

table 1: Key characteristics for modelling price reactions in optimisation models and in econometric models

In this paper we derive residential fuel price elasticities both using a bottom-up optimisation model and a panel coïntegration approach. In the following section we introduce some useful concepts allowing for a better understanding of price elasticities in techno-economic optimisation models. Then, in section 3 we present the techno-economic optimisation approach and in section 4 the econometric approach. In the final section we conclude and derive some guidance rules for the use of econometric estimations results in bottom-up optimisation models.

2 Energy demand and energy service price elasticities

Energy demand price elasticities express a relationship between the amount of energy consumed and the price of energy.

Energy service demand price elasticities express a relationship between the amount of energy service and the price (or cost) of the energy service

Optimisation models focus on technologies and the structure is based is on physical evidence. Energy demand results from various uses. The driving factor is the so called “energy-service” demand, a concept closely related to the utility provided by the energy. Typical energy services are: the comfort of having a space room temperature of 20 ° C, the light produced by lightbulbs, the entertainment provided by a television, clean clothes provide by the washing machine. The energy demand, or energy consumption, results from the choice of different technological options providing the required service level. The price elasticity of energy demand, *EDE*, can be linked to the price elasticity of energy service, *ESE* assuming a 'technological relation between ES and ED.

We first consider that the energy service is provided by a Leontief technology. In optimisation models the energy service is provided by one technology using capital and energy. In this case the relationship between the energy demand elasticity and the energy service price elasticity is given by (1) in which δ represents the budget share of energy in the overall spending for the service.

$$EDE = ESE * \delta \quad \text{or} \quad ESE = EDE/\delta \qquad (1)\ (1')$$

By definition $0 < \delta < 1$ and obviously in absolute terms $|EDE| < |ESE|$.

In the more general case, when different technological options are available, then the relationship is given by (2) where σ represents the substitution elasticity between energy and the other production factors. This equation is derived in appendix for a CES production function but it is generally true in a range when the substitution elasticity is assumed to be constant.

$$EDE = ESE * \delta - \sigma(1-\delta) \quad \text{or} \quad ESE = (EDE + \sigma(1-\delta))/\delta \qquad (2)\ (2')$$

Both *EDE* and *ESE* are negative, as required by economic theory. It is easy verified that now |*EDE*| <> |*ESE*| depending on the values of σ and δ. We can argue that |*EDE*|> |*ESE*| if the substitution elasticity is high and the budget share of energy in the overall spending for the energy service is small.

3. Bottom-up methodology

Presentation of the model

The model is a MARKAL application for the Flanders region in Belgium[2]. The existing stock of houses is represented by 24 main categories (single houses and apartments, age structure, heating system) and differentiates between different levels of insulation for roofs, walls, floors, and windows. Furthermore the model differentiates between old boilers and more efficient boilers. The model structure incorporates the possibility of additional insulating measures on different building components and some level of trade off between efficient boilers and insulation, as represented in figure 1. Technological options are characterized by the investment cost, efficiency and the degree of past implementation (in case of insulation). For each category, the models considers 2

[2] http://www.emis.vito.be/environmental-costing-model

boiler types, 3 levels of roof insulation, 3 glass qualities, 2 types of walls, 3 levels of floor insulation and an option for solar boiler for sanitary hot water production, leaving 215 options for improvement for houses with the lowest energy efficiency. However, most houses do not start from the lowest efficiency levels as a number of measures have already been implemented. Endogenous demolition of houses is not considered. For new houses there are options for different levels of energy efficiency, starting by the minimum requirements defined by the Flanders energy efficiency legislation going to passive houses, without specifying the details of the different building components.

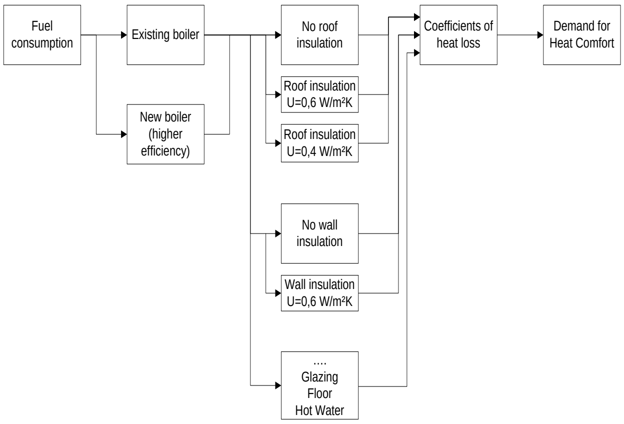

Figure 1: Simplified representation of the optimisation model for the residential sector Starting from the worst case, this structure has 11 options to improve energy efficiency for a house with the lowest energy efficiency level.

