Electricity and fuel consumption in Europe: a panel error correction model for residential demand elasticities.

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Abstract

Our objective is to derive robust long term demand elasticities for energy in different end-use sectors. These can be used as a reference for developing long term energy scenario's based on bottom-up, technology oriented, models such as Markal and TIMES. This paper focuses on the residential sector. Panel data from 13 EU member states have been used to derive elasticities, based on the error-correction (ECM) specification following Engle and Granger (1987). OLS standard deviations are likely to be biased in heterogeneous panels. A circular bootstrap methodology has been used to derive standard deviations and these has bee compared with OLS estimates. The long term income elasticity for electricity is 0.83 and a price elasticity of -.19. The short term price elasticity appears to be higher than the long term price elasticity. The long term income elasticity for fuels is 0.28 and the price elasticity -.16. Bootstrapped standard errors are twice as large as OLS estimates, but point estimates are still statistically significant.

Key words: residential electricity; residential fuel; co-integration, error correction

Introduction

According to the IPCC fourth assessment report, (IPCC 2007), CO_2 emissions will have to be reduced by 50% to 80% in 2050 compared to 2000, in order to limit the increase in global mean temperature to 2.0-2.4 °C. This target is very challenging and is putting a lot of pressure on the energy sector as this is the most important source of GHG emissions.

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Bottom-up, technology oriented, optimisations models like Markal and TIMES[2] are used in many countries to develop scenario's and analyse different types of policies to reduce GHG emissions. These models focus on evaluating different technology options which are represented in a partial equilibrium framework. The demand for energy is represented in a semi-endogenous way, i.e. demand is exogenous in a reference simulation but price elasticities allow for the evaluation of price induced demand shifts in alternative simulations, thus allowing for quantification of the welfare aspects of a policy. Typical scenario's cover a period of 20 to 50 years. Developing scenario's and evaluating policies requires assumptions on income and price elasticities.

This study focuses on the long term nature of the elasticities as this aspect is often ambiguous. Deriving long term price elasticities should be based on time series, as cross section data do not have the time dimension. But analysing time series also gives rise to particular problems, such as dealing with autocorrelation and choosing the appropriate historical period. Increasing the length of the time series might have a positive effect on the standard deviations. But it remains a study of historical data and still raises questions on the validity for the future, in particular for the very long horizon. We can consider two cases. First, elasticities being constant over time, implying that an extending the period will only affect the standard errors and not the point estimates. Second, elasticities changing over time in which case it becomes likely that we would be better off to rely on more recent data. So for energy scenario building, more recent data can be used.

A panel approach has the advantage that we have more variation in the prices and the quantities, a precondition for successful econometrics. In a way it, also covers aspects of the time dimension, as different countries have different per capita income, different cultural and political situations, different tax regimes and many other aspects that may change in time. Another advantage is that we avoid the discussion of getting different results for different countries.

Literature review

We have limited our study of literature to some recent publications. Reiss and White (2001) is the only study we have found that uses cross section data and incorporates

[2] See www.etsap.org for an extensive explanation of Markal and TIMES

detailed household appliance data. They estimate the mean annual electricity price elasticity for California households to be -0.39. Boonekamp (2007) uses a bottom-up technology driven simulation model for the Netherlands. This methodology considers a constant level of utility and focuses on price induced technology shifts. He derives a derives a price elasticity of -0.12 for electricity and -0.14 for gas. Dergiades and Tsoulfidis (2008) used the Autoregressive Distributed Lag approach to cointegration. They have found a long term income elasticity of -0.27 and a long term price elasticity of -1. for residential electricity demand in the US. Hondroyiannis (2004) also used a cointegration framework to analyse the residential electricity demand in Greece. His findings are a long term income elasticity of 1.56 and a price elasticity -.41. Narayan et all. used a panel cointegration analysis for residential electricity demand elasticities in G7 countries. The have found a long term income elasticity of 0.31 and a price elasticity -1.45. Finally, we would like to drawn attention to Xia et all. (2007). They explored different functional specifications to study in US residential electricity demand and found that the (one- equation) AIDS specification outperforms the translog or log-lineair model specifications.

