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by Domenico J. Marchetti and Giuseppe Parigi

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ENERGY CONSUMPTION, SURVEY DATA
AND THE PREDICTION OF INDUSTRIAL PRODUCTION IN ITALY

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Abstract

We investigate the prediction of Italian industrial production. We first specify a model based on electricity consumption; we show that the cubic trend in such a model mostly captures the evolution over time of the electricity coefficient, which can be well approximated by a smooth transition model *à la* Terasvirta, with no gains in predictive power, though. We also analyze the performance of models based on data of different business surveys. According to basic statistics of forecasting accuracy, the linear energy-based model is not outperformed by any other single model, neither by a combination of forecasts. However, a more comprehensive set of evaluation criteria sheds light on the advantages of using the whole information available. Overall, the best forecasting performance is achieved by estimating a combined model which includes among regressors both energy consumption and survey data.

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* Banca d' Italia, Research Department.

1. Introduction[1]

Industrial production is probably the single most important indicator of the business cycle. As such, it is a key variable for policy makers. However, in most industrial countries the corresponding index is released by statistical agencies with a delay of one or two months, due to the time necessary to collect information from a large number of production plants. Such delay makes predictions of industrial production crucial for government and central banks, since they are one of the most accurate (if not the only) sources of information on current developments in aggregate supply and demand.[2]

It is not surprising, therefore, that the prediction of industrial output has attracted much attention in both the forecasting literature and the field of applied business cycle analysis. Whereas univariate methods can offer satisfactory results, they are usually outperformed by multivariate models. Predictors usually include quantitative data on inputs employed in the production process, such as the consumption of electric power, or qualitative information on the current state of industrial activity derived from surveys carried out among business managers.

In this paper we present and evaluate a number of different models for forecasting Italian industrial production. We first search for the best specification with energy consumption data and tackle the problem of choosing the proper functional form. The results of our analysis confirm that the best forecasting performance is obtained by the linear specification generally employed in the literature (see Bodo and Signorini, 1987). However, the presence of a third-degree polynomial of the trend variable in this model should be interpreted as an indication of the importance of some form of non-linearity. In particular, we argue that the cubic trend can be seen as an approximation of the evolution over time of the

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[1] We are grateful to Filippo Altissimo, Giorgio Bodo, Alberto Locarno, L. Federico Signorini and, especially, Timo Terasvirta for useful comments. The usual caveats apply. The views contained here are those of the authors only and do not necessarily reflect those of Banca d'Italia.

[2] Among other things, the industrial production index may be successfully employed to obtain early estimates of GNP (see Parigi and Schlitzer, 1995, for an application to Italian national accounts).

coefficient of energy consumption.[3] In fact, by modelling the relationship between electric power consumption and industrial production according to a smooth transition function, as suggested by Terasvirta (1994, 1996), we were able to find a specification that does not include trend terms. We also analyze the predictive power of models based on data from business surveys conducted by, respectively, Isco (the Italian national institute for business cycle analysis) and CsC, the research department of Confindustria (the Confederation of Italian industry). We then compare and combine the predictions of the different models. According to basic statistics of forecasting accuracy over the whole out-of-sample period (for example, root mean square error, highest absolute error and the results of forecast encompassing tests) the linear model based on electricity consumption is better not only than each other model individually, but also than any combination of forecasts. However, further analysis shows that this finding could be misleading, as indicated by some results of the encompassing tests. In particular, the use of alternative cost functions (rather than the minimization of squared forecast errors) and the decomposition of the out-of-sample forecasting period into different sub-periods reveal that a better forecasting performance is obtained by using all sources of information. To this end, we propose a modelling strategy that gives better results than a simple combination of the forecasts of different models.

The structure of this paper is the following. In the next section we specify, estimate and evaluate a linear model based on electricity consumption. In Section 3 we explore alternative functional forms. After rejecting a log-linear specification, we model the relationship between output and the use of electric power according to a smooth transition specification. The estimation and evaluation of models based on survey data are contained in Section 4. In Section 5 we compare and combine the forecasts of the different models, and propose a combined model. Section 6 presents the conclusions.

[3] The relationship between electricity consumption and industrial production changes over time because of the effects of technological change. Furthermore, since the only data on electricity use which are readily available refer to total consumption - i.e. including electricity consumed by households and non-industrial sectors of the economy - the relationship with industrial output may change over time according to changes in the structure of the economy and household behavior.

2. A linear model based on electricity consumption

Electricity consumption has been used to forecast industrial production in Italy since the mid-eighties (see Bodo and Signorini, 1987, and the references cited). The problems associated with the use of such data are well known. In the first place, the data that the national electricity board (Enel) makes readily available refer to overall electricity consumption, not only industrial consumption. Forecasters have therefore to control for other uses of electric power (mainly those due to households and the service sector). Secondly, the energy intensity of the production process varies significantly across industries, being highest in metalworking and chemicals. Because of composition effects, small shifts in the industry mix of production, with no change in the aggregate level of output, may cause significant changes in overall electricity consumption. Thirdly, the use of electric power as the only predictor of output corresponds to assuming a one-factor production function, which is obviously an oversimplification of real production processes. All these issues have been thoroughly discussed in the literature (see Bodo and Signorini, 1987, and Bodo, Cividini and Signorini, 1991), where a theoretical rationalization of the use of electricity consumption data has been provided along with convincing empirical evidence on their reliability in forecasting industrial production.

Accordingly, the general form of the model described in this section is the following:

$$(1) \qquad y = \alpha + \sum_{i=1}^{8} \beta_i enel_i + \sum_{i=1}^{2} \gamma_i temp^i + \sum_{i=1}^{3} \delta_i time^i + \Theta(L) y + dummies + u \,,$$

where y is the index of industrial production, $enel_i$ is total (industrial and non-industrial) electricity consumption in the i-th regional district, *temp* is the national average weather temperature, *time* is a trend variable, *dummies* are seasonal dummy variables, and $\Theta(L)$ is a polynomial in the lag operator L. Variables refer to period t, unless otherwise specified. With regard to the dependent variable, we have followed the literature and chosen to adjust the index of industrial production and the electricity consumption data for trading-day variations.[4] In the initial specification of equation (1) we considered data on electricity consumption separately by regional district, in an attempt to avoid problems due to aggregation.[5] The data on climate are included in the regression in order to control for households' consumption of electric power. In fact, most of the variation in households' use of electricity is related, directly or indirectly, to the weather (heating during cold weather, air conditioning during hot weather, etc.). More specifically, the relationship between electricity consumption and climate is known to follow a U-shape, with a minimum level corrisponding to moderate conditions (10-20 ^{0}C), and increasing consumption with extreme temperatures. A third-degree function of time is included in the model specification to capture both the trend of non-industrial electricity consumption and the long-term effects of technological change on industrial energy intensity, if any. Lagged values of the dependent variable are included to help to capture short-term dynamics. Finally, dummy variables are used to capture the strong seasonality typical of monthly data on manufacturing output, particularly in countries like Italy where in August, for example, the level of production is about a half that of the other months of the year.

Potential interactions between the seasonal and business cycles have recently been explored by Cecchetti, Kashyap and Wilcox (1997). During a boom, the presence of capacity constraints can push firms to reorganize the pattern of production over the year and, in particular, to increase production in off-peak periods. There is another source of interaction between the seasonal variability of output and the state of the business cycle, specific to the Italian economy. In recent years, industrial production data adjusted for trading days have been characterized by a strong *procyclical* seasonal effect in August and December, due to the definition of calendar trading days and growing flexibility in the setting of holidays periods by firms. In particular, during expansions, firms tend to reduce the holiday period; however, such changes are not reflected in the adjustment for working days since calendar

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4 The index of industrial production adjusted for trading days, ip_{ADJUSTED} , is given by:

$ip_{ADJUSTED} = ip_{RAW} * \frac{td_{base}}{td_t}$, where ip_{RAW} is the raw index of industrial production, td_{base} is the average monthly number of trading days in the base year, and td_t is the number of trading days in month t (see Bodo and Signorini, 1987, and the Appendix in Bodo, Cividini and Signorini, 1991).

5 Overall, there are eight Enel regional districts: Turin, Milan, Venice, Florence, Rome, Naples, Palermo and Cagliari. The first four districts refer to the North, the remainder to the Center and South of Italy.

working days are fixed. We therefore included, along with the seasonal dummy variables, two additional dummy variables, respectively for the months of August and December, interacting with a measure of demand pressure.[6] Presumably, such variables capture not only the above procyclical “spurious” impact of the adjustment for working days, but also the kind of effects described by Cecchetti, Kashyap and Wilcox (for Italian industrial production, August and December are typical off-peak periods).

Equation (1) was estimated over the period 1986.1-1995.4. Over this period, the evolution of industrial output shows significant cyclical variability (see Figure 1a). The prolonged expansion of the eighties was followed by a recession which was first mild (1990-91) and then deep (1992-19); production recovered sharply in the years 1994-95. The end of the sample was chosen so as to leave quite a long out-of-sample period to test the forecasting properties of the models. The regressors representing electricity consumption in the four districts of the Center and South of Italy were dropped from the equation because the respective coefficients were not found to be significant (not surprisingly, since most Italian industries are located in the North). Accordingly, to control for households’ electricity consumption, we used data on the average temperatures in the northern regions, rather than the national average (the two measures can differ significantly). With regard to the electricity consumption data from the four northern districts, the null hypothesis of equal coefficients could not be rejected; the equal coefficients hypothesis was not rejected also for the lagged values (up to order four) of the dependent variable (see Table 1).

