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Comparing Seasonal Forecasts of Industrial Production*

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Abstract

Forecast combination methodologies exploit complementary relations between different types of econometric models. The development and growing use of such combinations results from the fact that this approach often delivers more accurate forecasts than the individual models on which these forecasts are based. This paper examines forecasts of seasonally unadjusted monthly industrial production data for 17 countries and the Euro Area, comparing individual model forecasts and forecast combination methods in order to examine whether the latter are able to take advantage of the properties of different seasonal specifications. In addition to linear models (with deterministic seasonality and with nonstationary stochastic seasonality), more complex models that capture deterministic nonlinearity (periodic autoregressions) or stochastic nonlinearity (self-exciting threshold autoregressive nonlinear models) are also examined. Forecast combinations consistently provide the best performance at short horizons, implying that utilizing the different characteristics captured by these models can contribute to improved forecast accuracy. Although periodic models perform relative well, nonlinear perform poorly.

Key words: Forecast combinations, seasonality, RMSPE, Periodic models, SETAR models.

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1. Introduction

Agents working with seasonal data often require forecasts of intra-year observations; for example, managers need to forecast future monthly demand for their products in order to ensure that they have sufficient stocks on hand to meet this demand. Indeed, the production of many commodities is itself highly seasonal, largely due to the traditional factory closures that take place during the summer and Christmas periods. Perhaps because of their marked intra-year patterns, economists interested in seasonality have often focused on industrial production series (for example, Beaulieu and Miron, 1991, Cecchetti and Kashyap, 1996, Matas-Mir and Osborn, 2004).

The nature of seasonality is also of interest to official statistical agencies, including EuroStat, which is responsible for data provision relating to the European Union. Although many economists concentrate on seasonally adjusted values, the process of seasonal adjustment may itself involve forecasting future intra-year values of the unadjusted series, as discussed by Ghysels, Osborn and Rodrigues (2006) in the context of the recently-developed X-12-ARIMA method of the US Bureau of the Census. There has, however, been surprisingly little empirical analysis of the accuracy of methods for forecasting seasonal economic time series.

Rather than selecting a single model for forecasting, an alternative approach is to combine forecasts derived from a range of models. This has particular attractions in the context of forecasting seasonal series, since there are a number of different ways of handling seasonality that may be appropriate depending on the properties of the series in question. For example, the seasonality may be of the deterministic form, it may exhibit nonstationary stochastic properties, it may be periodic (seasonally-varying coefficient) in nature, or it may exhibit non-linear interaction with the business cycle; see Ghysels and Osborn (2001) for discussion of some relevant models and their properties. Rather then choosing between these possibilities, a user may elect to adopt a forecast based on a combination of models. Indeed, the use of a suitably chosen combination may lead to improved forecast accuracy compared to the choice of a single method.

Since the early work of Bates and Granger (1969), several methods have been developed for combining forecasts. Since time series models are simplifications of complicated processes that are imperfectly understood, single models are typically incomplete representations of a data generation process (DGP). Hence, combinations of forecasts from different models, which may provide complementary information about the DGP, can assist in the approximation of the DGP. In practice, such combinations are often found to outperform forecasts produced by a single model (see, *inter alia*, Bates and Granger, 1969, Granger and Ramanathan, 1984, Stock and Watson, 1999). Against this, Hibon and Evgeniou (2005) find that the best individual forecast model performs as well as the best combination. Nevertheless, as these authors state, combining forecasts retains an advantage in being less risky than selecting among the available individual model forecasts.

This paper studies the post-sample accuracy of forecasts of seasonally unadjusted monthly industrial production indices (IPI) from 17 individual countries (Austria, Canada, Denmark, Finland, France, Germany, Greece, Hungary, Italy, Japan, Luxembourg, Netherlands, Portugal, Spain, Sweden, United Kingdom and USA) and an aggregate series for the Euro Area.

In total, we examine 17 (linear and nonlinear) forecasting models and 18 procedures for combining the information from these 17 models. Our aim is to examine the relative accuracy of these approaches and to investigate whether any general lessons emerge about whether combining forecasts improves accuracy for these series.

The outline of the paper is as follows. Section 2 briefly introduces the forecast models considered in this paper. In Section 3 we study the empirical properties of the IPI series, *i.e.*, we investigate whether the IPI series display seasonal non-stationarity, non-linearity and periodicity (seasonally-varying coefficients). Section 4 discusses predictive accuracy measures and introduces the combination methods considered. The substantive results in relation to forecast accuracy for the seasonal IPI series are contained in Section 5. Finally, Section 6 concludes the paper.