Methodology

The dataset

Historical data for 13 EU member states covering unequal historical periods between 1990 and 2005 were used. The data for BE, DK,FR, IT, NL,ES and UK are covering the whole period. For DE (1991-2005), FI, IE, PT (1995-2005), AT(1996-2005) and SW (1997-2005) we have less observations. Data has been obtained from EUROSTAT, except data for residential fuel consumption which was obtained from UNFCCC GHG National inventory submissions[3]. Residential fuel covers liquid (mainly fuel oil), gaseous (mainly natural gas) and solid fuels (mainly coal) and biomass. Biomass is important in some countries, but mostly covers only a small fraction of domestic fuel consumption.

[3] In EUROSTAT, some inconsistencies in fuel consumption data have been found. For the remaining UNFCC data are very similar to EUROSTAT data.

An aggregated residential fuel price was constructed from residential gas and fuel oil statistics. Solid fuels and biomass were ignored because of lack of data. All prices include taxes.

Private consumption expenditure, expressed in constant prices, was used as a proxy for real income and all prices were deflated by the consumer price index. Heating degree-days express the annual need for space heating, taking into account the year to year fluctuations in outside temperatures. They are constructed as the integrated difference between the building base temperature and the outside temperature when the outside temperature is below the base temperature. We used degree-days 18-18 because these data are readily available. Nevertheless we are aware that this might not be appropriate for all countries.

Model specification

A singular price shock may have different effects when measured over a short period or over a number of years (**Figure 1**). The short term price elasticity measures the immediate effect of a price shock. In the long run it converges to some new equilibrium situation, which might be higher or lower. It is often argued that long term effects are higher than short term elasticities. This is due to increased substitution possibilities as flexibility increases over time while energy consuming appliances need replacement. This view has inspired many econometricians for many years in specifying their model structure. It has been common practise to solve the problem of autocorrelation in the error term by introducing a lagged dependent variable in the RHS. This 'solution' also introduces an identification problem of the time dependent nature of the price elasticities. Indeed, introducing lagged dependent variables in (log) linear equations tend to overestimate the long term price effect in simulations. Denoting y as the logarithm of the dependent variable in (1) and x as the vector of the logarithm of independent variables, the simulated long term elasticities are given by $\alpha / (1-\delta)$. With $0 < \delta < 1$ long term elasticities always exceed the short term elasticities.

$$y_t = \alpha' x_t + \delta y_{t-1} + \varepsilon_t \quad (1)$$

To solve this problem we used the two steps ECM specification, following Engle and Granger (1987). This model specification makes a distinction between the long term and short term elasticity and does not impose any a-priory constraints. For the reader who is unfamiliar with the theory and for the purpose of further discussions, we briefly summarize the basic ideas behind this model specification.[4] A stationary time series x_t is said to be integrated of order zero, indicated as I(0). In stationary time series past values have no permanent effect on future values. In contrast to this for the random walk model[5]. A time series behaving like a random walk model is said to be integrated of order one, indicated as I(1). For a time series I(1), the first difference $\Delta x_t = x_t - x_{t-1}$ is I(0). A time series I(1) is also said to have a unit root. Granger and Newbold (1974) warned about the risk of obtaining spurious regressions with equations of type (2) when the dependent variables and the independent variables are I(1). This view changed dramatically in Engle and Granger (1987). Equations of type (2) may express a cointegrating relationship. This leaves two options when making OLS regressions of type (2). Either the result is spurious, or the result expresses a cointegrating relationship. A cointegrating relationship expresses a long term equilibrium between the variables. The error term expresses the deviation from the long term equilibrium. A condition for cointegration is that the error term $\varepsilon_{i,t}$ constitutes a stationary time series. Ordinary least squares provides consistent estimates of this cointegration relationship despite the fact that the error terms might be highly correlated. The error term is introduced in (3) to obtain the error correction specification. The value of κ in (3) expresses the speed of convergence to the long term cointegrating relationship. Note that the cointegrating relationship (2) still has little meaning if the value of κ is very small or statistical insignificant.

$$q_{i,t} = \alpha_{1i} + \beta_1 y_{i,t} + \gamma_1 p_{i,t} + \theta_1 hdd_t + \varepsilon_{i,t} \quad (2)$$

$$\Delta q_{i,t} = \beta 2 \ \Delta y_{i,t} + \gamma_2 \Delta p_{i,t} + \theta_2 \Delta hdd_t + \kappa \varepsilon_{i,t-1} + u_{it} \quad (3)$$

q : log (electricity or fuel consumption)

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[4] This expresses the interpretation of the author.