The final specification was the following:

$$y = \alpha + \beta \sum_{i=1}^{4} enel_i + \sum_{i=1}^{2} \gamma_i tempn^i + \sum_{i=1}^{3} \delta_i time^i + \mu \sum_{i=1}^{4} \frac{y_{t-1}}{4} + dummies + u \,, \tag{2}$$

where *tempn* is the average monthly weather temperature in the northern regions. The overall fit of the model is good and the misspecification tests give satisfactory results; the non-stationarity of some variables (namely, industrial production and electricity consumption)

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[6] The two dummy variables are linked to the dynamics of the index of orders released by Istat (called *orders* henceforth). The first dummy variable is always zero except in August, when it is equal to $orders_{t-2}$-$orders_{t-3}$; the second dummy is always zero except in December, when it is equal to $orders_{t-2}$-$orders_{t-4}$. Similar dummy variables for the other months were not found to be significant.

does not seem to create particular problems, since the residuals are clearly stationary, as shown by the result of the augmented Dickey-Fuller test. Furthermore, the Chow test of predictive power over a 12-month period gives a satisfactory result.

By using a rolling regression technique we computed one-step and two-step ahead *ex-ante* forecasts for each month over the period 1995.5-1997.9. The predicted values closely track the real ones (the correlation coefficient is equal to 0.997; see Figure 1b).[7] Over the whole period, the forecasts are clearly unbiased; the one-step ahead mean forecast error (ME) is -0.3 per cent and the root mean square error (RMSE) is just 1.4 per cent (see Table 2, second column), which is an excellent result compared with earlier literature. The two-step ahead forecasting performance is also very satisfactory. The predictions are still unbiased, with a mean error of 0.4 per cent; the RMSE is 1.5 percentage points, only one tenth of a percentage point higher than the one-step ahead forecasts (Table 2b, second column).

3. Alternative functional forms

3.1 Log-linear versus linear specification

The most common alternative to a linear specification is the log-linear form, particularly for economic variables which evolve over time in an exponential way. This seems to be the case of Italian industrial production during the most recent expansions. Accordingly, we considered a specification such as (2) but with the logarithms of industrial output and electricity consumption. After the usual specification search we estimated the following equation:

$$(3) \qquad ly = \alpha + \beta \sum_{i=1}^{4} lenel_i + \sum_{i=1}^{2} \gamma_i tempn^i + \sum_{i=1}^{3} \delta_i time^i + \mu \sum_{i=1}^{4} \frac{ly_{t-i}}{4} + dummies + u \,,$$

where ly and $lenel_i$ are the logarithms of, respectively, y and $enel_i$, and the other variables are as defined above. As with the linear model, the diagnostics results are satisfactory (see Table 4); the forecasting performance is, however, a little worse, with an RMSE equal to 1.7.

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[7] A brief string of non-negligible forecast errors is concentrated at the beginning of 1997, in the neighborhood of the most recent turning point in the cycle of Italian industrial output (Figure 1c); however, although the size was underestimated, the sign of variation of the dependent variable in February 1997 was correctly predicted (see Section 5).

In order to compare the linear and log-linear specifications, we considered a Box-Cox transformation of *y* and *enel* with different parameters for the two variables. We estimated:

(4) $$y = \frac{y^{\lambda_1} - 1}{\lambda_1} \text{ and } enel = \frac{enel^{\lambda_2} - 1}{\lambda_2};$$

when λ_i (i=1,2) is equal to 1, the linear specification has to be used; when λ_i=0, the log-linear form is to be preferred. Our estimates over the period 1986.1-1995.4 are $\hat{\lambda}_1 =$ 0.82 (0.35), $\hat{\lambda}_2 = 1.21(0.39)$ with the standard errors in parentheses. T_2 = 0.68 (p-value 71 per cent) is the joint test for the hypothesis that the two coefficients are not different from one; it is distributed as a $\chi^2(2)$. As can be seen, our results clearly suggest that the linear specification has to be preferred.[8]

3.2 A smooth transition model of industrial output and electricity consumption

We extended our analysis of the fuctional form by focusing on the cubic trend included in (2). In particular, we addressed the question of what kind of non-linear behavior is captured by the third-degree polynomial of time and whether there is a more appropriate way of modeling it, possibly improving the explanatory power and forecasting performance of the model. In general, univariate non-linear models have been used successfully in the literature to capture the asymmetries that characterize output fluctuations (for a review, see Granger and Terasvirta, 1993).[9] Our case is somewhat different, since asymmetrical cycles of industrial production are likely to be accompanied, at least to some extent, by corresponding fluctuations in electricity consumption. However, non-linear models can prove very useful in capturing the dynamics of the link between the two variables. Here we confine ourselves to the class of smooth transition regression (STR) models, which have recently attracted the attention of economists after the work of Timo Terasvirta and others (see Lin and Terasvirta,

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[8] The same result was obtained with the test proposed by Andrews (1971) and modified by Godfrey and Wickens (1981). A sort of rolling Box-Cox specification was estimated over different sample periods and the linear specification continued to be preferred.

[9] One class of non-linear parametric models that has become increasingly popular in recent years is that of neural networks, which derive their name from their alleged analogy to the way the human brain processes information. However, though fairly powerful and flexible, neural network models require the estimation of an extensive number of parameters and are therefore potentially unstable, unlike other families of parametric models.

1994, and Terasvirta, 1996).[10] These models provide a flexible generalization of switching regression models, by allowing for a smooth transition from one regime to another. The transition variable can be time or any observable economic variable. In the former case, STR models represent one of the latest developments in the literature on structural breaks in parameters originating in the classical work of Chow (1960). Furthermore, since this class of model is locally linear, it provides a suitable alternative against which the linearity assumption can be tested.

We performed linearity tests on the parameters of (2), respectively with and without trend terms. When testing for non-linearity with smooth transition regression models, the null hypothesis is that the relationship among the variables is described by a linear model:

$$y_t = x_t^{'}\pi + u_t \,. \tag{5}$$

Initially, y_t is defined as before and x_t is the vector of all regressors on the right-hand side of (2), with the exception of the trend terms. The alternative hypothesis is that the model is non-linear:

$$y_t = x_t^{'}\psi + x_t^{'}\theta F(z_t) + u_t \,, \tag{6}$$

where F is a bounded, continuous transition function. The transition variable z_t can be any stochastic, stationary economic variable, belonging or not to x_t, or time. Two common forms of F employed in the literature are the following logistic functions:

$$F = (1 + \exp(-\gamma(z_t - \alpha)))^{-1} \tag{7}$$

and

$$F = (1 + \exp(-\gamma(z_t - \alpha_1)(z_t - \alpha_2)))^{-1} \tag{8}$$

called, respectively, the LSTR1 and LSTR2 models (Terasvirta, 1996). They are clearly bounded between zero and unity; the coefficient γ corresponds to the speed of transition between the two parameter regimes, while the α coefficients indicate when, in the range of

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[10] Earlier contributions on related issues include Bacon and Watts (1971), Farley, Hinich and McGuire (1975), Tsurumi (1980), Ohtani, Kakimoto and Abe (1990), Varoufakis and Sapsford (1991).

z_t, the transition takes place. In the literature on structural change the transition variable is typically time, which is also a suitable variable when dealing with dynamic models of a strongly cyclical variable, such as industrial production (see Lin and Terasvirta, 1994, for an application to Dutch data).

Recent developments in the literature have shown that somewhat generalized tests of linearity for models like (5), when the alternative hypothesis is specified as in equation (6) - combined with equations (7), (8) or other logistic functions - can be carried out through the estimation of the following linear auxiliary regression (see Lin and Terasvirta, 1994, and Terasvirta, 1996):

$$y_t = x_t^{'}\lambda_0 + (x_t t)^{'}\lambda_1 + (x_t t^2)^{'}\lambda_2 + (x_t t^3)^{'}\lambda_3 + u_t \,. \tag{9}$$

Linearity - which, in this context corresponds to parameter constancy - can be tested simply by assessing the statistical significance of the vectors λi (i=1,2,3) through standard F tests.[11] The tests can be applied to the whole set of variables or to some subsets of variables only, with a gain in power. In the latter case, the parameters θ in equation (6) and the corresponding parameters λ_i in equation (9) are set to zero *a priori*, and the tests are carried out on the remaining parameters. In our case, we focused on the electricity consumption variable, which is by a long way the key determinant of the dependent variable, and set λ_i = (0, 0, 0, ... $\lambda_{i,enel}$, ..., 0) for i = 1,2 and 3, where $\lambda_{i,enel}$, is the parameter corresponding to the variable $\sum_{i=1}^{4} enel_i$.[12]

We followed the testing procedure suggested by Terasvirta (1996, slightly different from that proposed by Lin and Terasvirta, 1994), which is also potentially helpful for specifying the STR model, if linearity is rejected. The first step is a rather general test of linearity, corresponding to the null hypothesis:

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[11] The distribution of the test statistics related to equation (9) is analyzed in the literature under the hypothesis of y_t being stationary, which is not the case in our specification. However, industrial production and electricity consumption are clearly cointegrated and the residuals of equation (2) are stationary and well-behaved (further evidence, in addition to the mentioned results of the augmented Dickey-Fuller test, is available from the authors).

