Modelling evolutionary long-run relationships: an application to the Italian energy market

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Abstract

The paper considers a SUTSE model embedded in a dynamic framework to estimate an energy cost share model for the Italian economy in an evolutionary environment. This is achieved by allowing stochastic seasonal and trend components in the long-run specification and constructing an error correction mechanism to model short-run dynamics. Modelling instability in the structural time series approach has provided some improvement in the estimates of the elasticities of substitutions and of the price elasticities with respect to those obtained using deterministic trend and seasonal components. Tests for instability in the cointegrating regression support the evolutionary specification adopted.

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Introduction

Recent contributions to equilibrium econometric modelling would seem to point towards a richer modelling of long-run comovements in economic time series, in which not only the formulation of the long-run and its evolution, but also the transformation undergone by the economic environment is taken into account. Granger and Lee (1991) have introduced time-varying parameter cointegration theory to study situations in which it is the attractor of the system and/or the speed of adjustment which vary over time. This is to take into account the possible effects of structural change. Hall and O'Sullivan (1994) have provided an application, estimating an error correction model with time-varying speed of adjustment. Harvey (1989) has shown how to include a stochastic trend components in the error correction term and Harvey and Scott (1994) have embedded a stochastic seasonal component in the short-run specification of an error correction model. Granger and Terasvirta (1993) have introduced non-linear cointegration to model situations in which the strength of attraction of a long-run equilibrium varies according to certain rules, for instance on the basis of the gap existent between the actual and the long-run states of a process. Finally, Hall, Psaradakis and Sola (1995) have employed a finite-state Markov process with unknown transition probabilities to describe the stochastic shifts between alternative cointegrating regimes.

In the cases considered modified cointegration analysis has been found to yield a superior performance than conventional coinegration. This result may be also seen in the light of the fact that, as Clements and Hendry (1995) have pointed out, poor predictions may be the consequence of an error correction mechanism which is not correcting relative to the appropriate long-run relationship, a situation which may arise, for instance, when structural change has affected the equilibrium relation, or, as indicated by Engle *et al*. (1989), when the estimate of the cointegrating vector is inconsistent. Statistical tools to investigate stability in a cointegrating regression have recently been introduced (Gregory and Hansen 1996, Hansen 1992a,b, Quintos and Phillips 1993) and these tests may be of help in discriminating between conventional cointegration and cointegration with regime shifts.

In this paper an application to the Italian energy market is provided. Quarterly data for the period 1978q1-1994q4 have been used to estimate a dynamic factor cost share model, set in the error correction framework. After testing for instability in the cointegrating regression, the seasonal and trend components have been allowed to vary over time. The results suggest that the evolving long-run specification is more successful in describing the structural features of the Italian energy market than the conventional one. This is shown by the estimated pattern of the elasticities of substitution and of the partial price elasticities which yield values more consistent with the underlying economic theory. Some support is also provided by the forecast analysis, although contrasting outcomes are indicated by the criteria employed. While in fact parameter stability forecast tests select the structural time series specification as best forecasting model, the generalised forecast error second moment criterion suggests an opposite conclusion.

1 The model

A neoclassical model of producer behaviour, set in its dual formulation, has been specified using a translog functional form. Suppose the aggregate production function is specified with respect to capital (*K*), labour (*L*), energy (*E*), raw materials (*M*) and the level of technology (*T*):

$$Y = f\left(K, L, E, M, T\right) \tag{1}$$

The energy subsystem can be broken into the four main energy inputs (oil (E_o), electricity[1] (E_e), gas (E_g) and coal (E_c)). Under the assumption of homothetic weak separability of the production function in the four primary energy sources and of exogeneity of the factor prices and the output level (Shephard, 1953) the corresponding cost function in efficiency units may be written as

$$C = C\left(\frac{P_E}{A_E}\left(\frac{P_o}{A_o}, \frac{P_e}{A_e}, \frac{P_g}{A_g}, \frac{P_c}{A_c}\right), \frac{P_K}{A_K}, \frac{P_L}{A_L}, \frac{P_M}{A_M}, A, Y\right) \tag{2}$$

where the level of technology is composed of an index *A* of neutral technical progress and a number of indexes A_i representing factor saving technical progress. The optimisation problem may be solved in two stages (Denny and Fuss, 1975). In the first stage the economic agents optimise with respect to the fuel mix, while in the second stage the optimisation is concerned with capital, labour, materials and energy. Since the econometric model studied is concerned with the first stage alone, the hypothesis of homotheticity of the energy subsector has not been assumed a priori but has been explicitly tested. That is, total energy production enters as an additional explanatory variable in the energy model.

1: The electricity primary input is an aggregate input composed largely of hydroelectric, geothermal and nuclear energy. Nuclear energy is no longer produced internally, but imported from France in the form of electricity.

Once the aggregate energy price index $\frac{P_E}{A_E}$ is approximated by a translog cost function and an exponential augmentation form of the type $A_{jt} = A_0 e^{bt}$ is selected, partial differentiation with respect to factor prices (Shephard's Lemma) gives the following set of cost share equations

$$
\begin{aligned}
S_{ot} &= a_o + b_o t + \sum_j a_{oj} \ln p_{jt} + a_{oE} \ln E_t + u_{ot} \\
S_{et} &= a_e + b_e t + \sum_j a_{ej} \ln p_{jt} + a_{eE} \ln E_t + u_{et} \\
S_{gt} &= a_g + b_g t + \sum_j a_{gj} \ln p_{jt} + a_{gE} \ln E_t + u_{gt} \\
S_{ct} &= a_c + b_c t + \sum_j a_{cj} \ln p_{jt} + a_{cE} \ln E_t + u_{ct}
\end{aligned}
\qquad (3)
$$

where $a_i = -\sum_j a_{ij} A_0$, $b_i = -\sum_j a_{ij} b$, $i, j = o, e, g, c$ and u_{it} is a disturbance term added after differentiation. The restrictions of price symmetry and homogeneity require $a_{ij} = a_{ji} \ \forall i, j$ $i \neq j$ and $\sum_j a_{ij} = 0 \ \forall i$, $i, j = o, e, g, c$, respectively. The adding-up restriction requires that the cost shares must add up to one. This implies a singular disturbance variance-covariance matrix for the system. Therefore. the share of coal has been omitted and the remaining three cost shares have been estimated by FIML.[2]

2 Data analysis

The statistical properties of the series have been assessed by HEGY tests (Engle *et al.*, 1990). The HEGY test is carried out by estimating the auxiliary regression:

$$
\Delta^4 y_t = m + p_1 y_{1,t-1} + p_2 y_{2,t-1} + p_3 y_{3,t-2} + p_4 y_{3,t-1} + e_t \qquad (4)
$$

with

$$\Delta^4 y_t = (1 - B^4) y_t$$

$$y_{1t} = (1 + B + B^2 + B^3) y_t$$

$$y_{2t} = -(1-B)(1+B^2)y_t$$

$$y_{3t} = -(1-B^2)y_t$$

and

$$m = a_0 + \sum_{s=1}^{3} a_s D_{st} + b_0 t$$

The non rejection of the null hypothesis $p_1 = 0$ indicates the presence of a unit root at the yearly frequency. On the other hand, the non rejection of the null hypotheses $p_2 = 0$ or $p_3 = p_4 = 0$ indicates the presence of a unit root at the seasonal frequency. *Fseas* is an *F*-test for the joint statistical significance of the deterministic seasonal dummies.

As shown in table 1, the results suggest that the cost share equations system should be modelled as non-stationary, treating all of the series as I(1) processes. In addition, according to the tests, there is no evidence of stochastic seasonality at the 5% significance level and six series out of nine show signs of deterministic seasonality (P_e, S_o, S_e, S_c, S_g , E).[3]

Table 1: HEGY tests[4]

	S_o	S_e	S_g	S_c	P_o	P_e	P_g	P_c	E
π_1	-1.63	-2.22	-4.04	-0.99	-2.77	-3.15	-2.77	-3.95	-1.17
π_2	-5.57	-4.69	-4.12	-5.25	-4.85	-5.96	-4.46	-3.36	-3.38
π_3 , π_4	12.84	17.59	12.55	15.11	33.36	18.33	31.20	13.02	17.9
F seas	4.14	12.86	9.82	2.81	1.84	15.95	0.97	0.08	12.5

3 Stability analysis of the long-run equilibrium relationship

[2]: The use of ML guarantees that parameter estimates, estimated standard errors, and log-likelihood values are invariant to the choice of which equation is deleted (Berndt, 1991).

[3]: For the share of natural gas the null of unit root at the zero frequency is not rejected at the 1% level. For the coal price series ADF tests conducted on the corresponding yearly series over the period 1960-1994 suggests that a stochastic trend is an appropriate specification. The works of Shiller and Perron (1985) and Pierse and Snell (1995) indicate, in fact, that, in general, the power of unit-root tests depends more on the sample size than on the sample frequency. Then, a conclusion about the order of integration should preferably be drawn by low frequency data covering a longer time span. The results have been found to be robust to the introduction of a break components to take into account the fall in the oil price occurred in the mid 1980s.