The flexibility of the model can also be translated into a CO_2 abatement curve (see fig 2)[3]. The latter has been derived using increasing levels of CO_2 tax using a social discount rate of 4 %. At current energy prices, roof insulation and better glazing have negative marginal reduction costs. The efficiency gap is approximately 10%, either expressed as CO_2 emissions or fuel consumption. The existence of no-regret measures is a market anomaly which has been observed in different studies on energy-efficiency in the residential sector. Studies released in the early 80ts often explain this phenomenon by high implicit discount rates in energy efficiency investment, pointing to levels of 30 % and more. Hasset and Metcalf (1993) found a more rational explanation by introducing real options theory in their analysis and pointed out that uncertainty in future energy prices and the fact that energy saving investment is irreversible could explain a factor four between the market rate and the discount rate applied for energy saving investment. However Sanstad et all (1995) argued that real options theory was

[3] Negative CO2 reduction costs have been derived from the total system cost and the reduced cost of limiting cost efficient measures. Positive CO2 reduction costs have been derived by increasing levels of CO2 tax.

not able to explain 25 % observed implicit discount rates but only a an increase of the order 1%-2 %. Howard and Sanstad (1995) argued that high discount rates in energy related decisions are difficult to reconcile with standard models of rational choice and found that market failures related to asymmetric information, bounded rationality and transaction costs are major contributors to the so called “efficiency gap”.

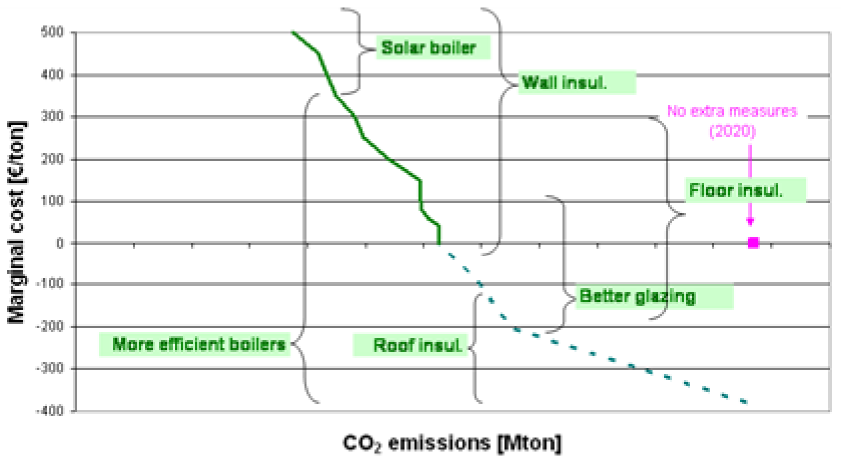

Figure 2: Marginal CO2 abatement cost curve for the residential sector in the

In order to fill the efficiency gap a sector specific hurdle rate of 15 %.has been used. The latter can be thought as representing a rational private discount rate, the Hasset and Metcalf effect, market failures that can be expressed as a fraction of capital spending (transaction costs, lack of capital), older people comparing life-expectations and investment pay-back time and many other unobserved issues.

Price elasticities

In order to derive fuel price elasticities (*EDE*) we have introduced a once and for all price increase of 20% of the 2010 price level for different values of *ESE* price elasticity of 0 and -.20. The results presented in table 2 are for the year 2025, i.e. 15 years after the introduction of the price increase. This period has been chosen in concordance with the time dimension in the econometric section below. Using a price increase of 20 % a *EDE* elasticity of -.63 is observed for *ESE* = 0 and -.78 for *ESE* =-.2. The price sensitivity is much higher for new houses than for existing ones, which can be explained by the fact that it is easier to reach higher energy efficiency levels when considered at the conceptual phase. Table 2 also provides figures for the budget share and the substitution elasticity. These have been calculated by substituting the *EDE* results with *ESE* 0 and *ESE* -.2 back in equation 2[4]. The budget shares are relatively high, which is explained by the fact that only incremental investment costs above standard technologies are represented.

