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On the Effectiveness of Demand Side Management Information Programs on Household Electricity Demand

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Abstract

We empirically study the effectiveness of a Demand Side Management (DSM) program for households based on customer information.

The literature points out that suppliers as well as consumers behave strategically such that DSM cannot work. Obviously, the supplier has no incentive to reduce the demand of his own product, and the consumer counteracts the supplier's measures by reducing his/her own effort.

Within the case of the Irish Electricity Supply Board (ESB) these effects are ruled out. On the one side, due to the country's specific geographical location and much higher increases than expected in electricity demand the ESB had to use all means to reduce electricity demand. And, on the other side, the instrument of customer information as a DSM device rules out strategic behavior of customers.

We find that customer information reduced overall electricity demand by roughly 7%. It was also effective as a load management device as demand fluctuations over the year were reduced. Finally, the short-run dynamic effect of DSM seems to be insignificant, this implies that DSM does not change demand behavior but reduces demand through consumers switching to more efficient electric appliances.

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1 Introduction

Since the eighties several instruments of Least Cost Planning (LCP) have been discussed in the literature (see Lovins (1985) or the book by Wirl (1997)). Beside supply side measures that reduce the costs of production and transmission of electricity there has been some discussion about demand side measures, i.e. Demand Side Management (DSM). DSM aims at reducing peak demand, overall demand and demand fluctuations (the latter one often refered to as load management).

There are two questions regarding DSM: Do electricity providers have an incentive to use DSM and do households/customers react to it. The first problem is that electricity is not sold as a service but as an input to produce a service. Therefore the provider has no incentive to increase the efficiency of electricity appliances used in households and firms because this would result in a demand decrease of his own product (see for example Wirl (1997)for an extended discussion). Additionally, and this is part of the second problem, Wirl (1994) argues that DSM might be even less attractive because rational households will strategically reduce their own investment in efficiency improvements as a response to suppliers' direct investments in electricity utilities. The latter theoretical argument might be true if DSM is based on investment programs. However, households are unlikely to counteract information programs by reducing their own effort if the fraction of informed households is low at the beginning of the implementation. It remains to be shown whether programs based on customer information are ineffective. We seek an empirical answer to that question by analyzing the Irish DSM-program which was mainly based on customer information.

We use Irish data for this study. The Irish Electricity Supply Board (ESB), a state owned utility, had to use all measures to reduce electricity consumption due to the specific geographical and political situation of Ireland and to higher than expected increases in electricity demand throughout the eigthies. Given the time needed to install new capacity due to administrative obligations and construction time, and a missing connection with the continental electricity grid, the ESB faced an upcoming shortage of generation capacity. Therefore the ESB had an incentive to reduce demand. To do so, the ESB invested into LCP including a large scale customer information DSM program. The instrument of a mainly information based DSM program rules out strategic behavior by households. Thus the Irish DSM program gives us the opportunity to analyze whether household demand reacted to it.

In this article we first describe the DSM program, present then the model and the hypothesis, and sum up our results along with the description of the econometric methodology. We find that the DSM program has an overall demand reducing effect in the long-run of roughly 7% relative to energy demand without DSM. Additionally, energy demand is less sensitive to temperature fluctuations after the implementation of the program, i.e. there are less demand fluctuations over the year. These findings are consistent with early estimates of the ESB.

Our evidence is based on monthly data covering the period October 1976 to December 1993. The potential long run effect of the DSM program on energy demand is first investigated within a cointegration framework. We model electricity demand from Irish households as depending on a proxy for income, and the price per unit of electricity and a weather variable. We account for the DSM program with a dummy variable, and also include a trend and seasonal dummies. The dynamic analysis within an error-correction model emphasizes again the long-run effect on overall demand and on demand fluctuations over the year due to temperature. Our results support the intuition that DSM programs reduce electricity demand of households not by changing their demand patterns for electricity related services but through them switching to efficiency improved electricity appliances. Also, as demand fluctuations are reduced over the year, DSM by customer information is an effective measure of load management.

2 The Irish DSM-program - Why and How

The Republic of Ireland is economically characterized by two factors: First a geographic isolation and second a high dependence on international trade. These factors affect the technology used to generate electricity. Geographic isolation together with a missing connection with continental Europe and the United Kingdom at the beginning of the nineties implied that the Irish electricity demand had to be satisfied by domestic generation. Additionally, it implies that higher than normal reserve capacities are needed to be able to meet unusually high demand periods as no generation capacity can be used from abroad. This restriction and the fact of underestimated demand increases in the early eighties lead to an upcoming shortage of capacities. In its annual report for 1993 the ESB stated that during the past six years the increase in electricity demand had been higher than expected and above the European average (ESB(1994a)). Officially, the ESB announced that capacities had not been adjusted to satisfy the highest probable increase in electricity demand as if it wouldn't have materialized it would have put a serious financial pressure (due to high capital investments) on the company (see ESB(1994b), p. 3). To understand the full extent of the problem, it is necessary to know that a realized shortage of generation capacity, i.e. a higher demand than can be generated, leads to a break-down of the grid due to basic laws of physics.