The Engle and Granger (1987) method consists of two successive steps. In the first stage a static regression (explaining the long-run) is run and the residuals are tested for stationarity. In this first stage the weak exogeneity of the regressors is assumed. [5] In the second stage, the stationary residuals are plugged in to the error correction system and an estimate of the dynamics and of the speed of adjustment of the system is obtained. Testing for a structural break in the cointegrating regression amounts to estimating augmented cointegrating regressions, letting the position of the break point vary over a portion 0.15*T*-0.85*T* of the data set. An ADF test (ADF*) is constructed from the residuals of each cointegrating regression and the null of no cointegration is tested using the critical values tabulated by Gregory and Hansen (1996). The augmented three share equations static system in the most general form may be written as

$$\mathbf{S}_t = \boldsymbol{\beta}\mathbf{x}_t + \boldsymbol{\beta}^*\mathbf{H}_{\tau t}\mathbf{x}_t + \boldsymbol{\alpha} + \boldsymbol{\varphi}_{\tau t}\boldsymbol{\alpha}^* + \boldsymbol{\delta}t + \boldsymbol{\Psi}\boldsymbol{\Gamma}_{\tau t}\mathbf{D}_t + \mathbf{u}_t \qquad t = 1,\ldots,T \qquad \mathbf{(5)}$$

where $\mathbf{S}'_t = \left[S_{ot} \quad S_{et} \quad S_{gt}\right]$, $\boldsymbol{\beta}$ and $\boldsymbol{\beta}^*$ are matrices of coefficients of dimension (3×5), $\mathbf{x}'_t = \left[\ln p_{ot} \quad \ln p_{et} \quad \ln p_{gt} \quad \ln p_{ct} \quad \ln E_t\right]$, $\boldsymbol{\delta}$ is a (3×1) vector of parameters corresponding to the linear time trend *t*, $\boldsymbol{\alpha}$ and $\boldsymbol{\alpha}^*$ are (3×1) vectors of intercepts, $\boldsymbol{\Psi}$ is a (3×3) matrix of parameters, $\mathbf{D}'_t = \left[cs_1 \quad cs_2 \quad cs_3\right]$ is a vector of centred seasonals, $\mathbf{u}'_t = \left[u_{ot} \quad u_{et} \quad u_{gt}\right]$ with $\mathbf{u} \approx \mathbf{IN}(\mathbf{0},\boldsymbol{\Omega})$, $\mathbf{H}_{\tau t}$ is a (5×5) matrix such that $\mathbf{H}_{\tau t} = \begin{cases}\mathbf{I}_d & \text{for } t > [T\tau] \\ \mathbf{0}_d & \text{for } t \le [T\tau]\end{cases}$ and $\boldsymbol{\varphi}_{\tau t}$ and $\boldsymbol{\Gamma}_{\tau t}$ are (3×3) matrices such that $\boldsymbol{\varphi}_{\tau t}, \boldsymbol{\Gamma}_{\tau t} = \begin{cases}\mathbf{I}_3 & \text{for } t > [T\tau] \\ \mathbf{0}_3 & \text{for } t \le [T\tau]\end{cases}$. Finally, **I** is the identity matrix and **0** is a matrix of zeros.

Model (5) has been estimated by FIML under the following restrictions on the shift components:

i) Level shift (C): $\boldsymbol{\delta} = 0$, $\boldsymbol{\Gamma}_{\tau t} = \mathbf{0}_3 \ \forall t$, $\mathbf{H}_{\tau t} = \mathbf{0}_d \ \forall t$;

---

[4]: The price and total energy series are in logs.

[5]: When the parameters of interest are the cointegrating vectors and the error correction coefficients, a necessary and sufficient condition for a conditioning variable to be weakly exogenous is to be not-error correcting (Johansen 1992a, Urbain 1992). Then, weak exogeneity has been tested via *t*-ratio and *F* tests conducted on the marginal models, to check that the coefficients of the added error correction terms are zero. The null of weak exogeneity for prices and total energy has been found to be non rejected by the data (see Morana, 1997).

ii) Level shift with trend (C/T): $\Gamma_{tt} = \mathbf{0}_3 \ \forall t$, $\mathrm{H}_{tt} = \mathbf{0}_d \ \forall t$;

iii) Regime shift (C/S): $\delta = 0$.

In *i*) the structural break is modelled as a single shift in the intercept, *ii*) is model (*i*) augmented with a linear time trend while *iii*) is model *ii*) in which the slope coefficients are allowed to vary at the time of the break. In table 2 the minimum values of the statistics and the location of the estimated breakpoints in the sample are reported.

Table 2: Energy cost shares, regime shift tests.

	So		**Se**		**Sg**	
stat.	***t*-value**	**break**	***t*-value**	**break**	***t*-value**	**break**
C	-6.79***	0.51	-6.35***	0.35	-6.85***	0.65
C/T	-6.81***	0.51	-7.18***	0.35	-7.14***	0.65
C/S	-6.63**	0.51	-6.53**	0.35	-7.14***	0.25

In table 2 "***" indicates rejection of the null of no-cointegration at the 1% level, "**" at the 5% level. The critical value for the ADF* statistics are from Gregory and Hansen (1996), Table 1.

The null of no-cointegration is strongly rejected according to all of the statistics. For the quarterly shares of oil and electricity the ADF* statistics agree on the location of the break point (1983q4 and 1987q1, respectively), while for the share of natural gas the C and C/T models give the same result (1988q4). However, for the share of natural gas the values assumed by the ADF* statistics are almost always greater than the tabulated critical values, so that a clear cut selection of a single break point is not possible. Since the ADF* statistics are powerful against traditional cointegration as well, the Hansen (1992a) instability statistics should be used to discriminate between conventional cointegration and cointegration with regime shift. Hansen (1992a) has proposed three statistics, namely the SupF, the MeanF and the L_c statistics, to test the null of cointegration. The SupF and MeanF tests are a derivation of the sample-split Chow (1960) test and consist of selecting the largest value and the average value from a sequence of Chow tests, calculated over the portion $\mathrm{T} = (0.15, 0.85)$ of the data set, respectively. The L_c test is an extension of the CUSUM test and it is powerful against changes in any of the parameters of the model, not only against instability in the mean of the series. All of the tests assume the timing of the break as unknown. As in the Chow (1960) test, the null hypothesis for all of these statistics is parameter constancy. The MeanF and the L_c statistics test the null against the alternative that the parameters follow a martingale process.

These statistics have been computed using fully modified estimates of the parameters (Phillips and Hansen, 1990) while the covariance matrix of the parameters has been calculated using a quadratic spectral kernel.

Table 3: Hansen (1992a) stability analysis.

stat.	So	Se	Sg
SupF	39.70	16.47	45.88
MeanF	15.52	11.09	20.63
Lc	1.19	1.17	1.81

As is shown above, all of the statistics detect the presence of instability of various degrees. Instability would seem to be stronger in the share of gas equation than in any of the other two shares. This result, therefore, would raise the issue of whether a broader concept of cointegration than that proposed by Engle and Granger (1987) might apply. This hypothesis is investigated in the rest of the paper.

4 Long-run relationships in a changing environment.

Harvey, Henry, Peters and Wren-Lewis (1986), Slade (1989) and Harvey and Marshall (1991) have questioned the practice of modelling technical progress using a deterministic time trend, noticing that it may be too restrictive, since proxying technical progress by a deterministic trend is equivalent to assuming that technical progress has been growing at an unchanging rate throughout the span of time covered by the analysis. In particular, this would impede taking into account the idea that the dynamics of technical progress may change over the business cycle. Following the structural time series approach, a stochastic structure may be employed to model both a slowly changing seasonal movement and a change in regime occurring at an unknown point in time. To do this, a stochastic specification has been employed for the seasonal dummy variables and for the trend level.