[5] The relationship with the random walk and the terminology used are easily established. Assume a one-dimensional random walk along the X axis. x_t refers to the position on time t and Δx_t is a random step length. The sequence of steps constitute a stationary time series. At any time the position $x_t = x_{t-1} + \Delta x_t$ and does not constitute a stationary time series but a time series of order one I(1).

y : log (real income approximated by total private consumption expenditure)

p : log (price electricity or fuel / consumption price index)

hdd : log (heating degree days)

i : country

Δ : difference operator

$\beta 1$, $\gamma 1$, θ_1 long term elasticities

$\beta 2$, $\gamma 2$, $\theta 2$ short term elasticities

α_i country specific regression constant

$\varepsilon_{i,t}$ error term in the cointegrating relationship

u_{it} error term in the ECM equation

The long term price elasticity γ_1 and the long term income elasticities β_1 are the central objects of this analysis. However, as just argued we also have to analyse the error correction specification (3) to make sure that the cointegrating relationship is meaningful. After having analysed the stationary character of the panel data, we will continue with a discussion some methodological issues.

Unit root tests

By imposing homogenous slope coefficients in (2) and (3) and by allowing only the constant to vary between different countries, we in fact ignore the cross-section dimension in the data. Analysis of the order of integration of the variables is consistent with this approach. We use a specification of the Augmented Dickey Fuller (4) with homogenous slope coefficients ρ and σ and a constant τ_i for each country. The number of lagged variables in the ADF-test has been fixed to one because of the short length of the time series. The relevant parameter is the t statistic of ρ.

$$\Delta y_{i,t} = \rho\ y_{i,t-1} + \sigma\ \Delta y_{i,t-1} + \tau_i + \varepsilon_{i,t} \qquad (4)$$

Table 1 : Augmented Dickey-Fuller unit root tests

Variable –Y	ADF-t

Private consumption	-0.699
Residential electricity consumption	-0.725
Real electricity price	-0.727
Fuel consumption	-2.925
Real fuel price	-2.451
Degree days	-6.714

Note: The 5 % critical value is -1.95

The ADF-t statistics in

Table 1 suggests that consumption, residential electricity consumption and the real electricity price are non-stationary I(1) whereas fuel consumption, the real fuel price and degree days are stationary. The test statistic for degree days suggests a high stationary character [6]. The non-stationary character for residential electricity consumption and total private consumption are intuitively comprehensible but the result for the real electricity price might be somewhat surprising. In the dataset, real electricity prices in almost all countries decreased in the period observed. This might be the result of technological improvements, in the production of electricity [7].

Some other methodological issues

With the unit root test in mind we arrive at two points of discussion. The first one is whether the ECM modelling, formalised in equations (2) and (3), is valid for fuels. The basic idea of cointegrating is to find a stationary linear combination of non–stationary time series. Clearly, one cannot argue about a cointegrating relationship if the time series are stationary. But the absence of non-stationary data does not violate (2) the conditions for a valid model specification, as it is not a spurious regression either. So we feel that, as a criterion to accept the ECM, it is far more important to demonstrate the stationary character of the error terms $\varepsilon_{i,t}$ in (2) as well as the point estimate and statistical significance of the error correction component κ in (3). Some other authors suggest that

[6] This result conflicts with the idea of global warming. But this result is based on relative short time series whereas global warming is a process of several decades.
[7] In this period growth in central production was mainly in CCGT plants with improved efficiencies up 55 % compared to 39 % for a classical gas fired plant and in the same period new technologies such as Combined Heat and Power became popular.

the ECM can still be valid for stationary processes (Keele and Deboef 2004), but some loss of efficiency in estimating the parameters cannot be ignored.