Also, the ESB faced and still faces relatively high generation costs, the share of imported primary energy being high compared to the European average. Especially periods of peak generation in which peat is used as fuel due to political and traditional reasons are costly.

These reasons provided the economic incentives for the ESB to start a large scale DSM program to reduce peak demand, demand fluctuations and overall demand. A potential side-effect of the program advocated, by the ESB and by most other electricity suppliers who had announced DSM activities as well, was thought to strengthen business relationships with large customers. An effect judged to be very important in the light of upcoming competition (ESB (1994b), p. 8).

The program was implemented using all three known instruments of DSM. These are changes in the price structure, incentive and information programs. With respect to private households the ESB concentrated on information programs. Changes in the price structure are not at the focus of this study as these were mainly directed at the industrial and commercial sector. In brief, they consisted of three part tariffs including a fixed fee depending on the maximum needed capacity announced previously by the industrial or commercial user, a fee depending on the actually used electricity, and a "demand charge", a daily fee which is determined ex post by the customer's highest demand over a day during the daily peak period (in winter this is the time between five and seven pm). The ESB also offered tariffs in conjunction with interruptible electricity supply, which means that industrial and commercial customers buy at a cheaper rate but face the risk of not being served in the case of capacity shortage. For households a special "night saver" tariff was introduced but the participation in this program turned out to be small. Therefore, electricity sold under this tariff is not included in our study.

Incentive programs were rarely applied and of relative little value. For households some minor rebates ("buy three energy saving bulbs for the price of two") were used during information campaigns.

The information program was targeted at small firms, retail outlets and private households. Information leaflets were added to households' electricity bills, efficiency improvements were advertised in specialized journals (e.g. DIY journals), special programs targeted schools (cooking competitions and instructing teachers), and energy efficiency certifications for appliances were introduced together with the Irish certification institution EOLAS. Finally, efficiency improving products (e.g. lagging jackets - hot water isolation, energy saving bulbs) were distributed by mail and in local ESB shops to increase the customers' access to these goods.

3 An econometric model of electricity demand

To our knowledge there has not been any econometric study on the effectiveness of DSM programs. The present analysis is based on traditional models of electricity demand and includes an additional variable that accounts for the DSM effect.

Houthakker (1951) presented one of the first studies in electricity demand. He includes cross-section data on income and on electricity prices as determinant variables, accounting simultaneously for potential demand given the existing appliances with an additional variable. Later studies drop the latter variable adding at the same time a weather variable as additional independent variable (see Wilson (1971)). Surveys of several studies are found in Taylor (1975) and Berndt (1991, ch. 7).

Scott (1991) studies the Irish electricity demand including the traditional determinant variables. We modify her approach, however, we use a different weather variable and a different price variable. A dummy variable accounts for the DSM program. Seasonal dummies capture the deterministic seasonality in the data. Given our interest in the evolution (growth rates) of energy demand we estimate a logarithmic functional form of the energy demand function instead of an estimation in levels as in Scott (1991). Household electricity demanded under the general supply tariff of the ESB (E) is the dependent variable. It does not include electricity sold under the "night saver" program, i.e. we concentrate on periods of peak demand. The retail sales volume index (RSV) serves as a proxy for disposable income as no monthly series is available for the latter. We include the real unit price of electricity (PPU) as further independent variable. The fixed fee has been dropped for the analysis as a first investigation determined the insignificance of the fixed fee. This reflects the fact that no major changes in the tariff structure occured throughout the observed period from September 1976 to December 1993. Anyway, even in the presence of fixed fee changes their negative income effect would be small (Houthakker (1951)). Our weather variable is the monthly average of daily minimum temperature (MINTEMP) measured at the weather station of Dublin airport because roughly half of the Irish population lives in the Dublin region. Scott (1991) uses days below 15.5 degrees Celsius weighted by the 1975 regional electricity grid demand (that is the general demand from the three sectors - households, commercial outlets and industry). The weight for the Dublin region in her study was 32,2% which should be higher by now due to increased urban concentration of population.

The deterministic part of the model includes seasonal dummies and a time trend. A preliminary analysis of the data (documented in the next section) gives evidence favorable towards a deterministic modeling of the seasonality. The included trend accounts for population growth and technological change. The gradual implementation and diffusion of the DSM-program is captured by an additional dummy variable that has value zero in the years before 1990, increases then linearly over the year 1990 to reach one in December 1990. Last, the inclusion of the variable resulting out of the product between minimum temperature and the DSM dummy allows to measure the effectiveness of the load management aspect of the DSM program.