The structural time series approach offers a framework in which the concept of equilibrium may be interpreted in a more dynamic perspective, since the comovements among economic variables may be analysed in the context of a slowly changing environment. Since the economic process is essentially a transformation process by which, under normal conditions, the economic system reproduces itself or slowly evolves, an econometric model flexible enough to capture these evolutionary features could prove to be a better approximation to reality. Stochastic structural components, therefore, have been employed to model the evolutionary environment, while prices and total energy have been employed to describe the long-run relationship. Following Harvey and Marshall (1991), the unrestricted three share equation system can be written in the seemingly unrelated time series equation (SUTSE) form as

$$
\begin{aligned}
\mathbf{S}_t &= \boldsymbol{\mu}_t + \boldsymbol{\gamma}_t + \mathbf{B}\mathbf{x}_t + \mathbf{u}_t \qquad\qquad t = 1,\dots,N \\
\boldsymbol{\mu}_t &= \boldsymbol{\mu}_{t-1} + \boldsymbol{\beta}_{T,t-1} + \boldsymbol{\eta}_t \\
\boldsymbol{\beta}_{T,t} &= \boldsymbol{\beta}_{T,t-1} \\
\boldsymbol{\gamma}_t &= -\boldsymbol{\gamma}_{t-1} - \boldsymbol{\gamma}_{t-2} - \boldsymbol{\gamma}_{t-3} + \boldsymbol{\omega}_t \\
\boldsymbol{\gamma}_{t-1} &= \boldsymbol{\gamma}_{t-2} \\
\boldsymbol{\gamma}_{t-2} &= \boldsymbol{\gamma}_{t-3}
\end{aligned}
\tag{6}
$$

where, $\mathbf{S}'_t = \begin{bmatrix} S_{ot} & S_{et} & S_{gt} \end{bmatrix}$, $\mathbf{B}$ is a matrix of coefficients of dimension (3×5) $\mathbf{x}_t$ is the vector of weakly exogenous regressors such that $\mathbf{x}'_t = \begin{bmatrix} \ln p_{ot} & \ln p_{et} & \ln p_{gt} & \ln p_{ct} & \ln E_t \end{bmatrix}$, $\mathbf{u}'_t = \begin{bmatrix} u_{ot} & u_{et} & u_{gt} \end{bmatrix}$ is the vector of irregular components with $\mathbf{u} \approx \mathbf{IN}(\mathbf{0}, \boldsymbol{\Sigma}_u)$, $\boldsymbol{\gamma}_t = \begin{bmatrix} g_{ot} \\ g_{et} \\ g_{gt} \end{bmatrix}$ is a stochastic seasonal dummy component with $g_{it} = \sum_{j=1}^{3} g_{t-j} + w_t$ $i = o,e,g$, $\boldsymbol{\omega}_t \approx \mathbf{IN}(\mathbf{0}, \boldsymbol{\Sigma}_w)$, $\boldsymbol{\mu}'_t = \begin{bmatrix} m_{ot} & m_{et} & m_{gt} \end{bmatrix}$ is the vector of trend components with $\boldsymbol{\eta} \approx \mathbf{IN}(\mathbf{0}, \boldsymbol{\Sigma}_h)$, $\boldsymbol{\beta}'_{T,t} = \begin{bmatrix} b_{oTt} & b_{eTt} & b_{gTt} \end{bmatrix}$ is the vector of drift components. The trend component is, therefore, a random walk plus drift. The error terms $\boldsymbol{\eta}, \boldsymbol{\omega}, \mathbf{u}$ driving the unobservable components are assumed to be mutually uncorrelated.

To investigate the appropriateness of the stochastic specification, three different models were estimated by the Kalman filter method. The first model is the most unrestricted one and allows for both stochastic seasonal and trend (stochastic level, fixed slope) components; the second model allows only for stochastic seasonals; finally, the third model is the most restricted one, and corresponds to the conventional static model, with fixed dummies and deterministic linear time trend. The selection of the most appropriate specification has been decided on the basis of specification and misspecification tests and of goodness of fit criteria. The equation standard error, the ratio of the prediction error variance and the mean deviation (*pev*/*md*), the Bayes-Schwarz information criterion

(BIC) and the coefficient of determination (R_S^2)[6] have been used to compare the goodness of fit and the appropriateness of the specification across the estimated models. The estimated residuals have been tested for serial correlation, heteroscedasticity and normality.

Table 3 reports the outcome of the specification tests and goodness of fit analyses, while table 4 reports the estimated standard deviations and the signal/noise ratios of the residuals driving the unobservable components. In square brackets the p-value for the Box-Ljung, heteroscedasticity (Harvey, 1989) and Doornik-Hansen normality test are reported. For the Durbin-Watson test "*" indicates rejection of the null of no serial correlation at the 5% significance level.

Table 3: Diagnostic checking and goodness of fit analysis.[7]

	So			Se			Sg		
variable	**mod. 1**	**mod. 2**	**mod. 3**	**mod.1**	**mod.2**	**mod.3**	**mod. 1**	**mod. 2**	**mod. 3**
std. err.	0.0169	0.0181	0.0184	0.0172	0.0178	0.0175	0.0119	0.0120	0.0128
Normality	4.5 [.11]	2.1 [.34]	0.6 [.75]	10 [.01]	1.0 [.61]	0.9 [.62]	1.0 [.60]	0.1 [.09]	3.4 [.18]
Heterosc.	0.5 [.93]	0.5 [.95]	1.3 [.25]	0.6 [.86]	0.7 [.82]	0.7 [.78]	0.5 [.93]	0.7 [.82]	0.9 [.60]
DW	1.95	1.01 *	1.14 *	1.81	1.11 *	1.10 *	1.7	1.5	1.6
Ljung-Box	7.9 [.35]	22 [.00]	20 [.00]	11 [.17]	14 [.05]	14 [.04]	15 [.03]	13 [.08]	20 [.00]
R^2_s	0.71	0.66	0.65	0.62	0.60	0.61	0.67	0.66	0.62
pev/md	1.17	1.20	1.11	1.27	1.16	1.19	1.14	1.08	1.24
BIC3/BIC*i*	1.1087	1.062	1 (-5.81)	1.1363	1.0744	1 (-5.92)	1.1027	1.040	1 (-6.55)

Table 4: Estimated standard deviations (q-ratio) of the residuals of the components.

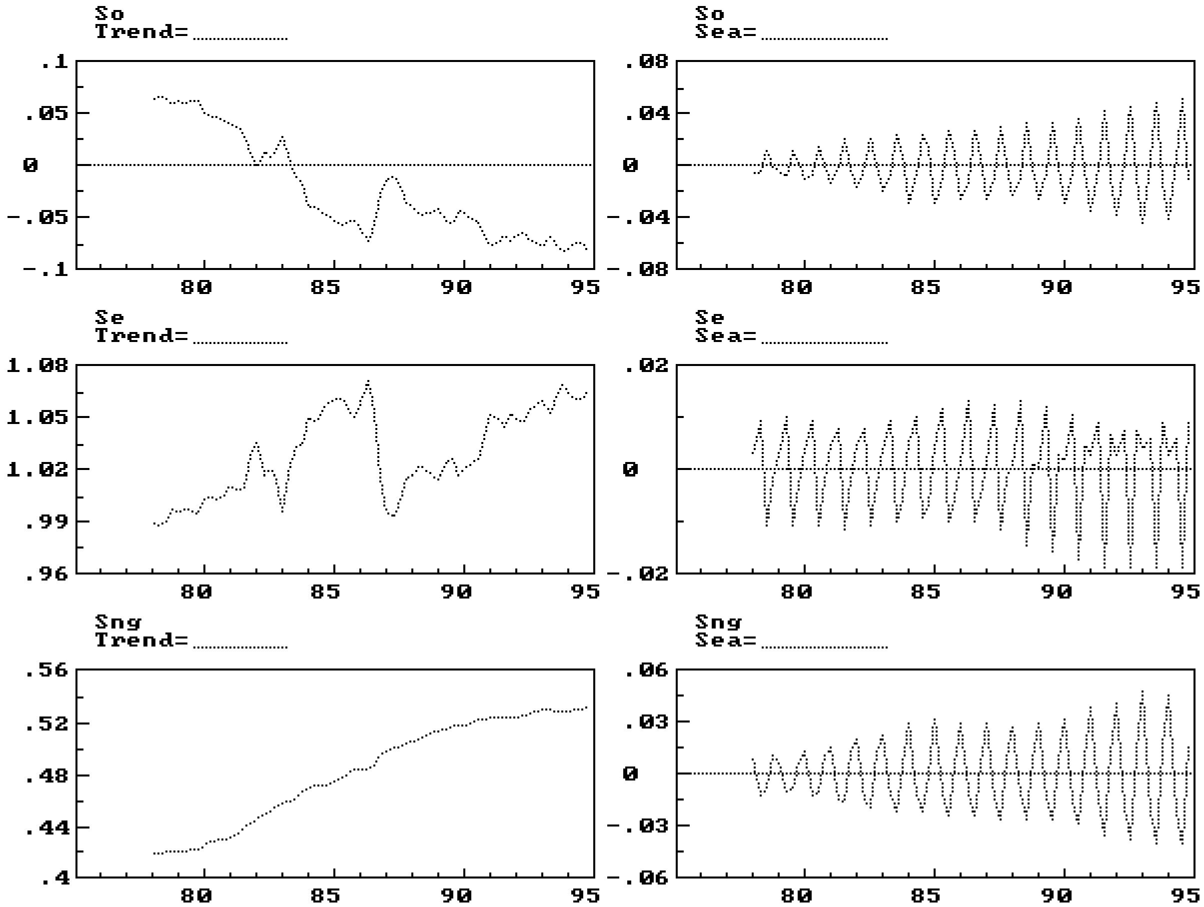
	So			Se			Sg		
comp.	**mod. 1**	**mod. 2**	**mod. 3**	**mod.1**	**mod.2**	**mod.3**	**mod. 1**	**mod. 2**	**mod. 3**
Irreg.	.006 (.48)	.018 (1.0)	.020 (1.0)	.008 (.64)	.019 (1.0)	.019 (1.0)	.008 (2.3)	.011 (1.0)	.014 (1.0)
Level	.012 (1.0)	-	-	.013 (1.0)	-	-	.004 (1.0)	-	-
Seasonal	.005 (.37)	.003 (.16)	-	.002 (.17)	.001 (.05)	-	.004 (1.0)	.003 (.28)	-