[12] In the early stages of our research we included lagged values of the dependent variable in the set of variables to be tested for parameter constancy, and did not reject linearity.

$$(10)\qquad H_0: \lambda_1 = \lambda_2 = \lambda_3 = 0.$$

Results are reported in Table 5a. Since this hypothesis is clearly rejected, a specific form of the transition function has to be chosen. To this end, we performed a sequence of nested tests corresponding to the following hypotheses:

$$(11)\qquad H_{03}: \lambda_3 = 0;$$

$$H_{02}: \lambda_2 = 0 \mid \lambda_3 = 0;$$

$$H_{01}: \lambda_1 = 0 \mid \lambda_2 = \lambda_3 = 0.$$

All these hypotheses are clearly rejected by data. With regard to the form of the transition function, Terasvirta (1996) suggests using an LSTR1 model, unless the rejection of H_{03} is the strongest. The results obtained do not convey any clearcut indication in the matter, since the rejection of each hypothesis is equally strong. We chose the following LSTR1 specification, which seems preferable on account of its increased empirical tractability:

$$(12)\qquad y = \alpha + \beta \sum_{i=1}^{4} enel_i + \sum_{i=1}^{2} \gamma_i tempn^i + \mu \sum_{i=1}^{4} \frac{y_{t-i}}{4} + \eta * F(t) \sum_{i=1}^{4} enel_i + dummies + u$$

where *F(t)* is defined as in (7) and z_t is equal to *time*.[13]

The results of the estimation of equation (12) are very similar to those of equation (2) (see Table 6). The model appears correctly specified; the estimates of the parameters of the non-linear term are highly significant and have the expected sign. The model is also fairly stable according to the Chow test of predictive power. The shape of the estimated transition function *F(t)* indicates that the change of regime is gradual and occurs roughly in the middle of the sample period (see Figure 2).

It is interesting to compare the role of trend in equations (2) and (12). While the trend variable enters the former equation as an independent regressor, in equation (12) it appears only as a transition variable. If a trend is included in equation (12), with polynomials up to the third order, the corresponding estimates are not statistically significant. On the other

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[13] We also estimated an LSTR2 model with the constraint $\alpha_1=\alpha_2$; the results, including the forecasting performance, were not substantially different.

hand, when we tested for non-linearity in (2) - in this case, *xt* in equations (5) through (9) is the vector of all regressors appearing in (2) including the trend terms - the null hypothesis of linearity could not be rejected (Table 5b). Altogether, these results suggest that the relationship between industrial output and electricity consumption evolves over time in a way which can be properly described by a smooth transition model. The role of the third-degree polynomial of time in equation (2) can be seen as a good approximation of this dynamic relationship; indeed, the approximation is so good that, when we tested for non-linearity of energy consumption in equation (2), we did not find it.

These indications are confirmed on the forecasting ground, which is what matters most for the purposes of this paper. As with the linear model, we evaluated the forecasting performance of equation (12) over the period 1995.5-1997.9 with a rolling regression. The results are worse than those of the corresponding linear model (Table 2, third column). The one-step and two-step ahead percentage RMSEs are, respectively, 1.7 and 1.8; the size of the mean error is large (respectively, -1.1 and -1.4 per cent) and the fraction of RMSE due to bias is very high, around fifty per cent. Overall, allowing the coefficient of electricity consumption to evolve (increase) over time seems to result in a clear tendency to overpredict industrial output. In the remainder of this paper, therefore, we will consider only the linear version of the model based on electricity consumption.[14]

4. Models based on business survey data

The use of business survey data for short-term forecasting has increased significantly in recent years. In Italy a useful source of updated information on manufacturing activity is the Isco monthly survey among about 4,000 industrial enterprises. Business managers are asked a number of qualitative questions concerning, among other things, the current level of production, orders and stocks of finished goods, and short-term forecasts (3-4 months ahead) of variations in output and orders. In order to quantify the answers to these questions, we

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[14] This conclusion, of course, may depend on the particular specifications that we considered. Different results might be obtained by using alternative models. In particular, since industrial production and electricity consumption are cointegrated, one may specify a model in first differences which takes into account the cointegration relationship between the variables.This is a promising topic for future research; we are grateful to Timo Terasvirta for pointing this out to us.

have used the net percentage balance between positive ("high" level, "increase") and negative ("low" level, "decrease") replies. This is one of the most common methods of extracting quantitative information from qualitative surveys, chosen for its robustness and simplicity; other methods have been proposed in the literature, but they typically provide similar results (see for example Visco, 1984, and Pesaran, 1987, for a review). In the case of Italian industrial output, the use of survey data was introduced by Bodo and Signorini (1985, 1987) and Giovannini (1985). Models based on survey data can be particularly useful in predicting turning points, since by definition the variables used react faster to any change in the business cycle. Econometric models of this kind typically include a number of survey indicators, plus seasonal dummy variables, trend and some dynamics. We carried out a specification search in the usual estimation period, and chose the following model:

$$y = \alpha + \beta \sum_{i=4}^{6} \frac{(ord + prodex - inv)_{t-i}}{3} + \gamma \sum_{i=t_0}^{t} ordex_i \tag{13}$$

$$+ \mu \sum_{i=1}^{3} \frac{y_{t-i}}{3} + \delta (y_{t-7} - y_{t-12}) + dummies + u\,,$$

where *ord* is the level of current orders, *prodex* is 3-4 months ahead expectations concerning production, *inv* is the level of stock and *ordex* is 3-4 months ahead expectations concerning orders (all variables are net percentage balances of the corresponding replies). Rather than a trend, in order to capture the long-term behavior of industrial output we followed Gerli and Petrucci (1995) and used the accumulation of orders expectations. Given the definition of orders expectations (this variable corresponds roughly to variations in orders), its accumulation over time should contain the past behavior of demand and, hence, capture the long-term behavior of output. It does so in a rather flexible way, unlike a deterministic trend, which typically has undesired forecasting properties in the neighborhood of a turning point. The null hypothesis of equal coefficients among the lagged moving averages of *ord*, *prodex* and *inv* (the latter with a negative sign) was tested and largely accepted by the data. As usual, some lagged values of the dependent variable help to capture the short-term dynamics.

The estimates of equation (13) are reported in Table 7. The overall fit is good and the coefficients of the survey indicators are highly significant, confirming the importance of these variables. However, the result of the Chow test for predictive power indicates that the stability of the model is less than optimal. As with previous models, we analyzed the forecasting performance with rolling regressions in the out-of-sample period 1995.5-1997.9 (Figure 3). The RMSE and other statistics based on forecast errors are higher than those featured in the model based on electricity consumption (Table 2). The two-step ahead forecasting accuracy is fairly similar to the one-step ahead, which is an actractive feature of models with survey data (see also Schlitzer, 1993).

A further source of information for short-term forecasts of Italian industrial output is the monthly survey of medium and large enterprises carried out by CsC among 116 firms; managers are asked the rate of change of their firm's production in the current month, is compared with the corresponding period of the previous year. The data are then elaborated by CsC through a simple, non-econometric procedure. First, the answers are weighted by the firms' sales and aggregated to obtain sectoral estimates of the growth rate of production; these estimates are then weighted by sectoral value added in order to obtain the predicted growth rate of aggregate production. The corresponding value of the level of the production index is finally adjusted by working days. With regard to forecasting ability, the CsC model has a lower one-step ahead RMSE than the Isco model and a similar two-step ahead RMSE. However, most statistics indicate that the model based on the CsC survey is outperformed by the model based on electricity consumption.

5. Comparison and combination of forecasts and a combined model

5.1 Comparison of forecasts

All the specifications described in the previous sections show a good forecasting performance according to usual, standard statistics. More specifically, they are characterized by unbiased forecasts, with very low values for RMSE, MAE and the like. Moreover, the results of the model examined are clearly better than those obtained by a univariate ARIMA (0,1,1) (0,1,1) model used as a benchmark.[15] Simple inspection of the basic statistics based

[15] The model has non-zero moving average parameters at lags 1 and 12, with one sequential and one seasonal differentiation. It is the so called "airline model", which has been chosen as the best specification in the period of interest according to the Hannan and Rissanen (1982) procedure (see Gomez and Maravall, 1996, for a description of the procedure employed for the specification search).

on forecast errors suggests that the linear model based on electricity consumption is to be preferred (see Table 2). However, this observation lacks rigorous statistical support: in the case of the RMSE, for example, it is not straightforward to assess whether the difference in the value of the statistic across specifications is statistically significant. In order to investigate this issue, we have computed a test statistic proposed by Diebold and Mariano (1995) and subsequently modified by Harvey, Leybourne and Newbold (1997) for small samples. The advantage of this test (hereafter called MDM) is to provide a statistical procedure to compare the forecasting accuracy of two models that is robust to the forecasting errors being non-Gaussian, non-zero mean, serially correlated and simultaneously correlated. More specifically, the null hypothesis of the MDM test is given by $E\left[g(e_{1t})-g(e_{2i})\right]=0$, where e_{1t} and e_{2t} are the forecast errors of two different models, and $g(e)$ is some function of them; in particular, by choosing a quadratic loss function, the MDM test may be seen as a test of the difference between the RMSE statistics.

Table 2.1 shows the results for the various models (including a combined model which will be discussed later). The striking result is that the predictions of the different models do not appear to be clearly different from each other, with the exception of those provided by the ARIMA model. The finding of only mild differences is likely to be due to the fact that all forecasts are strongly correlated with the true value, so that it is statistically difficult to distinguish among them. To assess the superiority of a particular set of predictions a sort of forecast encompassing analysis may be applied. For this purpose, we computed the tests proposed by, respectively, Chong and Hendry (1986) and Fair and Shiller (1990); we also considered another version of the MDM test proposed by Harvey, Leybourne and Newbold (1998; EMDM hereafter). In the latter case the test statistic is similar to the MDM test, but the null hypothesis is given by $E\left[(e_{1t}-e_{2t})e1t\right]=0$. In other words, the test investigates whether the covariance between the forecasting errors of two different models is equal to zero. When the null hypothesis is true, the forecasts of the first model are said to encompass those from the second model. The results of the three tests, with regard to one-step ahead forecasts, are shown in Table 3. The linear model based on electricity data is found to encompass most of the other models; the most noticeable exception is the CsC model, according to the Chong-Hendry and EMDM tests. Similar results were obtained with two-step ahead forecasts (see Table 3.1). In this case, the energy-based model encompasses the other models, with the exception of the Isco model, according to the EMDM test. On the one hand, therefore, the encompassing analysis seems to confirm the view that the linear model based on electricity consumption is to be preferred. On the other hand, however, some of the results suggest that gains in terms of forecasting performance may be obtained by also using the data from the Isco and CsC surveys. We shall now address this problem.