Hurdle rate: 15 %, Energy price increase: 20 %				
		Total	Existing	New
ESE = 0	EDE	-0.63	-0.25	-1.43
ESE =-0.2	EDE	-0.78	-0.42	-1.53
	δ [5]	0.75	0.86	0.50
	σ	2.52	1.76	2.84
Hurdle rate: 15 %, Energy price increase: 100%				
		Total	Existing	New
ESE = 0	EDE	-0.23	-0.16	-0.38
ESE = -0.2	EDE	-0.39	-0.31	-0.54
	δ	0.78	0.76	0.82
	σ	1.04	0.65	2.13

table 2: Observed energy demand elasticities in the optimisation model.

The second part in table 2 presents the results for a price shock of 100 %. For *EDE* we now observe lower values but the drop is significantly higher for new houses, although more energy-efficient options are available but the 15 % hurdle rate makes these very expensive. Higher capital spending in existing houses results in a lower budget share for energy. However, for new houses the price increase results in an increase of the budget share.

4. Econometric approach

4.1 Review of relevant literature

Contrary to bottom-up modeling, there is an extensive amount of scientific literature defining rules and standards for econometric analysis. The theoretical background in long term econometric analysis has dramatically changed by the work of Granger and Newbold (1974) on spurious regressions and by Engle and Granger on coïntegrating

[4] Values for the budget share parameter and the substitution elasticity can be derived from these results. Using ESE_1 for ESE =0 and ESE_2 for ESE=-0.2 and the corresponding symbols for EDE, δ is calculated as $(EDE_2-EDE_1)/(ESE_2-ESE_1)$ and σ is calculated as $(EDE_1- \delta.ESE_1)/(1-\delta)$

and error correction modeling (Engle and Granger 1987). Whereas in older studies the focus in standard econometric analysis was on describing the correlation properties, new insights in the nature of times series have generated a shift towards analyzing coïntegration properties. The coïntegration approach is standard technology in recently developed econometric models like NEMESIS (Fougeyrollas et all.2002,) and E3ME (Pollit 2010). We found a number of studies focusing on residential electricity demand and using the coïntegration approach which have some relevance for our study. Dergiades and Tsoulfidis (2008) used the Autoregressive Distributed Lag approach to coïntegration to analyze residential electricity demand in the US and found a long term income elasticity of -0.27 and a long term price elasticity of -1. Hondroyiannis (2004) also used a coïntegration framework to analyze the residential electricity demand in Greece. His findings are a long term income elasticity of 1.56 and a price elasticity of -0.41. Narayan et al.(2007) used a panel coïntegration analysis for residential electricity demand elasticities in G7 countries. They found a long term income elasticity of 0.31 and a price elasticity of -1.45.

There exist an extensive amount of literature on unit root statistics and coïntegration analysis. Maddala and Shaowen (1999) provide a comparative study of unit root tests with panel data and Breitung and Pesaran (2005) provide a review of the literature on unit roots and coïntegration in panels. The tests used for this paper are discussed in the following sections.

4.2 Methodology

Model specification

The objective is to derive long term income and price elasticities based on the following panel model specification:

$$Q_{i,t} = \alpha_i + \beta_i Y_{i,t} + \gamma_i P_{i,t} + \theta_i hdd_{\,i,t} + \varepsilon_{i,t} \qquad (3)$$

Q represents the log per capita residential fuel consumption, Y the log per capita real income of households, P the log of price of fuels deflated by the consumer price, hdd the log of degree days, ε the error term, and i an t respectively the index for the country (1..N)and time dimension(1..Ti) . In the first instance the intercepts and the slope coefficients are permitted to vary between countries. We allow for unbalanced panel data, i.e. the time dimension is permitted to vary between countries.