2. The Models

This section briefly presents the seasonal models that are later applied in forecasting. In line with Ghysels, Osborn and Rodrigues (2006), we first discuss representations of seasonality in the context of constant parameter linear models, with subsequent subsections considering non-linear (SETAR) and periodic models. Although most of this discussion is general in the sense of referring to S seasons per year, our empirical analysis of monthly IPI below (obviously) employs $S = 12$.

2.1. Linear Seasonal Models

For the purpose of presentation, consider the model

$$y_{Sn+s} = \mu_{Sn+s} + x_{Sn+s} \tag{2.1}$$
$$\phi(L)\, x_{Sn+s} = u_{Sn+s} \tag{2.2}$$

where y_{Sn+s} $(s = 1, ..., S, n = 0, ..., T-1)$ represents the observed value in season s (in our application this is a month) of year n, the polynomial $\phi(L)$ contains any unit roots in y_{Sn+s} and is specified in the following subsections according to the model being discussed, L represents the conventional lag operator, $L^k x_{Sn+s} \equiv x_{Sn+s-k}$, $k = 0, 1, ...,$ the driving shocks $\{u_{Sn+s}\}$ of (2.2) are assumed to follow an ARMA(p, q), $0 \leq p, q < \infty$ process, such as, $\beta(L)u_{Sn+s} = \theta(L)\varepsilon_{Sn+s}$, where the roots of $\beta(z) \equiv 1 - \sum_{j=1}^{p} \beta_j z^j = 0$ and $\theta(z) \equiv 1 - \sum_{v=1}^{q} \theta_v z^v = 0$ lie outside the unit circle, $|z| = 1$ and $\varepsilon_{Sn+s} \sim iid(0, \sigma^2)$. The term μ_{Sn+s} represents a deterministic kernel which is assumed to be either i) a set of seasonal means, *i.e.*, $\sum_{s=1}^{S} \delta_s D_{s,Sn+s}$ where $D_{s,Sn+s}$ is a dummy variable taking value 1 in season s and zero elsewhere, or ii) a set of seasonals with a (nonseasonal) time trend, *i.e.*, $\sum_{s=1}^{S} \delta_s D_{s,Sn+s} + \tau\,(Sn + s)$. In general, the second of these is more plausible for economic time series, since it allows the underlying level of the series to trend over time, whereas $\mu_{Sn+s} = \delta_s$ implies a constant underlying level, except for seasonal variation.

Linear forecasting models can be classified in terms of their assumptions about unit roots in $\phi(L)$. The two most common forms of seasonal models in empirical economics employ seasonally integrated models, with $\phi(L) = \Delta_S$ in (2.2), or deterministic seasonality with either $\phi(L) = 1 - L$ or $\phi(L) = 1$. In addition, seasonal autoregressive integrated moving average (SARIMA) models with $\phi(L) = \Delta_S\Delta$ retain an important role as a forecasting benchmark. Each of these three models is briefly discussed in a separate subsection below.

2.1.1. Seasonally Integrated Model

The seasonally integrated model assumes that seasonality is nonstationary, with seasonal (or annual) differencing of y_{Sn+s} required in order to render the process stationary. This implies that $\phi(L) = 1 - L^S = \Delta_S$ in (2.1) and, since $\Delta_S = (1-L)(1+L+L^2+...+L^{S-1})$, seasonal integration imposes the presence of unit roots not only at the zero frequency, but also at each of the so-called seasonal frequencies.

Stationary dynamics in economic time series are often represented as being of the autoregressive (AR) form. With this assumption, namely $\beta(L)u_{Sn+s} = \varepsilon_{Sn+s}$ in (2.2), the seasonally integrated model is

$$\beta(L)\Delta_S y_{Sn+s} = \beta(1)S\tau + \varepsilon_{Sn+s} \tag{2.3}$$

since $\Delta_S\mu_{Sn+s} = S\tau$. Thus, with the inclusion of an intercept, the seasonally integrated process of (2.3) has a common annual drift, $\beta(1)S\tau$, across seasons. Clearly, the essential features of the model are retained if a moving average component is added to (2.3). Notice that the underlying seasonal means μ_{Sn+s} are not observed, since the seasonally varying component $\sum_{s=1}^{S}\delta_s D_{s,Sn+s}$ of μ_{Sn+s} in (2.1) is annihilated by seasonal (that is, annual) differencing.