5.2 Combination of forecasts

It is well know that forecasts obtained by combining predictions of different models based on independent information sets are usually superior to individual forecasts. In other words, in most cases one can improve the best single forecast by combining it with predictions from different models, even if those predictions are less accurate on a one-to-one comparison base (see, for example, Granger and Newbold, 1986, and Clemen, 1989). Basically, combining forecasts is one way to aggregate information in order to reduce uncertainty, or increase accuracy: "just as investors create diversified portfolios to reduce risk, a combined forecast can be thought of as a smaller risk of an extremely large error than an individual forecast" (Winkler, 1989, p. 606). Given the evidence provided in the previous section, we considered several combinations of the forecasts provided by the three basic models described above (equation (2), equation (13) and the CsC model), in order to maximize the forecasting ability from all the information available. We experimented with several methods of combining forecasts, with both fixed and variable weights. In the latter case we used one of the main weighting schemes proposed in the literature (see Granger and Newbold, 1986):

(14) $$\hat{w}_n^{(i)} = \left(\sum_{t=n-v}^{n-1} e_t^{(i)^2} \right)^{-1} \Bigg/ \left(\sum_{j=1}^{M} \left(\sum_{t=n-v}^{n-1} e_t^{(j)^2} \right)^{-1} \right),$$

where $\hat{w}_n^{(i)}$ is the weight to be applied to the forecasts for time n produced by the i-th model, $e^{(i)}$ is the forecasting error associated with the i-th model and M is the number of forecasting models.[16]

[16] We only report the results obtained with v=5, which were better than those obtained with v=3.

The basic statistics relating to one-step ahead predictions are reported in Table 8. The most surprising finding is that combining forecasts yields only marginal improvements on the performance of the model based on electricity consumption, in spite of an extensive search for the most effective weights. We considered three different combinations: equation (2) with equation (13), equation (2) with the CsC model, and the three models together. For each combination we conducted a preliminary search for the weights that maximize forecasting accuracy, analyzing fixed and variable weights. The results were very similar across the three combinations considered: the best combination is characterized by an RMSE of 1.3 per cent, i.e. only slightly lower than that featured by equation (2) alone. Also, in most cases the slightly better root mean square error is associated with and compensated by a worse mean error (ME) or highest absolute error (HAE). Interestingly, the results show that flexible weighting schemes, such as that of equation (14), produce forecasts that, in terms of predicting accuracy, are equal to or worse than those obtained with the simple arithmetic average or other fixed weights.

Overall, therefore, the evidence found suggests that the various combination schemes do not lead to a better forecasting performance than the simple linear model based on electricity consumption.[17] This finding is puzzling in several respects. First, it is contrary to common results in the forecasting literature, as mentioned above. Second, in our specific case it is at odds with some results of the encompassing analysis. To investigate further if and how the additional independent information provided by the Isco and CsC data can be usefully exploited, we extended our analysis in two ways. First, we divided the out-of-sample period into three subperiods, corresponding to different phases of the business cycle, and compared the performance of the models in each of them. We chose the following subperiods: 1995.5-1995.12, characterized by continuing growth; 1996.1-1996.12, a period of stagnation, and 1997.1-1997.9, a period during which production recovered (Figure 1a). The results differed widely across periods and shed light on the relative performance of each model (see Table 9). In general, the evidence found shows that forecasting industrial

[17] One possible reason for this result is that multicollinearity among the forecasts of different models may result in unstable weights, which in turn produce combined predictions that are consistently lower or higher than the individual forecasts (see Winkler and Clemen, 1987). Improvements in forecasting accuracy due to combined predictions were however found in previous research on the Italian production index (see Bodo and Signorini, 1987, Annunziato and Malgarini, 1993, and Schlitzer, 1993).

production is much easier during a period of continuing growth (such as the first subperiod) rather than in years characterized by either stagnation after growth or recovery after stagnation. The most interesting result, however, is that in each subperiod the best forecasting performance is obtained by a different individual model. During the first subperiod, the CsC model provides the most accurate forecasts (with an RMSE equal to 0.8), although the performance of equation (2) is only slightly worse; in the second subperiod the best predictions, by far, are those of the model based on electricity consumption; finally, equation (13) is the most accurate forecaster during the recovery. However, in each subperiod the accuracy of combined forecasts is still equal to, or only slightly better than that of the forecasts of equation (2) alone. Therefore, on the one hand we found that each of the individual models has forecasting properties that can be very useful in a particular phase of the business cycle (this is consistent with the results of the encompassing tests); on the other hand, it is confirmed that the simple combination of forecasts is not the best way to exploit these properties.

Further evidence of the potential contribution of each individual model to the prediction of industrial production comes from the analysis of a more comprehensive set of evaluation criteria. In particular, we considered the performance of each model (and combination of forecasts) with respect to: (i) the number of absolute forecast errors greater than a given size; (ii) the prediction of the sign of variation of the dependent variable (seasonally adjusted) in the neighborhood of a turning point, and (iii) the prediction of the sign of variation of the dependent variable in the whole out-of-sample period. The results obtained convey significant additional information on the merits of each model (see Table 10). With regard to the first criterion, equation (2) is found to outperform the other two individual models, but is on turn clearly outperformed by the combined forecast, which includes the predictions of all three single models. Consider, for example, forecasting errors equal to or greater than 2 per cent of the mean of the dependent variable in the out-of-sample period. The number of forecasting errors of this size associated with the energy-based model is six; the corresponding number is lower by one third if the forecasts of the three models are combined. Similarly, if the critical size of the error is set to 2.5 per cent, the number of forecasting errors equal to or greater than the critical size associated with equation (2) is double that of the errors associated with the combined forecast. On the contrary, the second criterion, i.e. the ability to predict turning points, shows no differences among the forecasts compared. The simulations performed show that all the individual models would have correctly predicted the sign of the variation in industrial output in the neighborhood of the two most recent turning points (January 1996 and February 1997).[18] Finally, we analyzed the ability to predict the sign of the variation on average, over the whole sample. Although the percentage of correct predictions is quite high (around eighty per cent or more) for all models, equation (13) performs considerably better than the others (it correctly forecasts the sign of variation in ninety per cent of the periods). Once again, the performance of the combined forecasts is only slightly better than that of the model based on electricity consumption (and is worse than that based on Isco data).

Overall, the evidence reported in this section suggests the following. As one would expect, a sufficiently large set of evaluation criteria shows that, consistently with some of the findings of the encompassing analysis, the information contained in Isco and CsC survey data is potentially very useful to predict the future behavior of industrial production. However, the results also show that combining the forecasts of the individual models is not the best way to exploit all the information available, in spite of the usual and well-known properties of combined forecasts. The forecaster has therefore to find an alternative way to use the information provided by all the different sources. An attempt in this direction is described in the next section.

5.3 A combined model

Exploring alternative forecasting strategies, we combined electricity consumption and Isco data in the same model (at this stage we could not include the CsC data, since they correspond to non-econometric estimates of the dependent variable itself). The specification is the following:

$$(15) \qquad y = \alpha + \beta \sum_{i=1}^{4} enel_i + \sum_{i=1}^{2} \gamma_i \, tempn^i + \delta \; time + \varphi \sum_{i=4}^{6} \frac{ord_{t-i}}{3} + \eta y_{t-1} + dummies + u \,,$$

[18] With regard to the sharp recovery in industrial output of February 1997, the sign of variation is correctly predicted by all models but the size is underestimated.

where all variables are defined as before. The results of the estimation are reported in Table 11. The overall fit of the equation is better than that of equation (2), and the Chow test for predictive power shows a clear improvement. This result is confirmed by the statistics about the forecasts (see the corresponding row of Table 8). With regard to one-step ahead forecasts, over the whole out-of-sample period the RMSE is 1.3 per cent, i.e. as low as that of the best combined forecasts, and the HAE (2.4 per cent) is considerably lower than that of any other single or combined forecast; the two-step ahead RMSE is also remarkable, being equal to just 1.3 per cent (Table 2b). Also in this case the MDM test on the equality of the RMSE does not show any significant difference with respect to the model based on electricity consumption. However, at least where one-step ahead predictions are concerned, the latter model is encompassed by equation (15). The general improvement is confirmed by looking at both the three different subperiods and the alternative evaluation criteria previously described (Tables 9 and 10). The RMSE associated with equation (15) is lower than both other models and combinations of forecasts in the second and, especially, the third subperiod, while it is slightly worse in the first subperiod. None of the forecasts obtained with this combined model generates an error equal to or greater than 2.5 per cent of the mean of the dependent variable.

To use all the information available, we finally combined the forecasts obtained with equation (15) with those of the CsC model. The results were extremely satisfactory. Over the whole out-of-sample period, the one-step ahead RMSE is as low as 1.1 per cent; in the first and second subperiods it is down to, respectively, 0.7 and 0.8 per cent, while in the third subperiod it is higher but still among the best performances for that specific sample; the sign of variation of the dependent variable is correcly predicted in ninety-three per cent of the periods.

The above exercise should be interpreted as an effort to show that all the information provided by independent sources on a given phenomenon may be of some value and therefore should be used. The particular manner in which we combined electricity consumption, Isco and CsC data is conditional on the period we considered. The crucial point is that typical problems encountered in forecasting practice (collinearity, uncertainty, instability) may be somehow counteracted by a proper combination of different predictions.

The combination rule has to be robust to these problems and should change according to circumstances; in this regard, the experience of the forecaster may play a crucial role.