The second point of discussion relates to the use of some stationary variables in the cointegrating relationship. We discuss the example of hdd days in (2). From the thermal characteristics of buildings it follows that heating degree days should have an immediate effect when using yearly data [8] and valid elasticities are in the range [0-1]. Any delayed effect should be considered as spurious. Assuming $\Delta y_{i,t} = 0$ and $\Delta p_{i,t} = 0$, deriving steady state properties by substituting (2) in (3) and taking $\lim_{\kappa \to -1}$,we obtain (4) which equals (2) in the limit if $\theta_1 = \theta_2$. If on the contrary $\theta_1 = 0$ and $\theta_2 > 0$, then q_{it} is a function of $\Delta\, hdd_t$, conflicting with thermal characteristics of buildings. Empirically, we have also found marginally improving statistical results when including hdd in the long term equation.

$$q_{i,t} = \theta_2\, hdd_t + \alpha_{1i} + \beta_1\, y_{i,t-1} + \gamma_1\, p_{i,t-1} + (\theta_1 - \theta_2)\, hdd_{t-1} \quad (4)$$

A third issue is the use of substitute energies as explanatory variables in the RHS of (2) and (3). Different authors have included a substitute energy price in the equations, although with varying success (Nararyan et all. (2007), Derigiades and Tsoulfidis (2008)). In our analysis of this issue, the fuel price was positive in the electricity equation (4), consistent with economic theory, but the electricity price was negative in the fuel equation (4). A possible reason for this failure is a correlation between the electricity price and the fuel price. Some correlation could be expected as fuels are the main input to electricity production. However, many other factors like tariffs and distribution costs have an impact on the residential electricity and fuel prices and the correlation turned out to be 0.41 on average, a value that should not rose problems given the sample size. Another possible reason could be found in the specific nature of fuel-electricity substitutions? Electricity is used for mechanically driven applications, lighting, cooling, electronic devices, space heating, hot water production and cooking.

[8] Only when using daily data some delayed effect can be possible due to the heat mass stored in the building.

For the latter three functions, fuels and electricity are almost perfect substitutes. Observed substitution is limited due to the large price difference and the lifetime of equipment. But sometimes, the capital cost outweighs the price difference, like with second houses, small vacation apartments or passive houses. Surprisingly, the fact that electricity and fuels are almost perfect substitutes complicates the modelling. The reason for this is that a linear logarithmic model specification may not be appropriate when dealing with perfect substitutes. Indeed, people are more likely to be motivated by absolute price differences instead of relative prices. Just a simple example to demonstrate the problem. Consider a price of fuels 15 € /GJ and electricity 45 € /GJ. If both prices increase by, say 10%, then the absolute price does not change but the price difference increases by 10 %. This idea has been visualised in **Figure 2**, expressing the relationship between the logarithmic and absolute price differences in our sample. The correlation is only 0.46. Consequently, by using a logarithmic model specification, we are suffering from a considerable information loss. Model formulations that explicitly consider characteristics of technologies will be more suitable to analyse fuel-electricity substitution.

Bootstrapping standard deviations

One disadvantage of panel data is that problems related to cross section data and time series are accumulated. Heteroscedasticity is a typical problem in cross section data and autoregression in the error terms is inherent to time series. OLS still provides unbiased point estimates but standard errors are no longer valid.

To overcome this problem a circular block bootstrap methodology has been used. The bootstrapping is organised in the following way. Out of N (N = 179) for (1) and 166 for (2)) observations we randomly draw new samples of equal length. The first observation $x_{i,t}$ of each block is chosen randomly with replacement and a block Xl ={ $x_{i,t}$, $x_{i,t+1}$,… $x_{i,t+k}$ } is selected, k representing the block length. If t + k exceeds 2005, we continue with the first observation for country i. l blocks are selected with l = integer(N/k). One additional block of length N- l*k is added to match the original size. OLS is used to derive point estimates on the new sample. This is repeated 1000 times and bootstrapped standard deviations are calculated based point estimates. Note that the number of constants α_{1i} in equation (2) changes in the bootstrapping. In running new samples, it frequently happened that not all countries were represented, and the corresponding constant was left out.

Defining the optimal block length k is still problematic. The existing literature provides some guidance on defining the block length in time series (Politis and White (2003), Carlstein et all. (1998), Berkowitz and Kilian (1996). To our knowledge there are no references for panel data. If we choose $k = 1$, the time dependence of the data is ignored and the block size should be a fraction of the original time length, thus limiting the possible choices to the interval [2-9]. We have run experiments using different block length and have observed some asymptotic behaviour in the results. For $k > 4$ only marginal increasing standard error estimates (changes of 10 % between $k = 4$ and $k = 9$) were observed, suggesting that with $k = 4$, standard errors are not underestimated.