From an economic point of view, nonstationary seasonality can be controversial because the values over different seasons are not cointegrated and hence can move in any direction in relation to each other, so that "*winter can become summer*". This lack of cointegration appears to have been first noted by Osborn (1991). Prior to using a seasonally integrated model, tests can be conducted to investigate the validity of the unit root assumption, with the most popular approach to testing for seasonal integration being that of Hylleberg, Engle, Granger and Yoo [HEGY] (1990).

2.1.2. Deterministic Seasonal Models

When seasonality results in peaks and troughs within a particular season, year after year, it can be described by deterministic variables leading to what is conventionally referred to as *deterministic seasonality*. In this case the underlying seasonal pattern is assumed to display means that are constant over time.

A simple deterministic seasonal model can permit with stationary AR dynamics, with

$$\beta(L)y_{Sn+s} = \sum_{s=1}^{S}\beta(L)[\delta_s D_{s,Sn+s}] + \beta(1)(Sn+s)\tau + \varepsilon_{Sn+s} \tag{2.4}$$

where ε_{Sn+s} is again a zero mean white noise process, and $\beta(L)$ is a pth order polynomial. In this case, the deterministic component of the estimated model explicitly includes seasonal intercepts and a linear trend. However, the assumption of stationary dynamics may be unrealistic since it is common for economic time series to exhibit evidence of a zero frequency unit root. Therefore, $\phi(L) = 1 - L$ may be imposed in (2.2). Again assuming that the stationary dynamics are of the AR form, (2.1)-(2.2) then becomes

$$\beta(L)\Delta_1 y_{Sn+s} = \sum_{s=1}^{S} \beta(L)\Delta_1 \mu_{Sn+s} + \varepsilon_{Sn+s} \tag{2.5}$$

where $\Delta_1 \mu_{Sn+s} = \mu_{Sn+s} - \mu_{Sn+s-1}$, so that (only) the change in the seasonal means between seasons s and $s-1$ is identified.

2.1.3. SARIMA Model

When working with nonstationary seasonal data, both annual changes and changes between adjacent seasons are important concepts. This motivated the model

$$\beta(L)(1-L)(1-L^S)y_{Sn+s} = \theta(L)\varepsilon_{Sn+s} \tag{2.6}$$

which results from specifying $\phi(L) = \Delta_1\Delta_S = (1-L)(1-L^S)$ in (2.2). The intuition is that the filter $(1-L^S)$ captures the tendency for the value of the series for a particular season to be highly correlated with the value for the same season a year earlier, while $(1-L)$ captures the nonstationary nonseasonal stochastic component. It is worth noting that the imposition of $\Delta_1\Delta_S$ annihilates the deterministic variables (seasonal means and time trend) of (2.1), so that these do not appear in (2.6).

However, since $(1-L)(1-L^S) = (1-L)^2(1+L+L^2+...+L^{S-1})$, (2.6) imposes unit roots at all seasonal frequencies, as well as two unit roots at the zero frequency. As a result these models may be empirically implausible (see *e.g.* Osborn, 1990 and Hylleberg, Jørgensen and Sørensen, 1993). Nevertheless, they can be successful in forecasting due to their parsimonious nature and hence may provide a benchmark for forecast accuracy comparisons.

A specific SARIMA model of particular interest in seasonal modelling is the widely used "airline model", which imposes $\beta(L) = 1$ in (2.6), together with $\theta(L) = (1-\theta L)(1-\Theta L^S)$.

2.2. Seasonal SETAR Models

SETAR models are a class of model particularly suited for modelling of economic variables with asymmetric behaviour, since these allow for the classification of observations into different regimes according to the value taken by a specific threshold variable.