6. Conclusions

Forecasters of Italian industrial production face the problem of fully exploiting the rich information provided by several independent sources. With respect to the existing literature, our main contribution is two-fold. First, we have focused on the functional relationship between industrial production and electricity consumption. This relationship has been found to be highly non-linear. In particular, we show that it can be well approximated by a smooth transition regression model *à la* Terasvirta (1994, 1996). Although we obtained no gains in predictive power, the results suggest that some improvement may indeed be obtained by other specifications within that class of model or by varying coefficient estimators (e.g. Kalman filter). Another promising area for future research is the interaction between seasonality and the business cycle. We only touched on this issue by including some *ad hoc* dummy variables in the regressions.

The other main result of this paper concerns the optimal use of all the available information. We compared three models that use, respectively, data on electricity consumption and data from Isco and CsC business surveys. Over the whole out-of-sample period, simple statistics based on forecasting errors indicate that the model with electricity data is to be preferred. On the other hand, the results of the forecast encompassing analysis suggest that the information content of Isco and CsC data can help to improve the forecasting performance. Quite surprisingly, however, a combination of the predictions of the three models was found to yield only marginal improvements, contrary to common results in the forecasting literature. We therefore further investigated the relative merits of each model. For this purpose, we divided the out-of-sample period into three subperiods; we also analyzed a larger set of evaluation criteria. The results clearly show that the data from Isco and CsC surveys may provide a significant additional contribution to the prediction of industrial output. They also confirmed that, in spite of the search for the most effective weights, a simple combination of forecasts was not the best way to exploit this potential contribution, at least in the period considered. In the search for an alternative modelling and forecasting strategy, we found that the optimal use of all the information available was achieved by specifying an econometric model which includes data on electricity consumption and data from the Isco survey and then combining the forecasts of this model with those of the non-econometric CsC model.

Table 1

LINEAR MODEL WITH ELECTRICITY CONSUMPTION - EQUATION (2)
ESTIMATION AND DIAGNOSTICS
(1986.1-1995.4)

Variables	*Coefficients*	*t-statistics*
$\Sigma enel_i$	0.008	12.5
time	1.480	3.5
$time^2$	-0.011	-4.0
$time^3$	0.001	4.2
tempn	1.088	5.5
$tempn^2$	-0.048	-6.3
moving average of y	0.284	4.12

$\overline{R}^2 = 0.99$
S.E. = 1.19
number of obs. = 112

Misspecification tests
(percent p-value in parentheses)

Autocorrelation			*Heteroskedasticity*		
DW	1.87		$ARCH_{1-12}$	9.94	(62.1)
LM_{1-12}	1.04	(42.4)			
LB_{12}	28.65	(23.4)			
General specification			*Predictive power*		
RESET	0.35	(70.5)	CHOW	1.69	(8.0)
Unit root test on residuals					
ADF	-6.9				

Note: The dependent variable and electricity consumption data are adjusted for trading days. Regression also includes a constant and seasonal dummy variables.
Legend: S.E. standard error of regression; DW Durbin-Watson statistic; LM_{1-12} modified Lagrange multiplier test for residual autocorrelation of order 1 through 12, F(12,79); LB Ljung-Box test for residual autocorrelation, $\chi^2(24)$; CHOW Chow test of predictive power over the period 1995.5-1996.4, F(12,103); RESET test of functional form, F(2,89); $ARCH_{1-12}$ autoregressive conditional heteroskedasticity test for residuals of order 1 through 12, $\chi^2(12)$; ADF augmented Dickey-Fuller test (1% critical value: -5.8).

Table 2

ANALYSIS OF FORECASTING PERFORMANCE
(1995.5-1997.9)

a) One-step ahead

Statistics (percentage values)	Arima	Eq. (2)	Eq. (12)	Isco	CsC	Eq. (15)
RMSE	2.9	1.4	1.7	2.0	1.7	1.3
ME	-0.5	-0.3	-1.1	-0.1	-0.8	0.6
MAE	2.0	1.1	1.4	1.5	1.4	1.0
HAE	7.6	3.2	4.0	5.4	3.5	2.4
Regression coefficient of actual on predicted	1.013	1.013	1.015	1.019	1.00	1.01
Fraction of RMSE due to:						
bias	0.02	0.05	0.48	0.00	0.22	0.25
difference of slope from unity	0.01	0.03	0.02	0.02	0.00	0.01
residual variance	0.97	0.92	0.50	0.98	0.78	0.74

b) Two-step ahead

Statistics (percentage values)	Arima	Eq. (2)	Eq. (12)	Isco	CsC	Eq. (15)
RMSE	3.1	1.5	1.8	2.1	2.1	1.3
ME	-0.5	-0.4	-1.4	-0.1	-0.9	0.7
MAE	2.4	1.2	1.6	1.6	1.9	1.1
HAE	7.2	3.3	4.1	5.4	3.6	2.6
Regression coefficient of actual on predicted	1.013	1.008	1.012	1.017	.995	1.007
Fraction of RMSE due to:						
bias	0.03	0.07	0.57	0.00	0.19	0.29
difference of slope from unity	0.00	0.01	0.01	0.02	0.00	0.01
residual variance	0.97	0.92	0.42	0.98	0.81	0.70

Legend: RMSE root mean square error; ME mean error; MAE mean absolute error; HAE highest absolute error.

Table 2.1

MODIFIED DIEBOLD-MARIANO (MDM) TEST
(1995.5-1997.9)

a) One-step ahead

	Arima	Eq. (12)	Isco	CsC	Eq. (15)
Arima	-	-	2.4	2.2	2.5
Eq. (2)	-2.4	-1.5	-1.6	-1.8	0.7
Eq. (12)	-2.0	-	-0.7	-0.3	1.7
Isco	-	-	-	0.7	1.7
CsC	-	-	-	-	2.4

b) Two-step ahead

	Arima	Eq. (12)	Isco	CsC	Eq. (15)
Arima	-	-	2.7	2.1	2.6
Eq. (2)	-2.8	-1.1	-1.5	-1.9	-2.3
Eq. (12)	-2.1	-	-0.5	-1.0	-0.5
Isco	-	-	-	-0.1	0.3
CsC	-	-	-	-	0.3

Note: According to Harvey, Leybourne and Newbold (1997), in small samples the statistic is distributed as a Student t with n-1 degrees of freedom, where n is the number of forecast periods.

Table 3

COMPARISON OF ONE-STEP AHEAD FORECASTS
(1995.5-1997.9)

	Arima	Eq. (2)	Eq. (12)	Isco	CsC	Eq. (15)
			(a) Fair-Shiller test[1]			
Eq. (2) and Arima	-0.8	13.7	-	-	-	-
Eq. (12) and Arima	-0.2	-	11.6	-	-	-
Eq. (2) and eq. (12)	-	2.4	0.3	-	-	-
Isco and Arima	-2.2	-	-	5.7	-	-
Isco and eq. (2)	-	8.0	-	0.1	-	-
Csc and Arima	0.1	-	-	-	8.1	-
Csc and eq. (2)	-	4.6	-	-	0.1	-
Csc and Isco	-	-	-	1.6	4.2	-
Eq. (15) and eq. (2)	-	0.5	-	-	-	4.0
Eq. (15) and Isco	-	-	-	-0.8	-	9.0
Eq. (15) and Csc	-	-	-	-	1.2	8.0
			(b) Chong-Hendry test[2]			
Eq. (2) and Arima	0.1 (0.9)	0.9 (10.2)	-	-	-	-
Eq. (12) and Arima	0.1 (0.4)	-	1.0 (11.3)	-	-	-
Eq. (2) and eq. (12)	-	0.3 (.8)	0.8 (2.4)	-	-	-
Isco and Arima	-0.5 (-1.9)	-	-	1.5 (6.1)	-	-
Isco and eq. (2)	-	0.8 (6.2)	-	0.2 (1.5)	-	-
Csc and Arima	-0.2 (-1.5)	-	-	-	1.2 (8.5)	-
Csc and eq. (2)	-	0.7 (3.9)	-	-	0.3 (1.9)	-
Csc and Isco	-	-	-	0.2 (0.8)	0.8 (4.2)	-
Eq. (2), Isco and Csc		0.7 (3.7)		0.1 (.4)	0.3 (1.2)	
Eq. (15) and eq. (2)	-	-0.1 (-0.1)	-	-	-	1.0 (3.3)
Eq. (15) and Isco	-	-	-	0.1 (0.5)	-	1.0 (7.7)
Eq. (15) and Csc	-	-	-	-	0.2 (1.8)	0.8 (5.6)
			(c) Encompassing test (EMDM)[3]			
Eq. (2)	0.7	-	0.4	1.9	2.0	3.5
Eq. (12)	1.0	2.5	-	2.3	1.5	4.6
Arima	-	2.9	3.0	2.7	2.6	2.8
Isco	-1.5	2.3	2.3	-	1.9	2.4
CsC	-0.8	2.5	2.7	1.6	-	2.8
Eq. (15)	1.1	2.0	2.4	1.1	2.2	-

(1) The table shows White-consistent t-values of the estimates of the coefficients α_1 and α_2 in the regression: $(Y_t-Y_{t-12})/Y_{t-12}$ = constant + α_1 $(PREV1_t-Y_{t-12})/Y_{t-12}$ + α_2 $(PREV2_t-Y_{t-12})/Y_{t-12}$, where PREV1 and PREV2 are the forecasts produced by the two models being compared (see Fair and Shiller, 1990).
(2) The table shows estimates (White-consistent t-values in parentheses) of the coefficients α_1 and α_2 in the regression: Y_t = constant + α_1*$PREV1_t$ + α_2*$PREV2_t$ (see Chong and Hendry, 1986).
(3) See Harvey, Leibourne and Newbold (1998). In small samples the test statistic is distributed as a Student t with n-1 degrees of freedom, where n is the number of periods for which forecasts are available.