3.1 Hypothesis

If DSM works the parameter on the DSM dummy should be significantly negative. A positive parameter on the cross-effect between DSM and temperature would reflect the effectiveness on load-management as the program would reduce fluctuations in electricity demand due to temperature.

Regarding the hypothesis that DSM affects long-run behavior but does not change short-run demand patterns, we expect a significant parameter on the DSM dummy within the co-integrating analysis whereas it can be insignificant in the estimation of the error-correction equation.

4 Results

4.1 Data

As mentioned previously, the analysis covers the period September 1976 through December 1993. Monthly data on household electricity demanded under the general supply-tariff and data on the electricity unit price were provided by the ESB. The data originate from two household groups that are surveyed alternatively on a bimonthly basis. The unweighted averages of the successive observations of the two household groups form the series we are working with. The retail sales volume index (basis 1980) that serves as a proxy for income and the consumer price index used to deflate nominal figures are published by the Central Statistics Office. The Irish Meteorological Service provided the series on the monthly average of daily minimum temperature in the confines of Dublin.

The following analysis is based on the logarithm of all variables but the minimum temperature. An assessment of the unit root properties of the data precedes the estimation of the electricity demand model.

4.2 Unit root analysis

The data are displayed in figure 1. Obviously, we first have to deal with the seasonal and the trend properties of the series. In particular, we will assess whether the seasonal and the trend processes of the series are of a stochastic or a deterministic form, respectively. Franses (1991) extends the method developed in Hylleberg, Engle, Granger and Yoo (HEGY, 1991) for quarterly data and presents a decomposition of the autoregressive data generating process of a twelfth differenced univariate time series into its long-run and its separate seasonal frequency components. The decomposition allows to test within a unified framework for stochastic against deterministic specifications of the trend and the seasonal components. A deterministic trend specification would assume that the growth rate of a series is constant over time while a stochastic specification assumes that the mean growth rate of a series is constant over time. Similarly, deterministic seasonality displays a recurring seasonal pattern over the years while a changing seasonal pattern characterizes stochastic seasonality. Basically, the test results in the determination of the unit root properties of the series at the long-run and at the seasonal frequencies. It is a type of augmented Dickey-Fuller unit root test based on the auxiliary regression

$$\begin{aligned} y_{8t} = {} & \pi_1 y_{1t-1} + \pi_2 y_{2t-1} + \pi_3 y_{3t-1} + \pi_4 y_{3t-2} + \pi_5 y_{4t-1} + \pi_6 y_{4t-2} + \pi_7 y_{5t-1} + \pi_8 y_{5t-2} \\ & + \pi_9 y_{6t-1} + \pi_{10} y_{6t-2} + \pi_{11} y_{7t-1} + \pi_{12} y_{7t-2} + \sum_{i=1}^{k} \phi_i y_{8t-i} \\ & + \sum_{j=1}^{11} \alpha_j D_{jt} + \beta_0 + \beta_1 \mathrm{TREND}_t + \nu_t, \qquad (1) \end{aligned}$$

in which we test for the significance of the parameters $\pi_1, \ldots, \pi_{12}$ (see also Hylleberg (1994)).[1] Basically, transformations y_{it}, $i = 1, \ldots, 8$, of the original

[1] Define B as backshift operator $By_t = y_{t-1}$, $B^2 y_t = y_{t-2}$ and so on. Then, the transformations used are $y_{1t} = (1 + B + B^2 + \cdots + B^{11})y_t$ which retains the unit root at the zero frequency, $y_{2t} = -(1 - B)(1 + B^2)(1 + B^4 + B^8)y_t$ that preserves the frequency 6/12 corresponding to a two month period, $y_{3t} = -(1-B^2)(1+B^4+B^8)y_t$ that retains the frequency 3/12 (9/12) corresponding to a four month period, $y_{4t} = (-(1-B^4)(1-\sqrt{3}B + B^2)$ that retains the frequency 5/12 (7/12), and $y_{5t} = -(1-B^4)(1+\sqrt{3}B+B^2)(1+B^2+B^4)y_t$, $y_{6t} = -(1-B^4)(1-B+B^2)(1-B^2+B^4)y_t$, $y_{7t} = -(1-B^4)(1+B+B^2)(1-B^2+B^4)y_t$ retaining the frequencies 1/12 (11/12), 4/12 (8/12) and 2/12 (10/12), respectively, and finally, $y_{8t} = (1 - B^{12})y_t$.