In this study, we consider a seasonal two-regime, seasonal SETAR ($SSETAR$) model of order p of the form

$$y_{Sn+s} = \sum_{k=1}^{2}\sum_{s=1}^{S}[\lambda_s D_{s,Sn+s} + \delta_s D_{s,Sn+s}(Sn+s)]I_{k,Sn+s} + \sum_{i=1}^{p} \rho_i y_{Sn+s-i} + \varepsilon_t \tag{2.7}$$

with $s = 1, 2, ..., S$ and where $D_{s,Sn+s}$ represents the usual seasonal dummy variable for season s, $I_{k,Sn+s}$ corresponds to an indicator variable determined by q_{Sn+s-d}, q_{Sn+s-d} is a threshold variable and d is a delay parameter; the disturbance in each regime is assumed to be white noise. The regimes in (2.7) are defined by the value of q_{Sn+s} in relation to some threshold γ. In practice the threshold variable typically employs a lag of y_{Sn+s}, or a linear combination of lagged y_{Sn+s}; see, *inter alia*, Tsay (1989, p.23) and Hansen (1997, p.10). Notice that (2.7) allows only the intercept to vary over time, with the AR lag coefficients assumed to be invariant to the season and the regime. Although more general forms of SSETAR model can be employed, their greater flexibility implies the estimation of a larger number of coefficients. In our forecasting context, we prefer the more parsiminous version of (2.7).

Implicitly (2.7) assumes that y_{Sn+s} is stationary. To allow for unit root behavior, (2.7) may be estimated using $\Delta_1 y_{Sn+s}$; see Matas-Mir and Osborn (2004).

However, before this type of model is applied in empirical work, it is important to determine whether the data justifies its use through a test for threshold effects. Chan and Tong (1990) and Hansen (1997) suggest the following test statistic,

$$F(\gamma) = n\left(\frac{\widetilde{\sigma}^2 - \widehat{\sigma}^2(\gamma)}{\widehat{\sigma}^2(\gamma)}\right) \tag{2.8}$$

where $\widetilde{\sigma}^2$ and $\widehat{\sigma}^2(\gamma)$ represent the variance estimators acquired from the residuals of a linear and a SETAR model, respectively. The null hypothesis considers a linear model as appropriate, while the alternative of regime-dependent coefficients supports the SETAR model.

However, a difficulty in applying these tests for threshold effects relates to the presence of the nuisance parameter, γ, under the alternative hypothesis only. This problem, was first identified by Davis (1977) and invalidates the use of conventional asymptotic theory when the threshold effect, γ, is unknown; see also Andrews and Ploberger (1994) and Hansen (1996). In this case, critical values for (2.8) can be obtained using the bootstrap method as suggested by Hansen (1997, 2000).

2.3. Periodic Models

Periodic autoregressive (PAR) models provide another class of model for seasonally unadjusted data, where these models allow coefficients to change according to the seasons of a year. This seasonal parameter variation can prove useful in describing economic situations in which choices made by economic agents show distinct seasonal characteristics. Problems associated with dismissing periodicity are well described in Osborn (1991) and in Tiao and Grupe (1980).

PAR models assume that the observations for different seasons can be described by distinct autoregressive models. We consider the following PAR(S, p) model

$$y_{Sn+s} = \sum_{s=1}^{S}[\lambda_s D_{s,Sn+s} + \delta_s D_{s,Sn+s}(Sn+s)] + \sum_{s=1}^{S}\sum_{j=1}^{p_s}\alpha_{js} D_{s,Sn+s} y_{Sn+s-j} + \varepsilon_{Sn+s} \tag{2.9}$$

where S represents the periodicity of the data, p_s the order of the autoregressive component corresponding to season s, $p = \max(p_1, ..., p_S)$, $\varepsilon_{Sn+s} \sim iid\,(0, \sigma^2)$ and $D_{s,Sn+s}$ a seasonal dummy equal to 1 in season s and zero otherwise; see for instance Clements and Smith

(1997). In its unrestricted form of (2.9), the model coefficients can be estimated by ordinary least squares.

PAR models can be applied to either the levels of the series, as in (2.9), or after the application of first differences.

Similarly to the SETAR models previously discussed, it is also advisable in this case to first verify whether the data shows this type of properties before employing them in a forecasting model. There are different approaches available in the literature when testing for the presence of periodicity. The most direct is to consider the null non-periodic hypothesis

$$H_0 : \alpha_{is} = \alpha_i, \quad s = 1, ..., S, i = 1, ..., p \tag{2.10}$$

against the alternative that not all α_{is} are equal, which we denote as F_{PAR}. This test can be performed by the usual F-test, which (for T sample observations used for estimation of (2.9)) asymptotically follows an F distribution with $((S-1)\,p,\, T-(S+2)p)$ degrees of freedom; see Boswijk and Franses (1996).