COMPARISON OF TWO-STEP AHEAD FORECASTS
(1995.5-1997.9)

	Arima	Eq. (2)	Eq. (12)	Isco	CsC	Eq. (15)
			(a) Fair-Shiller test[1]			
Eq. (2) and Arima	-1.8	12.4	-	-	-	-
Eq. (12) and Arima	-1.0	-	11.0	-	-	-
Eq. (2) and eq. (12)	-	1.7	1.2	-	-	-
Isco and Arima	-4.0	-	-	9.6	-	-
Isco and eq. (2)	-	8.1	-	-0.1	-	-
Csc and Arima	-0.2	-	-	-	7.9	-
Csc and eq. (2)	-	5.1	-	-	-0.2	-
Csc and Isco	-	-	-	2.7	3.2	-
Eq. (15) and eq. (2)	-	6.8	-	-	-	-0.2
Eq. (15) and Isco	-	-	-	-0.4	-	1.9
Eq. (15) and Csc	-	-	-	-	2.5	2.9
			(b) Chong-Hendry test[2]			
Eq. (2) and Arima	0.1 (0.5)	1.0 (9.2)	-	-	-	-
Eq. (12) and Arima	0.0 (0.1)	-	1.0 (11.7)	-	-	-
Eq. (2) and eq. (12)	-	0.1 (0.3)	0.9 (3.6)	-	-	-
Isco and Arima	-0.4 (-1.8)	-	-	1.4 (6.1)	-	-
Isco and eq. (2)	-	0.8 (5.3)	-	0.2 (1.4)	-	-
Csc and Arima	-0.2 (-1.0)	-	-	-	1.2 (6.4)	-
Csc and eq. (2)	-	0.7 (4.8)	-	-	0.3 (1.8)	-
Csc and Isco	-	-	-	0.4 (2.0)	0.6 (2.9)	-
Eq. (2), Isco and Csc	-	0.7 (4.0)	-	0.1 (0.6)	0.2 (1.1)	-
Eq. (15) and eq. (2)	-	0.8 (4.7)	-	-	-	0.2 (1.0)
Eq. (15) and Isco	-	-	-	0.2 (0.4)	-	0.8 (1.4)
Eq. (15) and Csc	-	-	-	-	0.5 (2.6)	0.5 (2.2)
			(c) Encompassing test (EMDM)[3]			
Eq. (2)	0.4	-	0.7	3.2	1.6	1.4
Eq. (12)	1.2	2.4	-	2.7	1.3	2.4
Arima	-	3.4	3.4	3.1	2.8	3.2
Isco	-1.9	2.3	2.4	-	1.5	1.3
CsC	-0.5	2.7	3.3	2.3	-	2.1
Eq. (15)	-1.2	3.0	2.2	0.5	1.7	-

(1) The table shows White-consistent t-values of the estimates of the coefficients α_1 and α_2 in the regression: $(Y_t-Y_{t-12})/Y_{t-12}$ = constant + α_1 $(PREV1_t-Y_{t-12})/Y_{t-12}$ + α_2 $(PREV2_t-Y_{t-12})/Y_{t-12}$, where PREV1 and PREV2 are the forecasts produced by the two models being compared (see Fair and Shiller, 1990).
(2) The table shows estimates (White-consistent t-values in parentheses) of the coefficients α_1 and α_2 in the regression: Y_t = constant + α_1*$PREV1_t$ + α_2*$PREV2_t$ (see Chong and Hendry, 1986).
(3) See Harvey , Leibourne and Newbold (1998). In small samples the test statistic is distributed as a Student t with n-1 degrees of freedom, where n is the number of forecast periods.

LOG-LINEAR MODEL WITH ELECTRICITY CONSUMPTION-EQUATION (3)
ESTIMATION AND DIAGNOSTICS
(1986.1-1995.4)

Variables	*Coefficients*	*t-statistics*
$\Sigma lenel_i$	0.738	10.3
time	0.016	3.4
$time^2$	-0.0001	-3.9
$time^3$	0.000	4.1
tempn	0.011	4.6
$tempn^2$	-0.001	-5.1
moving average of ly	0.321	4.9

$\overline{R}^2 = 0.99$
S.E. =0.0134
number of obs. = 112

Misspecification tests
(percent p-value in parentheses)

Autocorrelation			*Heteroskedasticity*		
DW	1.92		$ARCH_{1-12}$	3.85	(98.6)
LM_{1-12}	0.83	(61.8)			
LB_{12}	30.00	(18.5)			
General specification			*Predictive power*		
RESET	0.35	(70.9)	CHOW	1.95	(1.1)
Unit root test on residuals					
ADF	-6.3				

Note: The dependent variable and electricity consumption data are adjusted for trading days. Regression also includes a constant and seasonal dummy variables.
Legend: S.E. standard error of regression; DW Durbin-Watson statistic; LM_{1-12} modified Lagrange multiplier test for residual autocorrelation of order 1 through 12, F(12,79); LB Ljung-Box test for residual autocorrelation, $\chi^2(24)$; RESET test of functional form, F(2,89); CHOW Chow test of predictive power over the period 1995.05-1997.04, F(24,115); $ARCH_{1-12}$ autoregressive conditional heteroskedasticity test for residuals of order 1 through 12, $\chi^2(12)$; ADF augmented Dickey-Fuller test (1% critical value: -5.8).

Table 5

LINEARITY TESTS

$$y_t = x_t'\lambda_0 + (x_t t)'\lambda_1 + (x_t t^2)'\lambda_2 + (x_t t^3)'\lambda_3 + u_t$$

$\lambda_i = (0, 0, 0, \ldots \lambda_{i,\, enel}, \ldots, 0)$

(1986.1-1995.4)

(a) x_t does not include cubic trend

Null hypothesis	*F-statistic (d.f.)*	*p-value (per cent)*
H_0: $\lambda_1 = \lambda_2 = \lambda_3 = 0$	46.3 (2,92)	0.00
H_{03}: $\lambda_3 = 0$	13.9 (1,91)	0.03
H_{02}: $\lambda_2 = 0 \mid \lambda_3 = 0$	25.9 (1,92)	0.00
H_{01}: $\lambda_1 = 0 \mid \lambda_2 = \lambda_3 = 0$	45.5 (1,93)	0.00

(b) x_t includes cubic trend

Null hypothesis	*F-statistic (d.f.)*	*p-value (per cent)*
H_0: $\lambda_1 = \lambda_2 = \lambda_3 = 0$	0.42 (3,88)	74.26
H_{03}: $\lambda_3 = 0$	0.14 (1.88)	70.67
H_{02}: $\lambda_2 = 0 \mid \lambda_3 = 0$	0.10 (1.89)	75.41
H_{01}: $\lambda_1 = 0 \mid \lambda_2 = \lambda_3 = 0$	1.03 (1,90)	31.40

Table 6

NON LINEAR MODEL WITH LSTR1 SPECIFICATION - EQUATION (12)
ESTIMATION AND DIAGNOSTICS
(1986.1-1995.4)

Variables and parameters	*Coefficients*	*t-statistics*
$\Sigma enel_i$	0.008	13.3
tempn	1.048	5.6
$tempn^2$	-0.047	-6.5
moving average of y	0.394	7.5
η	-0.001	-5.2
γ	0.059	5.9
α	139.1	29.4

$\bar{R}^2 = 0.99$
S.E. = 1.28
number of obs. = 112

Misspecification tests
(percent p-value in parentheses)

Autocorrelation			*Heteroskedasticity*		
DW	1.89		$ARCH_{1-12}$	12.76	(38.7)
LM_{1-12}	1.04	(42.2)			
LB	27.21	(29.5)			
General specification			*Predictive power*		
RESET	0.77	(46.4)	CHOW	1.80	(5.8)
Unit root test on residuals					
ADF	-7.0				

Note: The dependent variable and electricity consumption data are adjusted for trading days. Regression also includes a constant and seasonal dummy variables.
Legend: S.E. standard error of regression; DW Durbin-Watson statistic; LM_{1-12} modified Lagrange multiplier test for residual autocorrelation of order 1 through 12, F(12,81); LB Ljung-Box test for residual autocorrelation, $\chi^2(24)$; CHOW Chow test of predictive power over the period 1995.5-1997.4, F(12,105); RESET test of functional form, F(2,91); $ARCH_{1-12}$ autoregressive conditional heteroskedasticity test for residuals of order 1 through 12, $\chi^2(12)$; ADF augmented Dickey-Fuller test (1% critical value: -5.8).

MODEL WITH ISCO SURVEY DATA - EQUATION (13)
ESTIMATION AND DIAGNOSTICS
(1986.1-1995.4)

Variables	*Coefficients*	*t-statistics*
$\Sigma \dfrac{(ord + prodex - inv)}{3}$	0.077	5.1
Σ ordex	0.006	4.8
moving average of y	0.369	3.1
y_{t-7} - y_{t-12}	-0.192	-2.8

$\overline{R}^2$ = 0.99
S.E. = 1.79
number of obs. = 112

Misspecification tests
(percent p-value in parentheses)

Autocorrelation			*Heteroskedasticity*		
DW	1.95		$ARCH_{1-12}$	8.08	(77.9)
LM_{1-12}	0.98	(47.3)			
LB	22.6	(54.3)			
General specification			*Predictive power*		
RESET	0.78	(46.2)	CHOW	2.23	(1.5)
Unit root test on residuals					
ADF	-7.1				

Note: The dependent variable and electricity consumption data are adjusted for trading days. Regression also includes a constant and seasonal dummy variables.
Legend: S.E. standard error of regression; DW Durbin-Watson statistic; LM_{1-12} modified Lagrange multiplier test for residual autocorrelation of order 1 through 12, F(12,83); LB Ljung-Box test for residual autocorrelation, $\chi^2(24)$; CHOW Chow test of predictive power over the period 1995.5-1996.4, F(12,107); RESET test of functional form, F(2,93); $ARCH_{1-12}$ autoregressive conditional heteroskedasticity test for residuals of order 1 through 12, $\chi^2(12)$; ADF augmented Dickey-Fuller test (1% critical value: -5.8).