series y_t enter the regression, each extracting the feature of the series at a specific frequency. For instance, the transformation y_{1t} retains the long-run or the trend properties in the series (see figure 2). A test of the unit root hypothesis at the long-run frequency is equivalent then to the one-sided test $\pi_1 = 0$ against $\pi_1 < 0$. The remaining transformations retain the features of the series at seasonal frequencies, e.g. y_{5t} extracts the one-year cycle (see also figure 2), and the test for a seasonal unit root is equivalent to testing the zero hypothesis on the respective coefficients. However, due to the fact that the seasonal roots are complex conjugate, unit roots at seasonal frequencies are present only when pairs of the π's, π_i and π_{i+1}, $i = 3, 5, \ldots, 11$, are each equal to zero and simultaneously equal to zero. So, if in addition to $\pi_1 = 0$, π_2 through π_{12} are equal to zero then the twelfth difference operator $(1 - B^{12})$ may be appropriate to render the series stationary. Critical values for the separate t-tests on each π as well as for the F-tests on pairs of π's, and the joint F-test $\pi_3 = \cdots = \pi_{12} = 0$ are tabulated in Franses (1991). An equivalent test is found in Beaulieu and Miron (1993), their test equation and the transformations differ slightly from the ones presented here, however.

Table 1 summarizes our results. The Schwarz criterion is used to determine up to which length lagged left-hand variables are included in the regression. For all series, the t-tests as well as the F-tests on complex conjugate seasonal roots reject the unit root hypothesis in most cases. Moreover, the joint hypothesis $\pi_3 = \cdots = \pi_{12} = 0$ testing complex conjugate seasonal unit roots simultaneously is rejected for all series. Hence, the seasonality in the series does not seem to be driven by an integrated stochastic process, and the Δ_{12} filter is definitively inappropriate to account for the seasonality in the data. The unit root test at the long-run frequency (the test on π_1) is not significant for the retail sales volume index and the price per unit. For electricity demand and the minimum temperature however, the coefficient π_1 is significant at the 5% level. Taking into account that the test statistics are sensitive to sample size and using the critical value for π_1 documented in Beaulieu and Miron (1993) for the appropriate sample size shows that this coefficient is only marginally significant for electricity demand. The critical value at a 5% significance level is -3.28 for a sample size of 240 while the critical value given in Franses for a sample size of 120 is -3.24. Long-run nonstationarity cannot be rejected definitively for all series except for the minimum temperature. Therefore, we'll assume difference stationarity for electricity demand, the retail sales volume index and the price per unit series in the following. According to our results, the minimum temperature is assumed stationary in levels. To keep all remaining stochastic dynamics in the data, we will include dummy variables to account for the seasonality.

4.3 Long-run effects of DSM

The long-run effect of DSM on electricity demand is estimated by applying ordinary least squares to the equation

$$\begin{aligned}\mathrm{e}_t = \beta_1 \mathrm{rsv}_t + \beta_2 \mathrm{ppu}_t + \beta_3 \mathrm{mintemp}_t + \gamma_1 \mathrm{DSM}_t + \gamma_2 \mathrm{MINTDSM}_t \\ + \sum_{i=1}^{11} \delta_i D_{it} + \mu_1 \mathrm{TREND}_t + \mu_0 + u_t, \quad (2)\end{aligned}$$

where e, ppu, mintemp represent the logarithm of household electricity demand, the logarithm of the unit price, and the monthly average of daily temperature, respectively. The implementation of the DSM program is captured by the equally labeled dummy variable. The specification

$$DSM_t = \begin{cases} 0, & t \leq 1990 \\ 1/12, 2/12, \ldots 1, & 1990/01 \leq t \leq 1990/12 \\ 1, & t \geq 1991/01 \end{cases}$$

accounts for the gradual implementation of the program. Additionally, we include a trend (TREND) to account for potential technological developments that increase the use of electric appliances over time, and the monthly dummy variables D_{it} capture the deterministic part of the seasonality in the data. MINTDSM, mintemp multiplied by DSM, accounts for a potential crosseffect of DSM on the effect of temperature fluctuations on electricity demand.

The results of the estimation are displayed in table 2. First of all, note that the coefficient on DSM and MINTDSM are negative and positive, respectively. The significant first coefficient documents the (expected) long-run effect of DSM, reducing overall electricity demand by 7%. The second coefficient, marginally significant, has also the right sign. As people respond to DSM electricity demand becomes less sensitive to temperature. The remaining significant coefficients have the expected sign. Electricity demand reacts positively to income and negatively to temperature levels. Finally, two facts might explain the insignificance of the price coefficient. First, in developed countries electricity has become a basic need for households so that the price elasticity of electricity demand is small, i.e. big price movements would be required to affect demand patterns significantly. This leads to the second fact: As big price movements have not taken place in the observed period (i.e. electricity price was not the prime policy variable), the price variable is not a determinant of electricity demand.