As is shown in table 4, for the shares of oil and electricity, the estimated standard deviations of the residuals of the level components are much larger than those relative to the seasonal components, and approximately of the same size for the share of natural gas. From table 3 it appears that the more the model is restricted then the lower is the non-normality of the residuals, yet higher is their serial correlation and standard errors. In particular, for the share of oil, model 2 (fixed level, stochastic seasonals) is the least satisfactory model, showing the clearest failure of the serial correlation and normality tests. As far as the share of electricity is concerned models 2 and 3 would

[6]: $R_S^2 = 1 - SSE / SSDSM$, where SSE is the residual sum of squares and SSDSM is the sum of squares of first differences around the seasonal means. See Harvey, 1989.

show almost the same performance, consistent with the very low estimated standard deviations of the seasonal component residuals. It also fails the serial correlation tests more strongly than model 3, which suffers from non-normal residuals. Finally, model 2 performs best for the share of natural gas, showing normal residuals and failing the serial correlation tests less strongly than any of the other models. Interestingly, for the share of natural gas, the most restricted model performs worst of all. As far as the goodness of fit is concerned, as it is indicated by the R_S^2 statistics and the ratios of the BIC statistics (Schwartz (Bayes) information criteria) for model 3 over models 1 and 2, in general, the less restricted is the model the better is the fit. Lastly, the pev/md (prediction error variance/prediction error mean deviation (squares)) ratio is quite close to one for all of the models. The plots of the smoothed estimated structural components for the most unrestricted models are reported in figure 1.

Figure 1: Smoothed stochastic components (fixed interval smoother).



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[7]: Normality = $\chi^2(2)$; Heteroscedasticity = F(22,22), Ljung-Box = $\chi^2(7)$, Durbin-Watson: *lower bound value* = 1.26, upper bound value = 1.939.

As can be noticed from the graphs, the trend component is very close to a deterministic linear trend for the share of natural gas. For the other two series, especially for the share of electricity, the smoothed estimates show a clear fall in the level component. This is located around the years of the 1985 oil countershock and over time, it seems to shift back to its original level only for the share of oil. As far as the seasonal component is concerned, a slowly evolving movement is quite evident for the shares of oil and natural gas. For the share of electricity the change in the seasonal behaviour seems to be more similar to a level shift which would have taken place at the beginning of the 1990s, although after 1985 the amplitude of the seasonal movement would seem to have increased as well.

The outcome of the structural time series analysis, therefore, would seem to support the less restricted specification (mod.1), which allows for stochastic seasonal and trend components.

Following Anderson and Blundell (1982), the economic restrictions of price homogeneity and symmetry have been imposed on a dynamic version of the model. The three share equation system

$$\Delta\mathbf{S}_t = \sum_{i=1}^{n}\mathbf{\Gamma}_i\Delta\mathbf{S}_{t-i} + \sum_{j=0}^{m}\mathbf{\Pi}_j\Delta\mathbf{x}_{t-j} + \mathbf{A}\left[\mathbf{S}_{t-1} - \hat{\boldsymbol{\mu}}_{t-1} - \hat{\boldsymbol{\gamma}}_{t-1} + \boldsymbol{\beta}\overline{\mathbf{x}}_{t-1}\right] + \mathbf{u}_t \qquad \textbf{(6)}$$

has been estimated by FIML, where $\Delta\mathbf{S}'_t = \left[\Delta S_{ot} \quad \Delta S_{et} \quad \Delta S_{gt}\right]$, $\Delta\mathbf{x}'_t = \left[\Delta\ln p_{ot} \quad \Delta\ln p_{et} \quad \Delta\ln p_{gt} \quad \Delta\ln p_{ct} \quad \Delta\ln E_t\right]$, $\mathbf{\Gamma}_i$ and $\mathbf{\Pi}_j$ are matrices of parameters of dimension (3×3) and (5×3), respectively, and contain zeros since the set of regressors is not common across equations, $\mathbf{A}$ is a (3×3) feedback matrix, $\mathbf{u}'_t = \left[u_{ot} \quad u_{et} \quad u_{gt}\right]$ with $\mathbf{u} \approx \mathbf{IN}(\mathbf{0},\mathbf{\Omega})$. $\hat{\boldsymbol{\mu}}'_{t-1} = \left[\hat{\mu}_{ot-1} \quad \hat{\mu}_{et-1} \quad \hat{\mu}_{gt-1}\right]$ and $\hat{\boldsymbol{\gamma}}'_{t-1} = \left[\hat{\gamma}_{ot-1} \quad \hat{\gamma}_{et-1} \quad \hat{\gamma}_{gt-1}\right]$ are the estimated smoothed trend and seasonal components, $\boldsymbol{\beta}$ is a (3×4) matrix of long-run parameters, $\mathbf{S}'_{t-1} = \left[S_{ot-1} \quad S_{et-1} \quad S_{gt-1}\right]$ is a vector of shares, and $\overline{\mathbf{x}}'_t = \left[\ln(p_{ot}/p_{ct}) \quad \ln(p_{et}/p_{ct}) \quad \ln(p_{gt}/p_{ct}) \quad \ln E_t\right]$ with $\beta_{oe} = \beta_{eo}$, $\beta_{og} = \beta_{go}$, $\beta_{eg} = \beta_{ge}$. The adding up restriction implies that each column of the coefficient matrices $\mathbf{\Gamma}_i$, $\mathbf{\Pi}_j$ and $\mathbf{A}$ adds up to zero, that is $\mathbf{i}'\mathbf{\Gamma}_i = \mathbf{0}$, $\mathbf{i}'\mathbf{\Pi}_j = \mathbf{0}$ and $\mathbf{i}'\mathbf{A} = \mathbf{0}$. In particular, the restriction $\mathbf{i}'\mathbf{A} = \mathbf{0}$ implies that in the case of a diagonal system each share has to adjust at the same speed.

Since the adding-up restrictions strongly constrain the selection of dynamics, I have preferred to let the data determine the adjustment process, by constraining the feedback matrix only. The adding-up restrictions as the other economic restrictions (price homogeneity and symmetry), however, have been imposed on the long-run structure of the model. This would guarantee that the estimates of the long-run parameters are invariant with respect to which share equation is deleted.[8]

The reduction of the econometric model has been achieved sequentially, testing the statistical significance of the deleted variables by Likelihood-Ratio (LR) tests, and by taking into account the effect of the omitted regressors on the properties of the residuals. In all of the cases the adjustment process could be taken as not interrelated, so that the adjustment in each share equation depends only on the gap between the actual and long-run values of each corresponding share and the feedback matrix is diagonal. The adding-up restriction would require, then, the same speed of adjustment for the three shares. The likelihood ratio tests for the hypothesis of a diagonal feedback matrix ($a_{ij} = 0 \quad i = 1,\ldots,3\; j = 1,\ldots,3\; i \neq j$) and for the hypothesis of equal adjustment speeds ($a_{11} = a_{22} = a_{33}$), are $c^2(6) = 4.96\,[0.55]$ and $c^2(2) = 0.40\,[0.82]$, respectively. Finally, the economic restrictions of price symmetry has not been rejected by the data ($c^2(3) = 5.41\,[0.14]$).

Table 5: Quarterly econometric model (FIML estimates).

REM	**###So**		**###Se**		**###Sg**	
variable	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**
###S*o*_1			-0.2068	.0928		
###S*e*_1			-0.2353	.1044		
###S*e*_2	0.3030	.0679			-0.2942	.0588
###S*g*_1			-0.3302	.0984		
###S*g*_2	0.8054	.1107	-0.3034	.0935	-0.5530	.0748
###ln*E*	0.1287	.0309	-0.3010	.0289	0.1711	.0199
###ln*Po*	0.2784	.0321	-0.0985	.0306	-0.1438	.0196
### ln*Po*_2	0.1075	.0264			-0.1057	.0230
### ln*Pe*_1	-0.1539	.0374	0.1931	.0380		
###ln*Pg*	-0.0786	.0310	-0.1040	.0293	0.1943	.0192
### ln*Pg*_2	-0.1014	.0250			0.0797	.0218
###ln*Pc*	-0.0457	.0169				
***ECT*_1**	-0.3101	.0941	-0.3101	.0941	-0.3101	.0941

Table 6: Quarterly econometric model, properties of the residuals. [9]

[8]: The dynamic model was estimated also with the adding-up restrictions fully imposed. The estimated speed of adjustment parameters did not show any significant difference with respect to the estimates reported.