Table 8

COMBINATION OF ONE-STEP AHEAD FORECASTS
(1995.5-1997.9)

	RMSE	*ME*	*MAE*	*HAE*
Individual models (from Table 2a)				
Equation (2)	1.4	-0.3	1.1	3.2
Equation (12)	1.7	-1.1	1.4	4.0
Isco	2.0	-0.1	1.5	5.4
CsC	1.7	-0.8	1.4	3.5
Combined forecasts				
Equation (2) - Isco (fixed weights)[a]	1.3	-0.2	1.0	3.8
Equation (2) - Isco (changing weights)[b]	1.4	-0.1	1.1	3.6
Equation (2) - CsC (fixed weights)[c]	1.3	-0.5	1.1	3.3
Equation (2) - CsC (changing weights)[b]	1.3	-0.4	1.0	3.3
Eq. (2) - Isco - CsC (fixed weights)[d]	1.3	-0.4	1.0	3.6
Eq. (2) - Isco - CsC (changing weights)[b]	1.4	-0.3	1.0	3.4
Combined model				
Equation (15)	1.3	0.6	1.0	2.4
Equation (15) - CsC (fixed weights)[e]	1.1	0.1	0.8	2.3

(a): Weights equal to, respectively, 2/3 and 1/3. Simple arithmetic average gave slightly worse results. (b): Weights change according to equation (14) in the text. (c): Weights equal to, respectively, 2/3 and 1/3. Simple arithmetic average gave the same results. (d): Weights equal to 0.50 (Eq. 2), 0.25 (Isco) and 0.25 (CsC). Simple arithmetic average gave slightly worse results. (e): Weights equal to, respectively, 2/3 and 1/3.
Legend: RMSE root mean square error; ME mean error; MAE mean absolute error; HAE highest absolute error.

ONE-STEP AHEAD FORECASTING PERFORMANCE IN DIFFERENT SUBPERIODS

	Eq. (2)	Isco	CsC	Eq.(2)-Isco[a]	Eq.(2)-CsC[a]	Eq.(2), Isco and CsC[b]	Eq. (15)	Eq. (15)-CsC[a]
Continuing growth (1995.5 - 1995.12)								
RMSE	0.9	2.1	*0.8*	0.9	0.8	0.9	1.0	0.7
ME	-0.6	0.5	*-0.3*	-0.3	-0.5	-0.3	0.8	0.4
MAE	0.8	1.4	*0.7*	0.7	0.7	0.7	0.8	0.6
HAE	1.4	5.3	*1.5*	2.0	1.2	1.7	2.1	1.6
Stagnation (1996.1 - 1996.12)								
RMSE	*1.4*	2.3	2.2	1.4	1.4	1.4	1.3	0.8
ME	*-0.4*	-0.8	-1.9	-0.5	-0.9	-0.9	0.8	-0.1
MAE	*1.1*	1.8	1.9	1.0	1.1	1.1	1.1	0.6
HAE	*3.3*	4.8	3.3	3.8	3.3	3.7	2.4	2.1
Recovery (1997.1-1997.9)								
RMSE	1.7	*1.5*	1.8	1.6	1.6	1.6	1.4	1.5
ME	0.1	*0.3*	0.1	0.1	0.1	0.1	0.2	0.1
MAE	1.4	*1.3*	1.4	1.4	1.3	1.3	1.2	1.1
HAE	2.4	*2.5*	3.5	2.4	2.6	2.4	2.3	2.3

Legend: RMSE root mean square error; ME mean error; MAE mean absolute error; HAE highest absolute error. Forecasting statistics in the gray area are those associated with the best individual model in each subperiod.
Note: (a): Weights equal to, respectively, 2/3 and 1/3. (b): Weights equal to 0.50 (Eq. 2), 0.25 (Isco) and 0.25 (CsC).

Table 10

ALTERNATIVE EVALUATION CRITERIA OF ONE-STEP AHEAD FORECASTS
(1995.5-1997.9)

(a) Number of absolute forecast errors greater than a given threshold

	Eq. (2)	Isco	CsC	Eq.(2)-Isco[a]	Eq.(2)-CsC[a]	Eq.(2), Isco and CsC[b]	Eq. (15)	Eq. (15)--CsC[a]
# of forecast errors ≥ 2%[c]	6	7	7	6	4	4	4	4
# of forecast errors≥2,5%[c]	2	6	5	1	2	1	0	0
# of forecast errors ≥ 3%[c]	1	4	4	1	1	1	0	0

(b) Prediction of sign of variation[d]

	Eq. (2)	Isco	CsC	Eq.(2)-Isco[a]	Eq.(2)-CsC[a]	Eq.(2), Isco and CsC[b]	Eq. (15)	Eq. (15)--CsC[a]
% of periods with correct prediction	79	90	76	83	83	83	90	93

(a): Weights equal to, respectively, 2/3 and 1/3. (b): Weights equal to 0.50 (Eq. 2), 0.25 (Isco) and 0.25 (CsC). (c): The percentage value is computed with respect to the mean of the dependent variable. (d): Seasonally adjusted data. The prediction is correct if the sign of $(PRED_t-Y_{t-1})/Y_{t-1}$ is equal to the sign of $(Y_t-Y_{t-1})/Y_{t-1}$, where Y and PRED are, respectively, actual and predicted values.

Table 11

COMBINED MODEL - EQUATION (15)
ESTIMATION AND DIAGNOSTICS
(1986.1-1995.4)

Variables and parameters	*Coefficient*	*t-statistic*
$\Sigma enel_i$	0.008	15.6
time	-0.076	-6.0
tempn	1.09	6.2
$tempn^2$	-0.048	-7.1
moving average of ord	0.090	6.5
y_{t-1}	0.077	1.5

$\overline{R}^2$ = 0.99
S.E. = 1.12
number of obs. = 112

Misspecification tests
(percen p-value in parentheses)

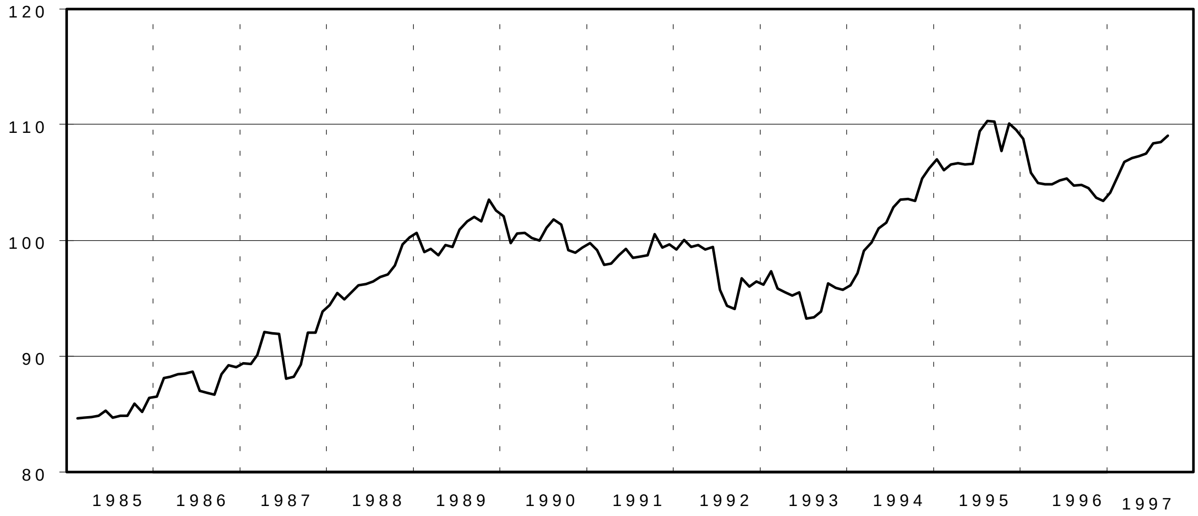
Autocorrelation			*Heteroskedasticity*		
DW	2.01		$ARCH_{1-12}$	11.42	(49.3)
LM_{1-12}	0.94	(51.4)			
LB	30.07	(18.2)			
General specification			*Predictive power*		
RESET	0.51	(60.2)	CHOW	0.79	(65.6)
Unit root test on residuals					
ADF	-7.1				

Note: The dependent variable and electricity consumption are adjusted for trading days. Regression also includes a constant and seasonal dummy variables, whose coefficients are not reported.
Legend: S.E. standard error of regression; DW Durbin-Watson statistic; LM_{1-12} modified Lagrange multiplier test for residual autocorrelation of order 1 through 12, F(12,80); LB Ljung-Box test for residual autocorrelation, $\chi^2(24)$; CHOW Chow test of predictive power over the period 1995.5-1996.4, F(12,104); RESET test of functional form, F(2,90); $ARCH_{1-12}$ autoregressive conditional heteroskedasticity test for residuals of order 1 through 12, $\chi^2(12)$; ADF augmented Dickey-Fuller test (1% critical value: -5.8).