The variables income and price are standard in this type of econometric analysis. Temperature fluctuations are represented by heating degree days[6]. In the EU, average observations for the period 1980-2009 are between 560 (Malta) and 5970 (Finland). It is easy to see that the value of θ should be in the range [0-1] and depends on the thermal characteristics of the houses as well as on the habits of the residents. Other authors often include some derived composite index. Dergiades and Tsoufildis (2008) and Narayan and Smyth (2005) use one composite index representing heating and cooling degree days. Nayaran et all (2007) do not include any temperature related variable. Silk and Joutz (1997) use weighted cooling degree days and weighted heating degree days. The weights are indices for cooling and heating appliances stock. Hondroyiannis (2004) uses the weighted average temperature which represents electricity for heating as the sign is negative.

The dataset

Historical for EU members states data have been compiled from EUROSTAT. Availability has been a major criterion in defining the panel. Data have been compiled for residential fuel consumption expressed in TJ and the related price (€/GJ), disposable income in current prices, the consumer price index, population and heating degree-days. Data for DK, FR, DE, IT, NL, ES, UK cover the period 1991-2008, for SI -1992-2008, FI, HU, IE, and PT 1995-2008 and AT 1996-2008 except for heating degree days which we have data from 1980 to 2009.

Unit root properties of the data

Our analysis is based on Levin et al. (2004) panel unit root tests and the ADF-t- tests for the individual time series. The null hypothesis is that the series are I(1). The Levin et all test starts from calculating individual ADF statistics. Both tests are parametric and require some expert judgement to decide on the parameters and the underlying model choice. Model-1 ADF test does not include a constant or time trend in the data

[6] These are calculated as the integral in time of the price difference between an assumed inside temperature of 18°C and the observed outside temperature, given that this difference is positive. For example, a day with an average temperature of 8° C counts for 10 degree days

generating process, model -2 ADF test includes a constant and model-3 ADF test additionally include a time trend. All tests are based on model -2 specification. Including a time trend seems inappropriate given the short lengths of the time series. The ADF test also requires a choice on the number of lags to be included. Here we have run various experiments and observed that the results are very sensitive to this parameter. Our approach is inspired by the suggestion of Levin et al. (2002) to follow the method recommended by Campbell and Perron: the maximum lag is fixed at 2 and if the t-statistic of the last lag < 1 then it is decided to use a lower smaller lag. The Levin-Lin panel data test requires an estimate of the long-run variance of the time series which involves the choice of a lag truncation parameter and a kernel. We used the Bartlett kernel as suggested by Levin et al. (2002) and the truncation parameter has been arbitrarily fixed at five.

Unit root statistics are presented in table 3. The Levin-et all statistic is below the 1 % significance level and rejects the null hypothesis of I(1) for heating degree days (hdd). This is confirmed by the individual ADF-t- statistics which, with the one exception of DK, all reach 10 % significance levels or better. For the fuel price P the opposite conclusion can be drawn. Based on the Levin-Lin statistic we cannot reject the null hypothesis of I(1) and this is also confirmed by the individual ADF-t statistics as none of them reaches the 10 % significance level. For real per capita income Y, the Panel Levin Lin test reaches the 10 % significance level. However there is some inherent uncertainty in the panel statistic. Indeed, as Levin et al. (2002) only report mean and standard deviation adjustments for 25 observations the statistic might be somewhat biased when used for 18 observations and given that the individual ADF statistics suggest that the series are I(1) we will not reject the null of I(1).

The result for fuel consumption (Q) is somewhat surprising. Indeed, per capita fuel consumption is closely related to the characteristics of the houses and we would expect some permanent effect. For instance, if the insulation of houses is improved, then this has a permanent effect. Improving energy efficiency of the boilers also has a permanent effect, i.e. it will never be reversed in the opposite direction. Construction and demolition activities also result in a permanent effect. From all these activities we would expect the series to be I(1) but based on the panel unit root test and the ADF statistics we would reject the null of I(1). To continue we have constructed the series Q* in which we have removed the noise from fluctuations in degree days, this based on the regression of equations (4) and subsequent calculation of Q* by (5)

$$\Delta Q_{i,t} = \gamma_i + \theta_i^* \Delta\, hdd_{i,t} + \varepsilon_{i,t} \qquad (4)$$

$$Q_{i,t}^* = Q_{i,t} - \theta_i^* \left(hdd_{i,t} - \overline{hdd}_{\,i} \right) \qquad (5)$$