The interpretation of the estimates given so far has to be further validated, however. The tests summarized in the previous section rejected the unit root hypothesis for the minimum temperature, while the unit root tests for the other variables were not rejected. Thus the estimator of the coefficients in the level regression will be consistent if the integrated regressors are cointegrated with the regressand (see Stock and Watson (1988) and Banerjee et al. (1993, Ch. 6). Cointegration has been introduced by Engle and Granger (1987) and means in this context that even if electricity demand, the retail sales volume index and the price per unit series are each stationary in first differences, there exists a linear combination of the variables that is stationary in its level. A further detailed exposition on cointegration and estimation of a single cointegration vector can be found in Banerjee et al. (1993, Ch. 4, 5 and 7).

To test for cointegration we therefore reestimate equation 2 without minimum temperature and its crossproduct with the dummy variable DSM, and perform a unit root test on the residuals of this regression. The result of this augmented Dickey-Fuller unit root test, based on the auxiliary regression

$$\Delta\hat{u}_t = \rho\hat{u}_t + \sum_{i=1}^{m} \phi_i \Delta\hat{u}_{t-i} + \epsilon_t, \tag{3}$$

is documented at the bottom of table 2. Clearly, the unit root hypothesis is rejected with a t-statistic of -3.00. The critical value of -2.576 at a 1% significance level is taken from McKinnon (1991) as the presence of estimated parameters in the relationship yielding the series to be tested for stationarity affects the test level of the usual Dickey-Fuller statistic.

Besides validating the consistency of the estimators in equation 2 this last result gives additionally a special meaning to the estimated relationship between the integrated level variables. As already mentioned, from the unit root analysis we know that each variable is driven by a stochastic trend, and hence, is nonstationary.The estimated level relationship yields a stationary series. This means that at least one stochastic trend drives all integrated variables, and that in the long-run the series will not drive too much apart. Occasional deviations from this long-run relationship will induce transitory dynamics that restore the level or equilibrium relationship between the variables.

4.4 Short-run effects of DSM

The following dynamic specification takes into account the long-run relationship of the variables estimated in the previous section. Within an error correction model (ECM) we will assess whether DSM affects electricity demand also in the short-run. Short-run meaning the pattern of electricity demand over the year. The model estimated is:

$$\Delta e_t = \alpha z_{t-1} + \tilde{\beta}_1 \Delta \mathrm{rsv}_t + \tilde{\beta}_2 \Delta \mathrm{ppu}_t + \tilde{\beta}_3 \mathrm{mintemp}_t + \sum_{i=1}^{p} \psi_i \Delta e_{t-i}$$
$$+ \tilde{\gamma_1} \mathrm{DSM}_t + \tilde{\gamma_2} \mathrm{MINTDSM}_t + \sum_{i=1}^{11} \tilde{\delta}_i D_{it} + \tilde{\mu_0} + \varepsilon_t, \quad (4)$$

where $z_t = \hat{u}_t$ represents the estimated deviation from the level relationship between electricity demand, the retail sales volume and the price per unit series:

$$z_t = \mathrm{e}_t - \hat{\beta}_1 \mathrm{rsv}_t - \hat{\beta}_2 \mathrm{ppu}_t - \hat{\gamma_1} \mathrm{DSM}_t - \sum_{i=1}^{11} \hat{\delta}_i D_{it} - \hat{\mu_1} \mathrm{TREND}_t - \hat{\mu_0}.$$

As these variables do not drift apart in the long-run, such deviations should induce a trend-reverting adjustment process. Hence, we expect α to be negative. The dummy variable DSM and its crossproduct with minimum temperature, $MINTDSM$, are again included to estimate whether the DSM program had an effect on the mean growth rate of electricity demand, and whether the growth rate of electricity demand was less sensitive to temperature fluctuations after implementation of DSM, respectively.

A previous estimate included up to 12 lags of the left-hand and all right-hand variables. The retail sales volume index and the price per unit turned out to be insignificant, so they are dropped in the final estimation of the VECM. According to the Schwarz criterion, eight additional lags of Δe_t seem appropriate. Table 3 reports the significant negative effect of the error term z_t and of the minimum temperature level. However, our focus is in particular on DSM and MINTDSM, and these variables seem to affect energy demand as expected mainly in the long-run rather than in the short-run. Despite their apparent insignificance we included both variables into the final estimation to report that nevertheless, the estimated coefficients have the right negative and positive sign, respectively.