Alternatively, following Franses (1996, pp.101-102) a residual-based approach can be adopted. As a first step, a non-periodic AR(p) model is estimated. Using the resulting residuals, periodicity is tested through the auxiliary regression,

$$\widehat{v}_{Sn+s} = \sum_{i=1}^{p} \phi_i y_{Sn+s-i} + \sum_{j=1}^{r}\sum_{s=1}^{S} \gamma_{js} D_{s,Sn+s} \widehat{v}_{Sn+s-j} + u_{Sn+s} \tag{2.11}$$

via an F-test for the joint significance of the γ_{js} for some order of autocorrelation r. Under the non-periodic null hypothesis, this F-statistic asymptotically follows a standard F-distribution with $(Sr, T-p-Sr)$ degrees of freedom. As an alternative option or a complementary procedure, the auxiliary regression

$$\widehat{v}^2_{Sn+s} = \omega_0 + \sum_{k=1}^{S-1} \omega_k D_{k,Sn+s} + e_{Sn+s} \tag{2.12}$$

can be used to check for seasonal heteroscedasticity. As argued by Franses (1996), neglected parameter variations may surface in the variance of the residual process. Thus, under the null hypothesis of no seasonal heteroscedasticity, an F-test for $\omega_k = 0, k = 1, ..., S-1$ asymptotically follows a standard F-distribution with $(S-1, T-p)$ degrees of freedom.

It should be noted, however, that a finding of seasonal heteroscedasticity does not necessarily imply that a PAR model should be used, since this could arise from a conventional constant-coefficient model subject to disturbances which have seasonally-varying variances.

3. Empirical Properties of Industrial Production

3.1. Data

The data used in this study is the logarithm of monthly Industrial Production data for 17 individual countries and the Euro Area. Therefore, the first difference has the interpretation of the monthly growth rate, and the annual difference as the annual growth rate. Table 3.1 reports some descriptive statistics for the annual and monthly growth rates, after outlier correction. Outlier detection and correction was carried out using the Tramo/Seats program developed by Gomez and Maravall (1996). For ease of interpretation, the differenced values are multiplied by 100 prior to the calculation of the statistics of Table 3.1.

Table 3.1: Descriptive Statistics

				Annual Growth		Monthly Growth	
Country	Outliers			Mean	SD	Mean	SD
	AO	TC	LS				
Austria	0	0	0	3.21	3.90	0.30	8.59
Canada	0	1	0	2.57	4.87	0.19	6.25
Denmark	0	2	0	2.40	6.55	0.20	17.16
Finland	3	0	2	3.39	5.81	0.29	14.92
France	0	0	1	1.14	3.15	0.08	15.13
Germany	2	0	1	1.37	3.37	0.10	6.71
Greece	2	3	1	1.09	4.11	0.09	8.04
Hungary	0	1	0	2.52	8.72	0.25	10.90
Italy	0	0	0	0.90	4.36	0.06	31.85
Japan	0	0	0	1.68	4.91	0.18	7.53
Luxembourg	1	1	2	3.29	6.01	0.24	12.53
Netherlands	0	0	0	0.99	4.16	0.07	7.84
Portugal	1	0	0	2.44	4.99	0.18	15.59
Spain	0	0	1	1.70	3.46	0.17	21.00
Sweden	3	0	2	2.64	4.52	0.22	26.46
UK	0	0	1	1.00	3.52	0.06	7.14
USA	2	2	1	2.52	3.67	0.21	2.01
Euro Area	3	0	3	1.55	3.09	0.12	11.12

Note: The columns labeled AO, TC and LS refer to the nature of outliers detected and indicate the respective number of outliers observed. Outlier detection and correction was carried out using the automatic procedure in TRAMO/SEATS.

Our data covers the period January 1980 to December 2005 (before differencing). However, outliers are removed only for the subsample used for the estimation of the models, *i.e.*, January 1980 to December 2002.

Although IPI growth over this period is positive in all cases, Table 3.1 indicates very different experiences across the countries considered for the mean and variability of IPI growth. For example, Italy, Spain and Sweden have a standard deviation of monthly growth around six to eight times that of annual growth, pointing to the highly seasonal nature of these IPI series.

The remainder of this section discusses some tests undertaken to examine the characteristics of our data series. Note that the outlier corrected subsample to December 2002 is used for this analysis.

3.2. Seasonal Nonstationarity

In principle, the appropriate modelling of seasonality depends on whether the series is seasonally integrated or is stationary around deterministic seasonal means. Therefore, preliminary tests for seasonal nonstationarity are undertaken prior to developing a specific forecasting model.