The values for θ* and the unit root statistics for Q* are reported in the last columns in table 5. The panel unit root and the ADF statistics now suggest that Q* has a unit root. This analysis suggest that it might be appropriate analysing the properties of (6) against (3), offering the advantage that all variables are I(1).

$$Q_{i,t}^* = \alpha_i + \beta_i Y_{i,t} + \gamma_i P_{i,t} + \varepsilon_{i,t} \qquad (6)$$

	Q		Y		P		Hdd		θ*	Q*	
DK	-2.747	(0)	-0.561	(0)	-1.628	(1)	-2.316	(0)	0.567	-1.685	(0)
FR	-2.693	(0)	-0.088	(0)	0.124	(0)	-4.208	(0)	0.474	-2.008	(2)
DE	-3.770	(0)	-1.790	(0)	0.422	(0)	-3.027	(0)	0.597	-2.339	(0)
IT	-1.822	(0)	-1.615	(0)	-2.141	(0)	-2.670	(2)	0.613	-1.261	(0)
NL	-1.397	(0)	-1.335	(0)	0.787	(0)	-2.944	(0)	0.745	0.515	(0)
ES	-1.450	(2)	-0.661	(1)	-0.851	(0)	-3.542	(0)	0.126	-0.793	(0)
UK	-2.492	(0)	-1.610	(0)	-0.192	(2)	-2.844	(0)	0.734	-1.861	(2)
Panel Levin-Lin	-1.922		-1.300		3.533		-4.514			1.221	
N observations	117		118		116		117			115	
Critical values:	ADF -t- test 10 % -2.64, 5% -2.99, 1% -3.75 for 25 observations Panel Levin-Lin test: 10 % -1.282, 5% -1.645, 1% -2.326										

table 3: Results of the unit root tests for the countries with 18 observations. Figures between brackets indicate the number of lags included in the ADF statistic

Coïntegration analysis

The analysis of the coïntegration properties are based on the panel coïntegration tests presented in Pedroni (1999) and slightly modified in Pedroni (2004). The Pedroni tests allow for homogeneous or country specific fixed effects and slope coefficients. The particular strength of panel analysis is to demonstrate the existence of homogeneous slope coefficient against the heterogeneous variant. In table 4 the slope coefficients for the income and price effects have been reported. They have been derived by OLS and DOLS. Although the model specification involves important autocorrelation in the error terms, OLS still provides unbiased slope coefficients but it is not efficient. DOLS takes this autocorrelation more explicitly into account by including lagged and leaded RHS variables in the regression. The drawback is that DOLS requires considerable longer times series for estimation. Therefore OLS has been used for all countries in the dataset (N=13) and DOLS only when allowed by the length of the time series (N=7). Whenever negative income effects or positive price effects have encountered, the variable has been omitted and the other parameters have been re-estimated. One remarkable observation is that income elasticities are consequently higher when DOLS is applied. For price elasticities no such analogues conclusion can be drawn. Another difference is that DOLS required less interventions as only one parameter (DK price) has been fixed, whereas in the corresponding sample in OLS two additional parameters (DE price and NL income) have been fixed.

	OLS		DOLS	
	Income	Price	Income	Price
AT	0.32	-0.20		
DK	0.09	0.00	0.17	0.00
FI	0.00	-0.14		
FR	0.04	-0.07	0.64	-0.51
DE	0.57	0.00	0.96	-0.07
HU	0.43	-0.14		
IE	0.22	-0.01		
IT	1.59	-0.34	2.70	-0.02
NL	0.00	-0.30	0.05	-0.30
PT	0.28	-0.06		
SI	0.10	-0.08		
ES	0.59	0.00	0.96	-0.35
UK	0.08	-0.18	0.36	-0.02
Homogenous N=7	0.31	-0.10	0.56	-0.10
Homogenous N=13	0.25	-0.11	0.46	-0.10

table 4: Heterogeneous and homogeneous income and price panel elasticities. Values in red have been fixed at zero.

The Pedroni tests reported in table 5 are standard normal distributed based on the correction parameters reported by Pedroni (1999). The panel v test converges to a positive figure and the other testconverge to negative values. The null hypothesis of no-coïntegration is rejected by big positive values for the panel v test and big negative values for the other tests.