[9]: AR 1-8 (Doornik and Hendry, 1994) = F(8,39); Normality (Doornik and Hansen, 1994) = c^2(2); ARCH 4 (Engle, 1982) = F(4,39); Heteroscedasticity (White, 1980) = F(30,16).

	###So	###Se	###Sg
s	0.0203	0.0199	0.0122
AR 1-8	1.88 [0.09]	1.80 [0.11]	1.36 [0.24]
ARCH 4	1.27 [0.30]	1.83 [0.14]	0.90 [0.47]
Normality	0.75 [0.69]	0.76 [0.68]	1.94 [0.38]
Heterosc.	0.48 [0.96]	0.80 [0.71]	0.28 [1.00]

The estimated long-run parameters from the corresponding solved dynamic model are reported below.

Table 7: Quarterly econometric model, solved long-run.

long-run	So	Se	Sg	Sc
variable	**Coeff.**	**Coeff.**	**Coeff.**	**Coeff.**
ln*E*	0.1165	-0.2588	0.1201	0.0221
ln*Po/Pc*	0.2424	-0.1142	-0.0883	-0.0444
ln*Pe/Pc*	-0.1142	0.1734	-0.0550	-0.0042
ln*Pg/Pc*	-0.0838	-0.0550	0.1359	0.0029

5 The bias of technical progress

Harvey and Marshall (1991) have shown that an estimate of the biases of technical progress (T_{it}) for the generic *i*th share (S_{it}) may be obtained by rewriting the definition of Binswanger (1974) such as

$$T_{it} = 100\left[\tilde{\mu}_{t/N} - \tilde{\mu}_{t-1/N}\right] / S_{it} \qquad \textbf{(7)}$$

where $\tilde{\mu}_{t/N}$ is the smoothed estimate of the corresponding trend component. In figures 2a-2c the annual averages of the estimated biases of technical progress for each share are plotted.

Figure 2a: Share of oil, bias of technical progress, annual average.

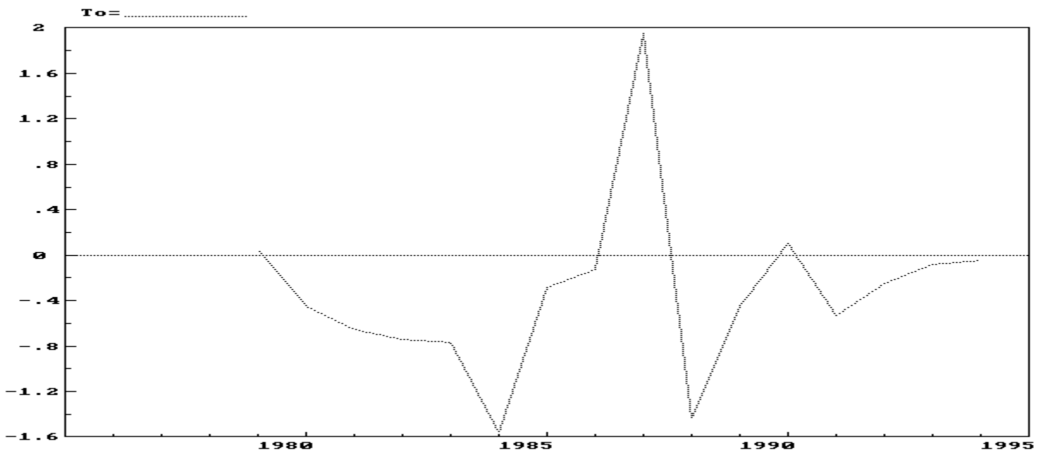


Figure 2b: Share of electricity, bias of technical progress, annual average.

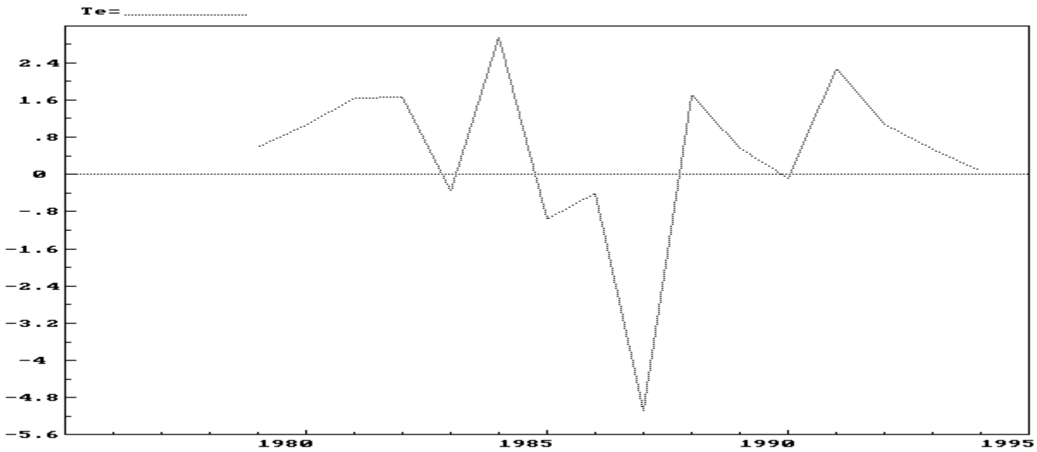


Figure 2c: Share of natural gas, bias of technical progress, annual average.

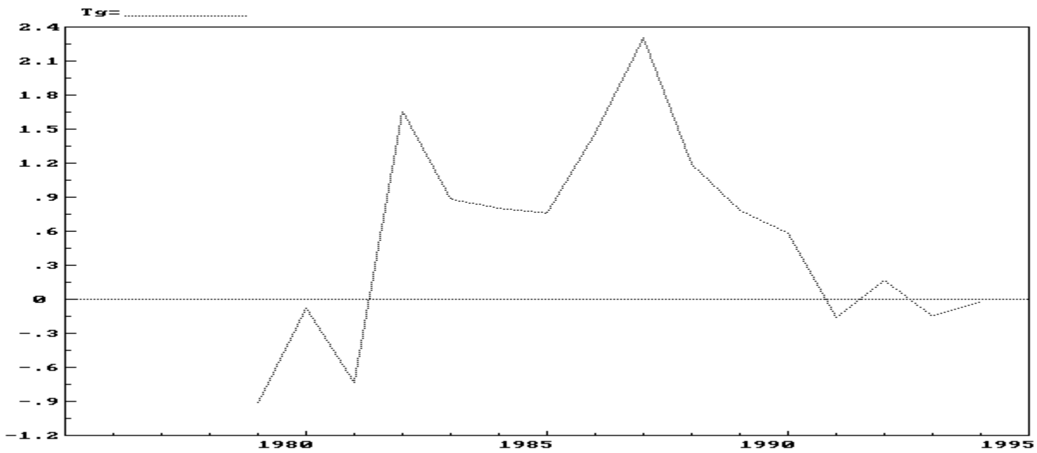
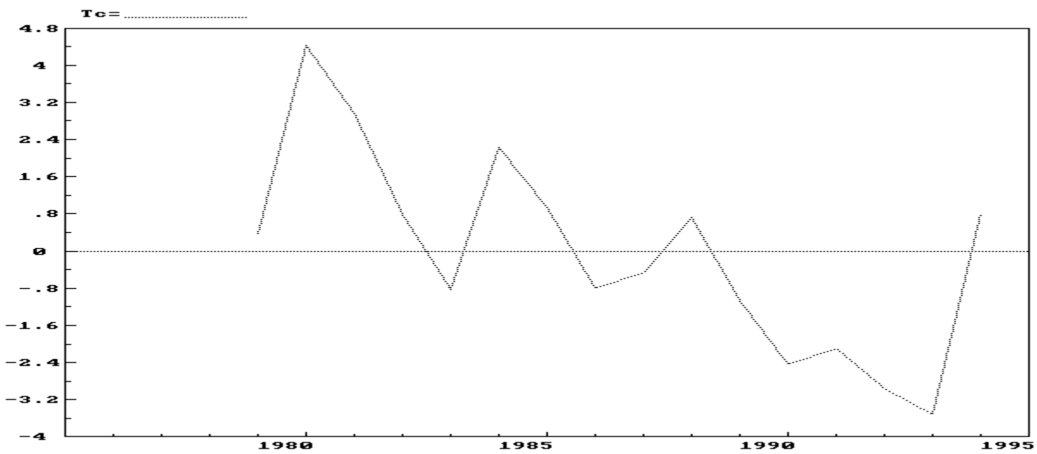


Figure 2d: Share of coal, bias of technical progress, annual average.