The Q-statistic and the Breusch-Godfrey serial correlation LM-test at the bottom of table 3 give some diagnostic measures. They are not significant with p-values of 0.49 and 0.16, respectively. Finally, an R^2 value of 0.97 documents a good data fit, a plot of the fitted values along with the residuals is found in figure 3.

5 Conclusion

In the present paper we show that DSM program can work under certain real world conditions. The Irish case provided us data from a situation in which the electricity supplier, the ESB, had to use all measures to reduce electricity demand and therefore used a DSM design that rules out strategic behavior by households, the studied target group.

The analysis gives evidence that DSM programs based on customer information can successfully decrease electricity demand. In the Irish data we find that electricity demand is roughly 7% less after implementing the program relative to what it would have been without the implementation of the DSM program. Moreover, the program affects electricity demand in the long-run rather than in the short-run. It is likely to stem from changes in the use of electricity appliances, thus the DSM program does not change the demand pattern for electricity related services but affects long-run investment decisions of households.

Given our results and the discussion in the literature about the strategic behavior of suppliers and customers, we conclude that if DSM is politically wanted, one could employ an independent institution to distribute DSM information. Regulation of electricity providers should force them in a mandatory way to contribute to such an institution rather than leaving the investment in DSM measures to the providers' choice.

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6 Tables

Table 1: Seasonal unit root tests. ^{b} denotes significance at the 5% level. The results are based on an estimate of the auxiliary regression (1), the Schwarz criterion is used to determine k. The equation for mintemp is estimated without a trend.

t-statistics	variable			
	e	rsv	ppu	mintemp
	$k = 3$	$k = 0$	$k = 0$	$k = 2$
π_1	-3.2820^b	-2.4791	-1.5784	-3.2910^b
π_2	-5.1569^b	-3.3933^b	-3.4539^b	-1.6694
π_3	-5.7383^b	-1.2571	-4.3183^b	1.4945
π_4	-2.4546	-5.7891^b	-4.4908^b	-6.2739^b
π_5	-1.2982	-6.7364^b	-5.4496^b	-1.9961
π_6	0.8521^b	-6.6812^b	-5.1834^b	-3.8075^b
π_7	-0.4630^b	3.4767^b	-0.6830^b	3.5827^b
π_8	-0.7803	-5.5752^b	-1.8992	-1.6941
π_9	-3.7745^b	-5.1850^b	-5.6368^b	0.0776
π_{10}	-0.5728	-7.6004^b	-4.6260^b	-5.8520^b
π_{11}	-4.0216^b	1.6556	-1.8437^b	3.2389^b
π_{12}	-1.1256	-6.8131^b	-3.6687^b	-2.9812
F-statistics				
π_3, π_4	19.5678^b	17.9204^b	21.8549^b	21.4135^b
π_5, π_6	8.4759^b	24.5988^b	15.4882^b	11.3984^b
π_7, π_8	3.0511	23.0553^b	15.5885^b	10.0779^b
π_9, π_{10}	8.1734^b	31.0364^b	19.0663^b	23.2449^b
π_{11}, π_{12}	15.6364^b	26.7130^b	18.5371^b	6.5969^b
$\pi_3, \ldots, \pi_{12}$	12.5614^b	42.8099^b	66.4568^b	17.6673^b

Table 2: The long-run effect of DSM. The dependent variable is electricity demand (e), sample period 76/9-93/12.

variable	coefficient	stand. error	t-statistic
rsv	0.3896	0.0624	6.2418
ppu	0.0111	0.0290	0.3818
mintemp	-0.0095	0.0019	-4.9145
DSM	-0.0706	0.0149	-4.7312
MINTDSM	0.0033	0.0017	1.9318
D_1	-0.0097	0.0111	-0.8797
D_2	-0.0641	0.0110	-5.8512
D_3	-0.0997	0.0108	-9.2318
D_4	-0.1626	0.0110	-14.7847
D_5	-0.2145	0.0128	-16.6956
D_6	-0.2382	0.0162	-14.7000
D_7	-0.2315	0.0194	-11.9611
D_8	-0.2246	0.0188	-11.9636
D_9	-0.2074	0.0163	-12.7299
D_{10}	-0.1697	0.0129	-13.1549
D_{11}	-0.0935	0.0108	-8.6839
TREND	0.0025	5.68E-05	43.1988
C	3.9098	0.3090	12.6549

R^2	S.E.	SIC
0.97	0.0318	-6.5234

Augmented Dickey-Fuller unit root test on $\hat{u}_t$

$m = 9$, t-statistic on ρ: -3.00

(McKinnon 1% critical value: -2.58)

Table 3: The short-run effect of DSM. The dependent variable is the growth rate of energy demand (Δ e), sample period 76/10-93/12. The Schwarz criterion is used to determine the number of lagged Δ e's included in the estimation.