Results

The results for the long term cointegrating equation (2) are presented in Table 2 The ADF-t statistic results relate to the residuals of the long term cointegrating relationship (2). As before it includes one lagged variable. The results suggests that the residuals are stationary both for electricity and fuels. The long term price elasticity equals -0.186 for electricity and -0.157 for fuels. Income elasticities are 0.83 and 0.28 respectively. Bootstrapped standard errors are significantly higher compared to traditional OLS estimates, but nevertheless the results remain statistically significant for income, price and heating degree days. Heating degree days have more impact on fuel consumption than on electricity. This is consistent as fuels are mostly used for heating.

Table 3 presents the result for the error correction model (3). The bootstrapped standard errors for block size $k > 1$ are identical to those obtained for $k = 1$, indicating that we are no longer dealing with autocorrelation in the error terms. The error correction coefficients are above 0.33 and are statistically significant. Approximately 80 % of the deviations of the long run equilibrium are absorbed in the short run ECM equation in a period of 4 years.

Let us analyse how these adjustments take place. Note first that this error correction mechanism is only relevant when the elasticities in (2) and (3) are different. We observe that θ_1 being equal to θ_2, for fuels, consistent with the thermodynamic nature of this relationship as discussed in equation (4). For electricity, the point estimates and the standard errors show that P ($\beta 1 > \beta 2$) = .93 and P ($|\gamma_1| < |\gamma 2|$) = .92. The long term income elasticity is higher than the short term income elasticity and the long term price elasticity is smaller (in absolute values) than the short term price elasticity. Both results are significant at the 10% level. Similarly, for fuels, P ($\beta 1 > \beta 2$) = .85 and P ($|\gamma_1| > |\gamma 2|$) = 0.93. The long term price elasticity for fuels is higher than the short term, significant above 10%, whereas short and long term income effects are not significantly different above 10%.

Silk and Joutz (1997) also found that the short term price elasticity in the US was numerically larger than the long term price elasticity, although not significantly different. Immediate and delayed price effects are related to the existence of alternatives, lifetime of appliances and the time required to take action. Often a first reaction to a price shock is to consume less and accept the welfare loss. As a second reaction one will look for alternatives. The more of that exist, the more sustainable that the price effect will be. For many electrical appliances hardly any alternatives exist. This is quite different for fuels. Improving insulation is realistic opportunity to compensate the original welfare loss and reduce fuel consumption permanently. The energy efficiency of many electrical applications has improved, but to a much smaller extent.

Table 2 : Results for the long term equilibrium equations (3)

	β_1	Γ_1	θ_1	ser	ADF t-stat
Electricity					
	0.830	-0.186	0.170	0.059	-4.09
OLS T-stat	19.12	-4.80	2.67		
BS T-stat k = 1	15.11	-3.45	2.44		
BS T-stat k = 4	8.97	-1.94	2.08		
Fuels					
	0.277	-0.157	0.451	0.053	-4.67
T-stat OLS	8.21	-6.90	10.30		
T-stat BS k = 1	5.85	-4.21	6.03		
T-stat BS k = 4	3.20	-2.71	5.24		

Note : ADF-t 5 % critical value is – 4.11

Table 3: Results for the error correction model (4)

	β2	γ2	Θ2	κ	ser
Electricity					
	0.558	-0.3876	0.0884	-0.332	0.043
OLS T-stat	5.16	-8.04	2.46	-5.15	
BS T-stat k = 1	3.56	-3.78	2.89	-3.59	
Fuels					
	0.145	-0.059	0.456	-0.347	0.038
OLS T-stat	1.49	-2.03	14.34	-5.55	
BS T-stat k = 1	1.60	-2.03	8.62	-4.29	

Finally the validity of model results for the different countries in the panel are analysed. For this purpose we have calculated the Dickey-Fuller statistics on the country residuals in the long term equation (2). For electricity, this test identifies a non-stationary relationship for Denmark, Netherlands, Portugal and the United Kingdom. For fuels non stationery is observed for Ireland, Spain and Sweden.