From the plots above it emerges that over the period 1979-1994 the biases of technical progress would have shown some variation. However, in general, apart for the period of the oil price countershock, the biases for natural gas and electricity are positive while for oil the bias is negative. On the other hand, for coal the bias is positive up to 1986 and negative thereafter. The mean rates of technical progress over the time span considered are 0.51% for electricity, 0.61% for natural gas, -0.33% for oil and -0.06% for coal. Therefore, according to the estimates above, over the period 1979-1994 technical progress in Italy would have biased towards using natural gas and electricity and saving oil and coal.

6 The process of energy substitution

The estimated parameters from the structural time series specification have been used to obtain estimates of the Allen partial elasticities of substitution and partial price elasticities. The average share over the sample has been used as the point of approximation. Substitution (σ) and price elasticities (ε) have been calculated by the formulas

$$\hat{\sigma}_{ij} = \frac{\left(\hat{\beta}_{ij} + \hat{S}_i \hat{S}_j\right)}{\hat{S}_i \hat{S}_j} \quad i \neq j \qquad\qquad \hat{\sigma}_{ii} = \frac{\left(\hat{\beta}_{ii} + \hat{S}_i^2 - \hat{S}_i\right)}{\hat{S}_i^2} \tag{8}$$

$$\hat{\varepsilon}_{ij} = \hat{S}_j \hat{\sigma}_{ij} = \frac{\left(\hat{\beta}_{ij} + \hat{S}_i \hat{S}_j\right)}{\hat{S}_i} \quad i \neq j \qquad\qquad \hat{\varepsilon}_{ii} = \hat{S}_i \hat{\sigma}_{ii} = \frac{\left(\hat{\beta}_{ii} + \hat{S}_i^2 - \hat{S}_i\right)}{\hat{S}_i} \tag{9}$$

where $i, j = o, e, g, c$, $\hat{\beta}_{ij}$ are the estimated parameters of the price variables and $\hat{S}_i$ are the estimated energy shares taken at their average values. In table 9a and 9b estimates obtained in a previous study (Morana, 1997) using a deterministic specification for the trend and seasonal components from both quarterly (1978q1-1994q4) and yearly (1960-1994) data are reported for comparison.

Table 8: Allen elasticities of substitution and partial price elasticities (structural model).

average share	Elasticities of substitution				Partial price elasticities			
	o	e	g	c	o	e	g	c
o	-0.02	0.12	0.01	-0.37	-0.01	0.03	0.00	-0.02
e		-0.13	-0.51	0.69	0.07	-0.03	-0.08	0.04
g			0.23	1.32	0.01	-0.12	0.04	0.08
c				-2.78	-0.21	0.17	0.20	-0.02

Table 9a: Allen elasticities of substitution and partial price elasticities, quarterly estimates.

average share	Elasticities of substitution				Partial price elasticities			
	o	e	g	c	o	e	g	c
o	0.11	0.25	-0.10	-0.85	0.01	0.06	-0.02	-0.05
e		0.16	-0.36	-2.01	0.14	0.04	-0.05	-0.12
g			-0.06	2.55	-0.06	-0.08	-0.01	0.15
c				9.42	-0.47	-0.48	0.39	0.55

Table 9b: Allen elasticities of substitution and partial price elasticities, yearly estimates.

average share	Elasticities of substitution				Partial price elasticities			
	o	e	g	c	o	e	g	c
o	-0.14	0.21	0.25	-0.39	-0.07	0.02	0.06	-0.01
e		-0.13	0.02	-1.09	0.11	-0.04	0.00	-0.07
g			-2.14	1.45	0.13	0.01	-0.22	0.09
c				6.71	-0.20	-0.35	0.15	0.40

As shown in the table above, the elasticities estimated using the structural time series specification are rather different from those calculated using a deterministic specification for both the trend and seasonal components. Firstly, the own price elasticities for oil, electricity and coal are of the appropriate negative sign. Only for natural gas the estimates indicate a violation of the concavity assumption at the selected point of approximation. Secondly, a different pattern of substitution among the energy inputs is suggested. According to the estimates, coal is a complement for oil while gas and electricity are a substitute for oil and coal and a complement for electricity. The only common features between the two quarterly models are the substitutability of gas and coal and of oil and electricity and the complementarity of coal and oil and of electricity and gas. On the contrary, the pattern of substitution indicated by the structural model replicates almost exactly the one suggested by the annual estimates.[10] The fact that the pattern of substitution suggested by the structural model mirrors that obtained from the annual model can be taken as evidence in favour of the appropriateness of the structural specification. [11] However, the superiority of the structural specification with respect to the conventional quarterly model should be established also on the basis of the relative forecasting performance of the error correction models embodying the different long-run specifications.

7 Forecasts analysis

The econometric models have been estimated over the period 1979q1-1989q4 and static forecasts have been computed for the period 1990q1-1994q4, that is the difference in shares have been forecast over a horizon of 20 periods. In assessing the forecasting performance of the models, two main criteria have been used, that is, 1-step ahead (static) forecasts have been evaluated by parameter constancy-based and mean squared forecast error (MSFE)-based criteria (GFESM). These two typologies of criteria offer complementary information, since parameter constancy evaluates the empirical model against the post sample realisation of the data used to estimate the model, while the MSFE evaluates the empirical model against alternative models.

Parameter constancy forecast tests are devised to test the null hypothesis of no structural change in any of the parameters between the horizon over which the model is estimated and the horizon over which it is forecast. Two statistics have been employed to test for predictive failure at the system level (Doornik and Hendry, 1994), namely

$$\mathrm{h}_1 = (nH)^{-1}\sum_{i=1}^{H}\hat{\mathbf{u}}'_{T+i}\tilde{\boldsymbol{\Omega}}^{-1}\hat{\mathbf{u}}_{T+i} \approx F(nH, T-k) \qquad \textbf{(10)}$$

$$\mathrm{h}_2 = (nH)^{-1}\sum_{i=1}^{H}\hat{\mathbf{u}}'_{T+i}\hat{\boldsymbol{\Psi}}_{T+i}^{-1}\hat{\mathbf{u}}_{T+i} \approx F(nH, T-k) \qquad \textbf{(11)}$$

where $\hat{\mathbf{u}}_{T+i}$ is a (3×1) vector of forecast errors at time $T+i$ ($\Delta\mathbf{S}_{T+i} - \Delta\hat{\mathbf{S}}_{T+i}$), $\tilde{\boldsymbol{\Omega}}$ is the variance covariance matrix of the residuals calculated from in sample information ($t = 1,\ldots,T$), $\tilde{\boldsymbol{\Psi}}_{T+i}$ is the

[10] : The only difference is that according to the quarterly structural model electricity is a complement for gas and a substitute for coal.

[11]: In a previous study (Morana, 1997) the yearly model has been found likely to provide a more reliable description of the long-run than the quarterly conventional model. This is also on the basis of the super exogeneity properties of the yearly model.

variance-covariance matrix for the forecast errors at time $T+i$, n is the number of equation in the model ($n=3$) and H is the length of the horizon over which the model is forecast ($H=20$).

The h_1 statistic, differently from the h_2 statistic, ignores parameter uncertainty, that is the fact that the parameters of the models are not known but have to be estimated. It yields a measure of numerical parameter constancy. On the other hand, the h_2 statistic can be interpreted as model specification test and it is suitable to be used in model selection.

The generalised forecast error second moment (GFESM) (Clements and Hendry, 1993) is the determinant of the complete (stacked) forecast error second moment matrix, that is

$$GFESM = \left| E\left[\hat{u}\hat{u}'\right] \right| \tag{12}$$

where $\hat{u}' = \left[\hat{u}_{o,T+1} \quad \hat{u}_{e,T+1} \quad \hat{u}_{g,T+1} \quad \dots \quad \hat{u}_{o,T+H} \quad \hat{u}_{e,T+H} \quad \hat{u}_{g,T+H}\right]$ is a $(nH \times 1)$ vector of forecasts errors, that is a vector constructed by stacking the forecast errors from the n ($n=3$) equations for each point in time ($T+1,\dots,T+H$) in a single vector. The GFESM criterion for one-step ahead forecasts may be calculated as the determinant of the estimated MSFE matrix. In the case at hand the estimated MSFE matrix is a (3×3) symmetric matrix, with the element on the main diagonal calculated as

$$MSFE_j = \frac{1}{H}\sum_{i=1}^{H}\left(\Delta S_{j,T+i} - \Delta\hat{S}_{j,T+i}\right)^2 \tag{13}$$

and the off-diagonal terms as

$$MSFE_{jk} = \frac{1}{H}\sum_{i=1}^{H}\left(\Delta S_{j,T+i} - \Delta\hat{S}_{j,T+i}\right)\left(\Delta S_{k,T+i} - \Delta\hat{S}_{k,T+i}\right) \tag{14}$$

with $j,k = o,e,g \quad j \neq k$.