variable	coefficient	stand. error	t-statistic
z_{t-1}	-0.1385	0.0293	-4.7270
mintemp	-0.0027	0.0007	-3.8511
Δe_{t-1}	0.6099	0.0681	8.9562
Δe_{t-2}	-0.7412	0.0823	-9.0103
Δe_{t-3}	0.6414	0.0938	6.8354
Δe_{t-4}	-0.6101	0.1040	-5.8657
Δe_{t-5}	0.2941	0.1026	2.8682
Δe_{t-6}	-0.4224	0.0933	-4.5265
Δe_{t-7}	0.0487	0.0804	0.6062
Δe_{t-8}	-0.2012	0.0656	-3.0689
DSM	-0.0021	0.0049	-0.4384
MINTDSM	0.0004	0.0007	0.5655
D_1	-0.0748	0.0054	-13.8877
D_2	-0.0668	0.0090	-7.4334
D_3	-0.0690	0.0104	-6.6384
D_4	-0.0659	0.0119	-5.5381
D_5	-0.0462	0.0132	-3.4940
D_6	-0.0390	0.0141	-2.7616
D_7	-0.0076	0.0142	-0.5390
D_8	-0.0264	0.0124	-2.1343
D_9	-0.0204	0.0100	-2.0510
D_{10}	-0.0235	0.0077	-3.0436
D_{11}	0.0083	0.0053	1.5593
C	0.0574	0.0080	7.1399

R^2	S.E.	SIC	Q-statistic
0.97	0.0109	-8.5417	$P(Q_{20})= 0.49$

Breusch-Godfrey serial correlation LM-test
(with 4 additional lags of residuals:)
F-statistic: 1.66, P-value: 0.16

7 Figures

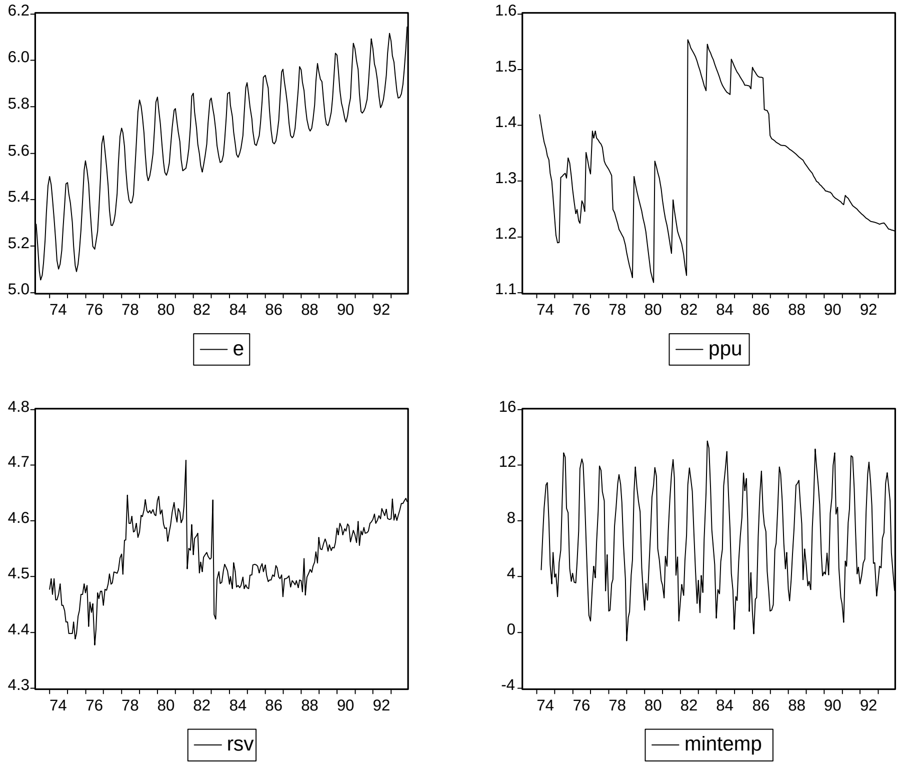

Figure 1: Time series used in the analysis. Electricity demand (e), the price per unit (ppu), the retail sales volume (rsv), all in logarithm, and the average daily minimum temperature (mintemp).