A first observation is the significant difference for heterogeneous slope and homogeneous slope coefficients. For heterogeneous slope coefficients both the OLS and DOLS case, the Panel t, the parametric panel t, the group t test and the parametric group t test all reject the null hypothesis of no- coïntegration at the 5 % significance levels. From the panel v test, the panel ρ test and the group ρ test we cannot drawn conclusions as they do not reject the null hypothesis of no-coïntegration but they also do not allow to reject the null of coïntegration. For DOLS we observe higher significance levels for the panel t and the parametric panel t test compared to OLS. This is not confirmed in the group t test and the panel group t test, but the shift in the two panel tests is more outspoken. This again can be interpreted as an indication that DOLS is superior to OLS, even for relative small time series.

For homogeneous slope coefficients the conclusions are different. None of the tests allow rejecting the null of no-coïntegration. In fact none of the test sorts the write sign. Consequently we accept the null of no-coïntegration both for the OLS and DOLS results.

	heterogeneous-slope (N=7)		homogeneous-slope (N=7)		Full sample (N=13)
	OLS	DOLS	OLS	DOLS	OLS
Panel ν	0.202	-1.508	-1.795	-2.280	0.129
Panel ρ	-0.154	-0.258	1.496	1.352	-0.661
Panel *t*	-1.959**	-2.885***	1.364	0.906	-4.138 ***
Panel *t* parametric	-2.238**	-3.023***	1.510	1.225	-4.368 ***
Group ρ	0.223	0.625	2.832	2.523	0.345
Group *t*	-6.562***	-4.311***	2.844	2.441	-8.738***
Group *t parametric*	-3.845***	-2.898***	2.482	1.694	-5.095***
Critical values	Panel ν	Other			
10%	1.282	-1.282	*		
5%	1.645	-1.645	**		
1%	2.326	-2.326	***		

table 5: Pedroni coïntegration tests

The coïntegration tests for homogeneous slope coefficients demonstrate that Europe cannot be considered as a homogeneous area. With heterogeneous slope coefficients, the coïntegration statistics indicate that the regressions are not spurious, both for OLS and DOLS. In general the DOLS estimates are somewhat higher, both for the income and price coefficients. Economic consistency and the coïntegration tests suggest some preference for the DOLS results. We therefore conclude that price elasticities are in the range [0 -0.51] with an average value of -.18[7]. Values above -0.3 are not exceptional.

5. Conclusions

The objective of this study was to provide some guidance in quantifying the energy service price elasticity by comparing energy demand price elasticities in the

[7] The homogenous panel estimates are lower but they have been rejected

optimisation model with econometric results. To this end we have first established a relationship between the energy demand elasticity and the energy service elasticity (equation 2). This relationship involves two parameters: the budget share of energy in the cost of the energy service and the substitution elasticity. We have also provided a means for quantifying these parameters on different aggregation levels. Basically the budget share determines how much the energy demand elasticity is determined by the energy service elasticity.

Quantifying price elasticities in optimisation models could be implemented as a matter of good practise as it allows for comparison with econometric estimates or literature review although this remains an intellectual exercise due to fundamental differences between optimisation models and econometric models pointed out in table 1. For instance, it might be useful to exclude new breakthrough technologies before measuring the price elasticity.

In this particular case we have found that the optimisation model was more elastic than what was observed econometrically, even when ESE = 0. From this comparison in a simplistic way we conclude that in this particular case the "best guess" for the energy service elasticity is 0. However, in general non-zero energy service elasticities might be useful, representing human behaviour in the short run as well as unknown technologic development.

Assuming the energy demand elasticity is "known", either from econometric analysis, literature review or any other source, the following procedure can be used to quantify energy service elasticities. The first step is the determination of budget share and the substitution elasticity. This requires a reference scenario and two additional model runs. In the first additional run the energy demand elasticity (EDE1) for the optimisation model is determined when using zero energy service price elasticity. Then, using some arbitrary variable for the energy service elasticity (ESE2), the energy demand elasticity is determined again (EDE2). Then the budget share δ is calculated as (EDE1-EDE2)/ESE_2 and the substitution elasticity σ is as $EDE_1/(\delta\text{-}1)$. Then using these values, the energy service elasticity is given by equation (2') where EDE represents the "known" energy demand elasticity.