The advantage given by this determinantal measure is that it takes into account the correlation existent among forecast errors at a given point in time. According to this criterion the ranking across models is attained by preferring the model with smallest GFESM. In the table below model C is the econometric model which embodies the conventional long-run specification while model S embodies the structural long-run specification.

Table 10: 1-step (ex post) forecast analysis 90 (1) to 94 (4).[12]

1-step	***C***	***S***
h_1	1.40 [.14]	1.36 [.17]
h_2	1.16 [.32]	1.10 [.39]
GFESM	3.567	4.897

From the table above it can be seen that no clear cut evidence is provided by the forecast analysis. In fact, according to the parameter constancy forecast tests, model S offers a superior performance than model C. However, the GFESM criterion would suggest an opposite conclusion.

8 Concluding remarks

The analysis carried out in this paper has provided some evidence of the presence of a slowly evolving seasonal movement in the Italian energy series, not detected by conventional HEGY tests, which a deterministic dummy specification may fail to capture appropriately. As shown by Engle, Granger and Hallman (1989), using a deterministic seasonal specification in such a situation may result in inconsistent estimates of the long-run parameters. Moreover, some instability in the trend component in the quarterly share models has been indicated as well. Modelling instability in the way described has given some improvement in the estimates of the elasticities of substitution and of the price elasticities, providing results which are more consistent with economic theory than those obtained using the conventional methodology. The structural time series approach, by allowing the detection and modelling of instability in long-run relations, would seem to be a powerful tool for long-run economic modelling. Further research in this direction should be encouraged.

[12]: h_1, h_2 = F(60,36). The GFESM figures reported are the original figures multiplied by 10^{12}.

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Appendix

A1 Data construction

Energy Prices

Source: OECD (IEA): Energy Prices and Taxes

Frequency: Quarterly (seasonally unadjusted): 1978q1-1994q4. Yearly: 1960-1994.

Definition: Industry end-user prices (MTOE) in national currency.

P_o: oil industry price; the series is a weighted average of the HFOIP (heavy oil fuel industry price)and LFOIP (light oil fuel industry price) series, with weights calculated from the Quarterly Oil Statistics and Energy Balances (OECD).

P_g: natural gas industry end-user price

P_c: steam coal industry end-user price

P_e: electricity industry end-user price

Energy Quantities:

Source: OECD (IEA): Quarterly Oil Statistics and Energy Balances and Energy Balances of OECD Countries.

Frequency: Quarterly (seasonally unadjusted): 1978q1 1994q4. Yearly: 1960-1994.

Definition: Quantities are expressed in million tons of oil equivalent (MTOE), and refers to primary energy supply.

Q_c: coal

Q_o: oil

Q_g: natural gas

Q_e: electricity; the series includes the generation of electricity from hydro/geothermal, nuclear, and the provision from electricity (net) trade.

A2 Stability analysis (graphs)

Figure 2a: Quarterly share of oil: Gregory and Hansen (1996) ADF* statistics.

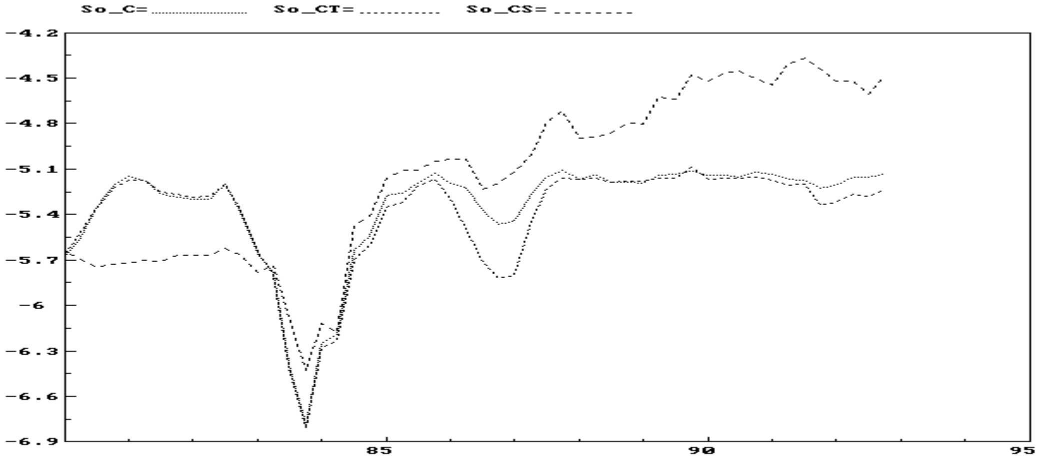


Figure 2b: Quarterly share of electricity: Gregory and Hansen (1996) ADF* statistics.

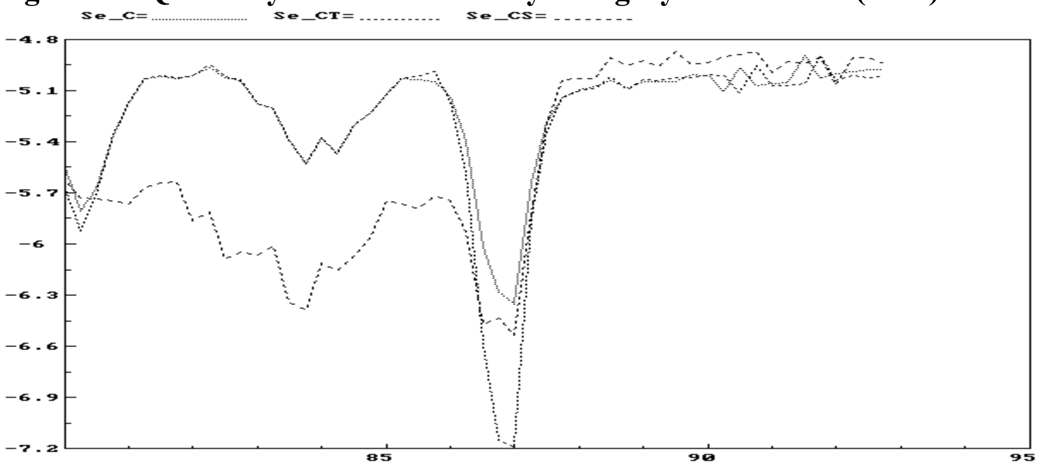


Figure 2c: Quarterly share of natural gas: Gregory and Hansen (1996) ADF* statistics.

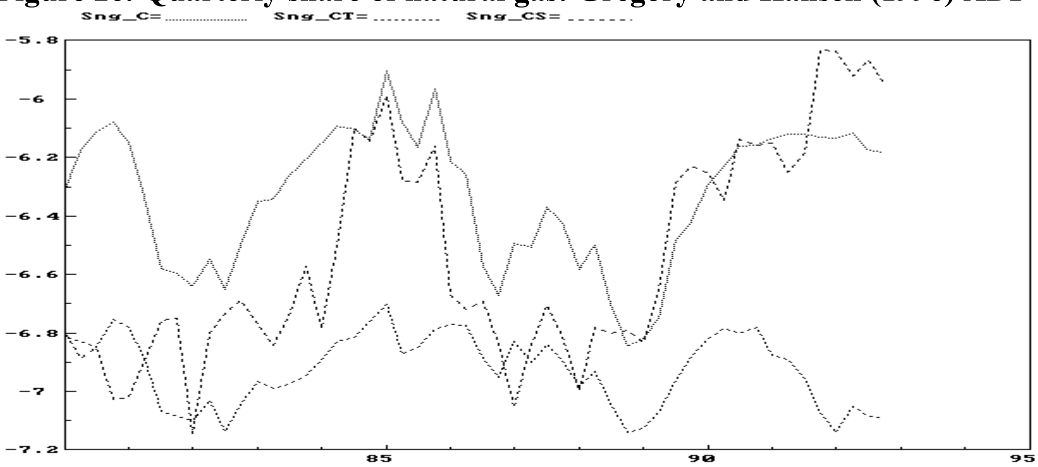


Figure 3a: Quarterly shares of oil: Hansen (1992a) SupF statistic.

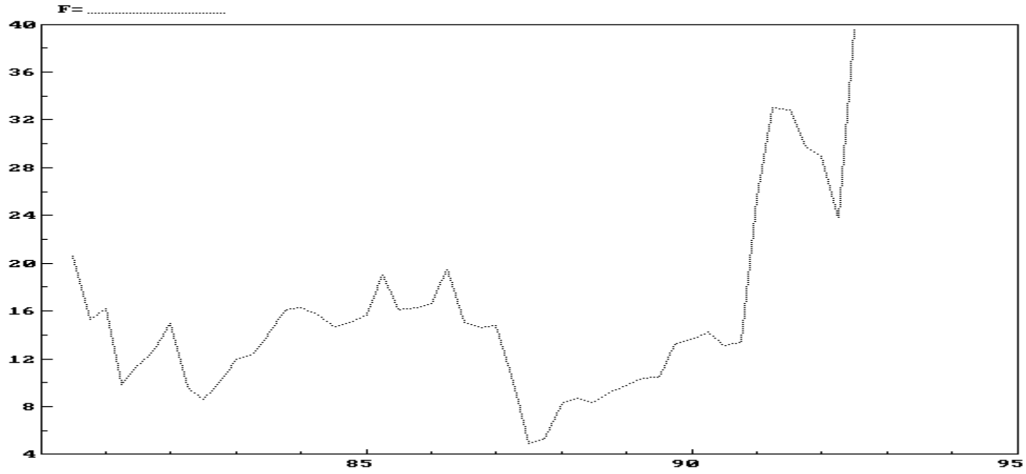


Figure 3b: Quarterly shares of electricity: Hansen (1992a) SupF statistic.