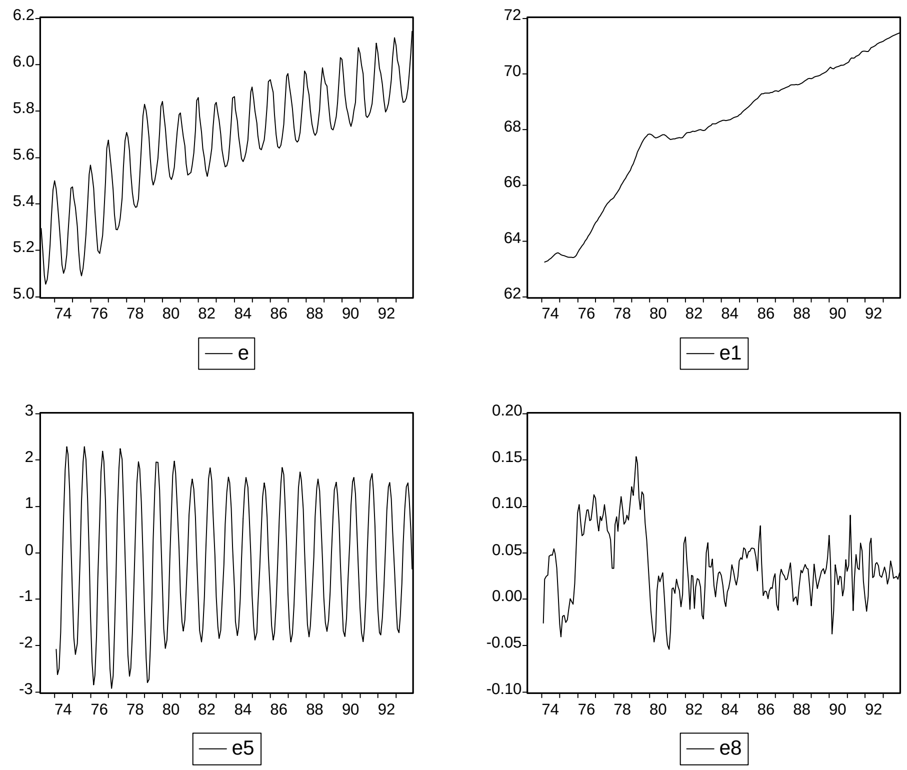

Figure 2: Electricity demand (e), its transformation retaining the long-run frequency (e1) and the one-year cycle (e5), and its twelfth difference (e8), the yearly growth rate.

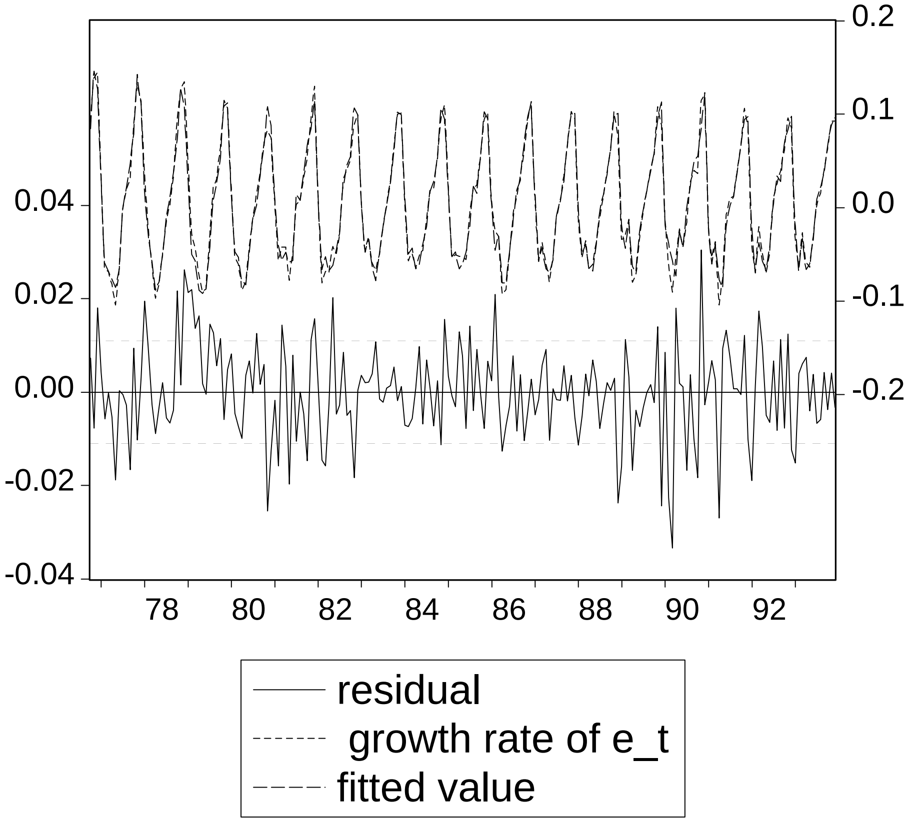

Figure 3: The actual and fitted value of the growth rate of electricity demand and the residuals of the dynamic regression.