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ANNEX: nergy demand elasticity expressed as a function of the energy service elasticity (Vanregemorter's law)

For a CES production function

$ES(K,ED) = [\delta_k \ K^{\left(\frac{\rho-1}{\sigma}\right)} + \delta_e \ ED^{\left(\frac{\rho-1}{\sigma}\right)} \ ]^{\left(\frac{\sigma}{\sigma-1}\right)}$ (1)

the associate unit cost function has the form

$PES(PK,PED) = [\delta_k{}^{\sigma} \ PK^{(1-\sigma)} + \delta_e{}^{\sigma} \ PED^{(1-\sigma)} \ ]^{\left(\frac{1}{1-\sigma}\right)}$ (2)

and factor demand is expressed as

$ED = \left(\frac{PES}{PED}\right)^{\sigma} ES \ \delta_e$ (3)

From (2)

$$\frac{\partial PES}{\partial PED} = \frac{1}{(1-\sigma)} \left[\delta_k{}^{\sigma} \ PK^{(1-\sigma)} + \delta_e{}^{\sigma} \ PED^{(1-\sigma)}\right]^{\frac{1}{1-\sigma}-1} . \delta_e \, (1-\sigma) PED^{-\sigma}$$

$$\frac{\partial PES}{\partial PED} = \delta_e{}^{\sigma} \ \frac{PES}{PES^{1-\sigma}} \ PED^{\ -\sigma} = \ \delta_e{}^{\sigma} \ \left[\frac{PES}{PED}\right]^{\sigma}$$

and using (3)

$$\frac{\partial PES}{\partial PED} = \frac{ED}{ES}$$

From (3)

$$\frac{\partial ED}{\partial PED} = \delta_e{}^{\sigma}\sigma \ \left(\frac{PES}{PED}\right)^{\sigma-1} \left[\frac{\partial PES}{\partial PED} \ . \frac{1}{PED} - PES \frac{1}{PED^2}\right]. ES + \delta_e{}^{\sigma} \ \left(\frac{PES}{PED}\right)^{\sigma} \frac{\partial ES}{\partial PES} \ \frac{\partial PES}{\partial PED}$$

Re-arranging and using (4) we get

$$\frac{\partial ED}{\partial PED} = \delta_e{}^{\sigma}\sigma \ \left(\frac{PES}{PED}\right)^{\sigma-1} \frac{1}{PED} \left[\frac{\partial PES}{\partial PED} \ . -PES \frac{1}{PED}\right]. ES + \delta_e{}^{\sigma} \ \left(\frac{PES}{PED}\right)^{\sigma} \frac{\partial ES}{\partial PES} \ \frac{ED}{ES}$$

Multiplying both sides by *PED/ED* and the definition of *EDE*

$$EDE = \delta_e{}^{\sigma}\sigma \ \left(\frac{PES}{PED}\right)^{\sigma-1} \frac{1}{PED} \left[\frac{\partial PES}{\partial PED} \ - PES \frac{1}{PED}\right] ES \frac{PED}{ED} + \delta_e{}^{\sigma} \ \left(\frac{PES}{PED}\right)^{\sigma} \frac{\partial ES}{\partial PES} \ \frac{ED}{ES} \ \frac{PED}{ED}$$

Using (4) and definition of *ESE*

$$EDE = \sigma \ \frac{ED}{ES}\frac{PED}{PES}\frac{1}{PED}\left[\frac{ED}{ES} \ - \frac{PES}{PED}\right] ES \frac{PED}{ED} + \frac{ED}{ES} ESE \ \frac{PED}{PES}$$

and because

$$\delta = \frac{ED \, .PED}{ES.PES}$$

We get

$$EDE = \sigma \, \delta \frac{ED}{ES}\left[1 \ - \frac{PES}{PED} \ \frac{ES}{ED}\right] ES \frac{1}{ED} + \delta \ ESE \ = \ \sigma \, \delta \left[1 \ - \frac{1}{\delta}\right] + \delta \ ESE \ = \ \sigma \, [\delta \ - 1] + \delta \ ESE$$