It would contribute to the understanding of electricity and fuels consumption to analyse why these countries behave differently in comparison to the European average. Spain has the highest increase in fuel consumption in the panel (+ 40 % between 1990 and 2005), which might be related to tourism and population growth. Ireland is somewhat peculiar as in 1990 it was one of the poorest countries in EU15 and in 2005 one of the richest. Also a significant number of immigrants have settled in this period. Fuel consumption increased by 24 %, the second highest increase in the panel. Introducing population in the equations, i.e. replacing q by q/pop and y by y/pop in (3) improves Dickey-Fuller statistics to -1.28 and -1.42 for Ireland and Spain respectively. Sweden is somewhat peculiar too. Fuel consumption dropped by 35 % between 1997 and 2005 as a results of different policy actions to reduce GHG emissions. Heat production in new dwellings is now mainly (over 80 %) based on heat-pumps.

For electricity it seems hard to find reasonable explanations. Electricity consumption for DK, NL, PT and UK has been plotted against the EU15 average in **Figure 3**. The curve for DK is extremely flat in the period observed (1996-2005) and for PT is extremely steep. NL and UK do not deviate too much form the average of EU-15. Some further research is required to explain this difference.

Table 4: Dickey fuller test on the residuals of equation (2)

	Electricity	Fuels
AT	-2.50	-4.01
BE	-2.78	-2.95
DK	-0.62	-2.21
FI	-2.14	-1.70
FR	-3.03	-2.87
DE	-4.71	-2.90
IE	-2.96	-0.88
IT	-2.27	-2.36
NL	-0.63	-2.08
PT	0.19	-3.69
ES	-1.98	-1.12
SE	-3.17	-0.11
UK	0.32	-1.91

Conclusions

Developing long term energy scenarios requires reference figures for income and price elasticities. The objective of this analysis was to derive income and price elasticities from panel data. For electricity the point estimate for the long term income elasticity is 0.83 with a 90 % probability interval [0.68-0.92]. The point estimate for the price elasticity is -0.186 with a 90 % probability interval [-0.354 - -0.028]. The income elasticity for fuels is much lower. The point estimate is 0.28 with a 90 % probability interval [0.13-0.42]. The fuels price elasticity point estimate equals -0.16 and the 90 % probability interval [-0.25 - -0.06].

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FIGURES

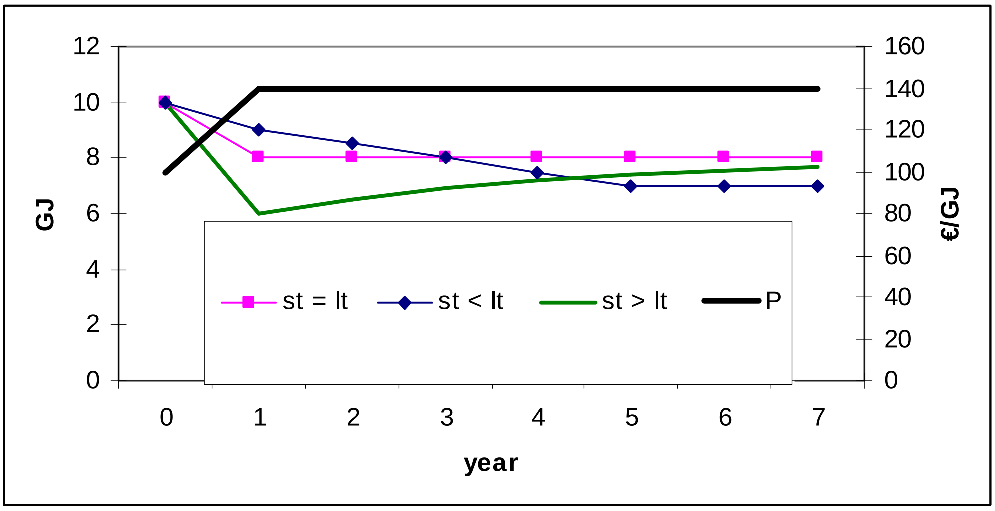

Figure 1: Short and long term elasticities in one picture.