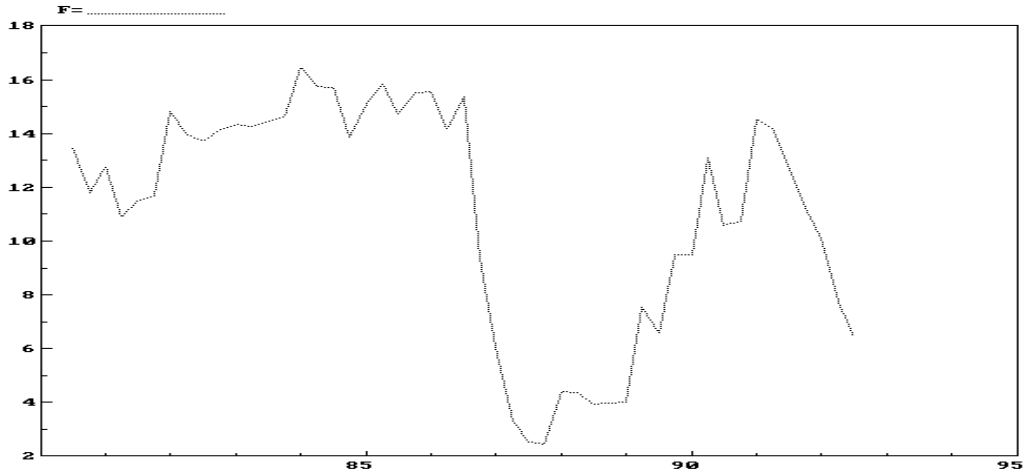
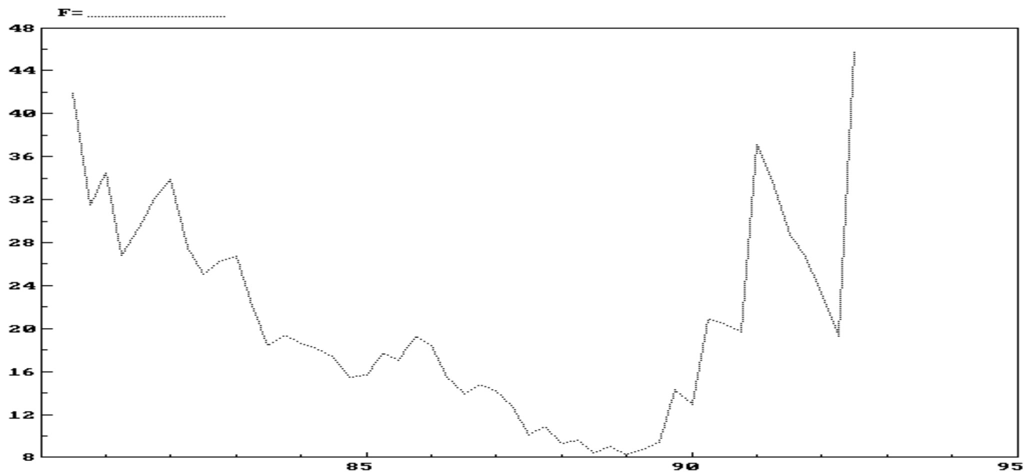


Figure 3c: Quarterly shares of natural gas: Hansen (1992a) SupF statistic.



A5 Kalman filter estimation

The state-space form of the long-run structural model is

$$\begin{aligned} \mathbf{S}_t &= \mathbf{Z}_t \boldsymbol{\alpha}_t + \mathbf{u}_t \quad t = 1,\dots,N \\ \boldsymbol{\alpha}_t &= \mathbf{T}\boldsymbol{\alpha}_{t-1} + \mathbf{R}\boldsymbol{\upsilon}_t \end{aligned} \qquad \textbf{(A1)}$$

where $\mathbf{Z}_t$ is a (3×30) matrix partitioned as

$$\mathbf{Z}_t = \begin{bmatrix} \mathbf{I}_3 & \mathbf{I}_3 & \mathbf{I}_3 & \mathbf{0}_{(3\times 6)} & (\mathbf{I}_3 \otimes \mathbf{x}'_t) \end{bmatrix} \qquad \textbf{(A2)}$$

$$\boldsymbol{\alpha}'_t = \begin{bmatrix} \boldsymbol{\mu}'_t & \boldsymbol{\beta}'_{Tt} & \boldsymbol{\gamma}'_t & \boldsymbol{\gamma}'_{t-1} & \boldsymbol{\gamma}'_{t-2} & \mathbf{B}_1 & \mathbf{B}_2 & \mathbf{B}_3 \end{bmatrix} \qquad \textbf{(A3)}$$

where $\mathbf{B}_i$ $i = 1,2,3$ is the *i*th row of matrix $\mathbf{B}$

$$\mathbf{T} = \begin{bmatrix} \mathbf{I}_3 & \mathbf{I}_3 & \mathbf{0}_{(3\times 6)} & \mathbf{0}_{(3\times 6)} & \mathbf{0}_{(3\times 6)} & \mathbf{0}_{(3\times 6)} \\ \mathbf{0}_{(3\times 3)} & \mathbf{I}_3 & \mathbf{0}_{(3\times 6)} & \mathbf{0}_{(3\times 6)} & \mathbf{0}_{(3\times 6)} & \mathbf{0}_{(3\times 6)} \\ \mathbf{0}_{(3\times 3)} & \mathbf{0}_{(3\times 3)} & -\mathbf{I}_3 & -\mathbf{I}_3 & -\mathbf{I}_3 & \mathbf{0}_{(3\times 15)} \\ \mathbf{0}_{(3\times 3)} & \mathbf{0}_{(3\times 3)} & \mathbf{I}_3 & \mathbf{0}_{(3\times 3)} & \mathbf{0}_{(3\times 3)} & \mathbf{0}_{(3\times 15)} \\ \mathbf{0}_{(9\times 3)} & \mathbf{0}_{(9\times 3)} & \mathbf{0}_{(9\times 3)} & \mathbf{I}_3 & \mathbf{0}_{(3\times 3)} & \mathbf{0}_{(3\times 15)} \\ \mathbf{0}_{(9\times 3)} & \mathbf{0}_{(9\times 3)} & \mathbf{0}_{(9\times 3)} & \mathbf{0}_{(15\times 3)} & \mathbf{0}_{(15\times 3)} & \mathbf{I}_{15} \end{bmatrix} \qquad \textbf{(A4)}$$

$$\mathbf{R} = \begin{bmatrix} \mathbf{I}_3 & \mathbf{0}_{(3\times 3)} & \mathbf{0}_{(3\times 3)} & \mathbf{0}_{(3\times 21)} \\ \mathbf{0}_{(3\times 3)} & \mathbf{0}_{(3\times 3)} & \mathbf{0}_{(3\times 3)} & \mathbf{0}_{(3\times 21)} \\ \mathbf{0}_{(3\times 3)} & \mathbf{0}_{(3\times 3)} & \mathbf{I}_3 & \mathbf{0}_{(3\times 21)} \\ \mathbf{0}_{(21\times 3)} & \mathbf{0}_{(21\times 3)} & \mathbf{0}_{(21\times 3)} & \mathbf{0}_{(21\times 21)} \end{bmatrix} \qquad \textbf{(A5)}$$

$$\boldsymbol{\upsilon}'_t = \begin{bmatrix} \boldsymbol{\eta}'_t & \mathbf{0}_{(1\times 3)} & \boldsymbol{\omega}'_t & \mathbf{0}_{(1\times 3)} & \mathbf{0}_{(1\times 3)} & \mathbf{0}_{(1\times 5)} & \mathbf{0}_{(1\times 5)} & \mathbf{0}_{(1\times 5)} \end{bmatrix} \qquad \textbf{(A6)}$$

with $\boldsymbol{\upsilon}_t \approx \mathbf{IN}(\mathbf{0}, \boldsymbol{\Omega})$.

Following Harvey (1989), once the model is set in the state-space form, ML estimation of the unknown hyperparameters (variance parameters) of the system matrices can be carried out via the Kalman filter and the prediction error decomposition. Finally, smoothed estimates of the state vector conditional on all of the sample information have been calculated by the fixed interval smoother.