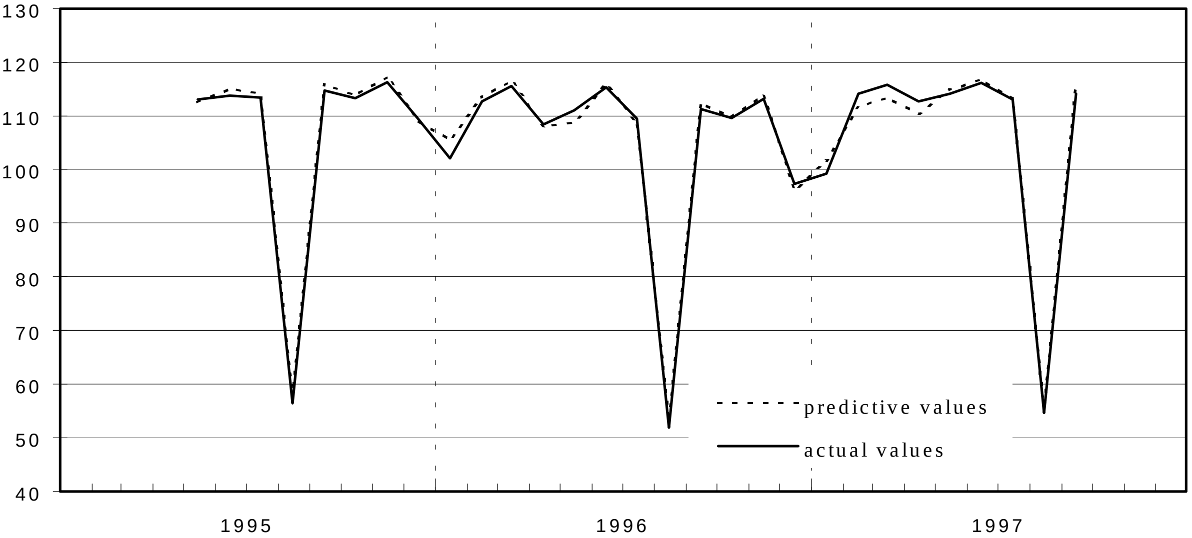
Figure 1

INDUSTRIAL PRODUCTION, ACTUAL AND PREDICTED VALUES

a) Actual values, seasonally adjusted
(3 - term centered moving average)



b) One-step ahead forecasts obtained with equation (2)



c) One-step ahead forecast errors with equation (2)

Note: Data refer to industrial production adjusted by working days.

Figure 2

TRANSITION FUNCTION F(t)

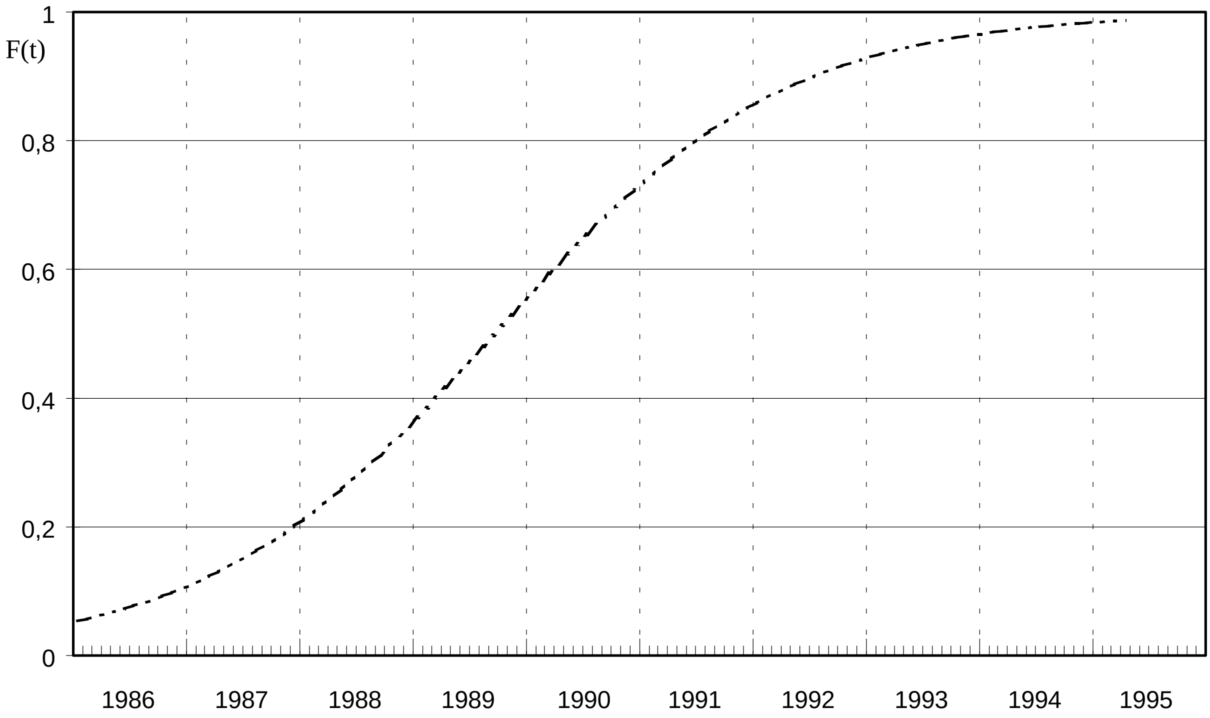
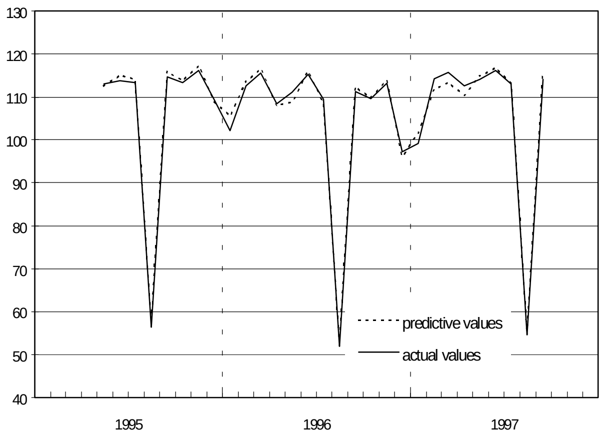


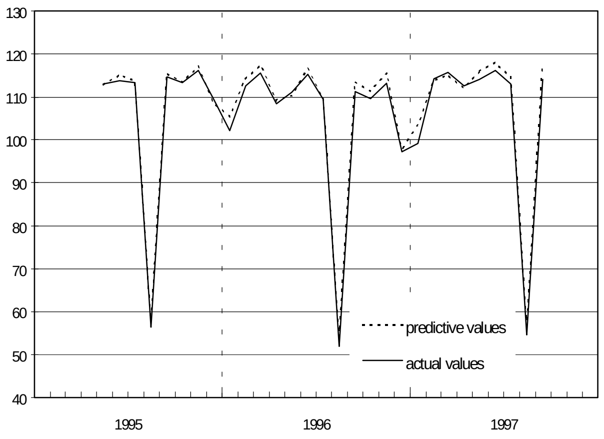
Figure 3

FORECASTING PERFORMANCE OF DIFFERENT MODELS

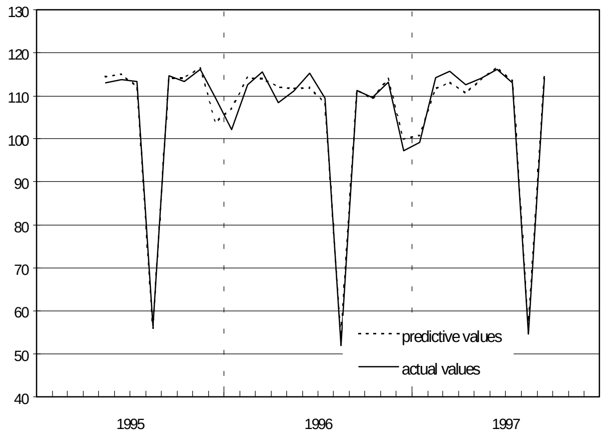
Linear model with electricity data - Equation (2)



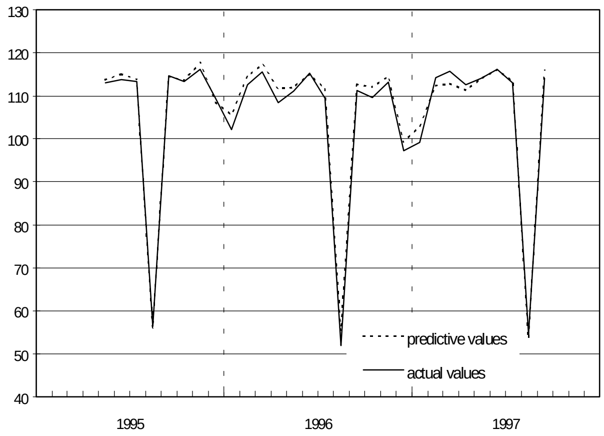
Non-linear model with electricity data - Equation (12)



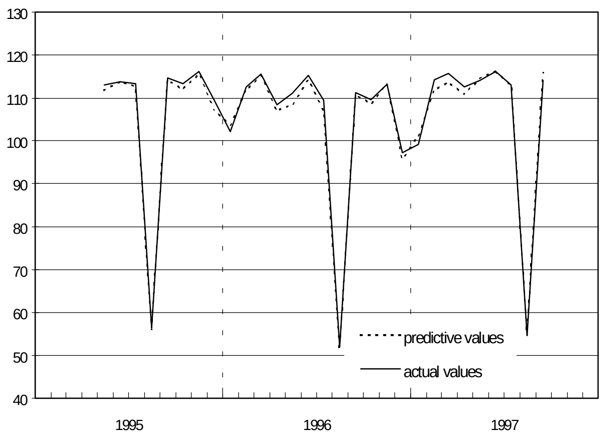
Model with Isco data - Equation (13)



Csc model



Equation (15)



Note: data refer to industrial production adjusted by working days.

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