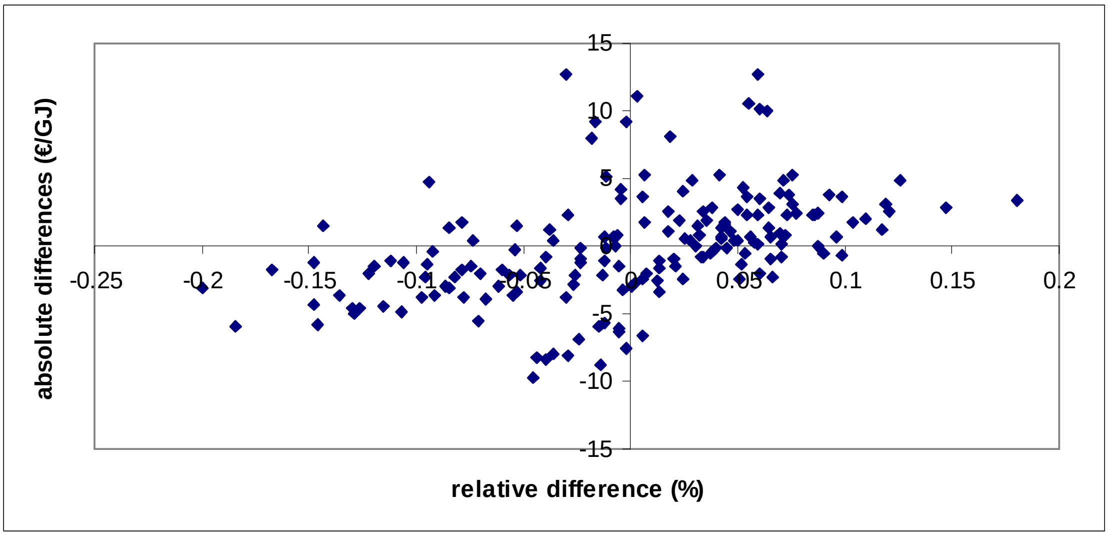

Figure 2: The information loss when using logarithmic model specifications for nearly perfect substitutes. On the X-axis is plotted the logarithmic differences from the country specific sample mean of the price difference between electricity and fuels. On the Y-axis we have the absolute differences from the sample mean

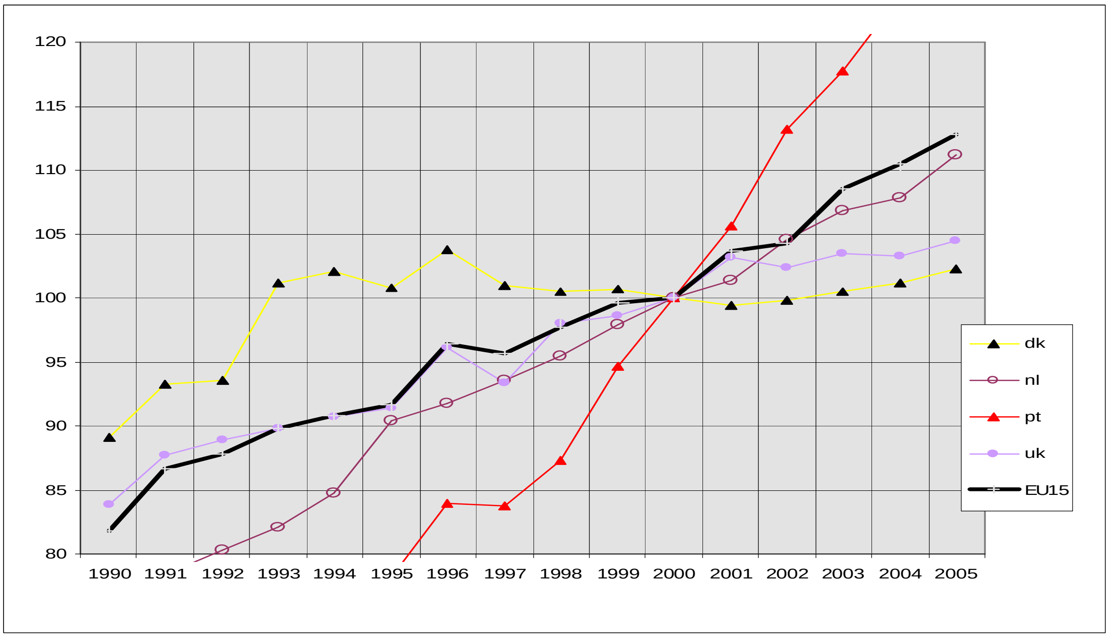

Figure 3: Evolution of residential electricity consumption in DK, NL, PT and UK, and EU-15 average