In order to test for seasonal nonstationarity, and following Smith and Taylor (1999), expanding $\phi(L) = \Delta_{12}$ in (2.2) around the unit roots at different frequencies (*i.e.*, zero, π and $\exp(\pm i 2\pi k/12)$ with $k = 1, ..., 5$), including the necessary deterministic component and a set of lags of the dependent variable to account for potential autocorrelation, yields the following specific HEGY test regression for unit roots in monthly data ($S = 12$)

$$\begin{aligned}\Delta_{12} y_{12n+s} &= \mu_{Sn+s} + \pi_0 z_{0,12n+s-1} + \pi_6 z_{6,12n+s-1} \\ &+ \sum_{k=1}^{5} \left(\pi_{\alpha k} z^{\alpha}_{k,12n+s-1} + \pi_{\beta k} z^{\beta}_{k,12n+s-1} \right) + \sum_{l=1}^{p} \phi_l \Delta_{12} y_{12n+s-l} + \varepsilon_{12n+s} \quad (3.1)\end{aligned}$$

where the regressor variables in (3.1) used to test for the unit roots are linear transformations of lagged values of y_{Sn+s}, μ_{Sn+s} represents a deterministic kernel (a set of seasonal dummies or a set of seasonal dummies and trend) and p is the order of lag augmentation considered. The regressors used to test for the zero and Nyquist frequencies unit roots are given as

$$z_{0,12n+s} = \sum_{j=0}^{11} L^j y_{12n+s}, \qquad z_{6,12n+s} = \sum_{j=0}^{11} \cos\left[(j+1)\pi\right] L^j y_{12n+s}$$

while the pairs of variables that test the complex unit roots at other frequencies are

$$z^{\alpha}_{k,12n+s} = \sum_{j=0}^{11} \cos\left[(j+1)\omega_k\right] L^j y_{12n+s}; \qquad \text{and} \qquad z^{\beta}_{k,12n+s} = -\sum_{j=0}^{11} \sin\left[(j+1)\omega_k\right] L^j y_{12n+s}$$

where $\omega_k = 2\pi k/12$, $k = 1, ..., 5$. The variables just defined have the effect of imposing all unit roots implied by Δ_{12} except for a single unit root (or, for the pair $z^{\alpha}_{k,12n+s}$ and $z^{\beta}_{k,12n+s}$, a pair of complex unit roots) and hence the respective coefficient(s) evaluate the nonstationary dynamic properties of the process at a specific frequency.

More specifically, the presence of unit roots implies exclusion restrictions for the coefficients π_0, π_6 and the pairs $\pi_{\alpha k}$, $\pi_{\beta k}$, $k = 1, ..., 5$; the overall null hypothesis of seasonal integration implies all these are zero. To test seasonal integration against stationarity at one or more of the seasonal or nonseasonal frequencies, HEGY suggest using: t_0 (left-sided) for the exclusion of $z_{0,12n+s}$; t_6 (left-sided) for the exclusion of $z_{6,12n+s-1}$; F_k for the exclusion of *both* $z^{\alpha}_{k,12n+s-1}$ and $z^{\beta}_{k,12n+s-1}$, $k = 1, ..., 5$. These tests examine the potential unit roots separately at each of the zero and seasonal frequencies, raising issues of the significance level for the overall test (Dickey, 1993). Consequently, Ghysels, Lee and Noh (1994) also consider joint frequency OLS F-statistics. Specifically $F_{1...6}$ tests for the presence of all seasonal unit roots by testing for the exclusion of $z_{6,12n+s-1}$ and $\{z^{\alpha}_{k,12n+s-1}, z^{\beta}_{k,12n+s-1}\}^{5}_{k=1}$, while $F_{0...6}$ examines the overall null hypothesis of seasonal integration, by testing for the exclusion of all regressors in (3.1). These joint tests are further considered by Taylor (1998) and Smith and Taylor (1998, 1999).

In Table 3.2 we present the results for the test statistics just described obtained from the application of the test regression of the form of (3.1), augmented with a set of seasonal dummies and lags of the dependent variable, on the IPI series. The maximum lag order considered for augmentation was 24 and a testing down procedure, as suggested by Ng and Perron (1995), used to determine the effective lag order (this order is indicated in Table 3.2 in the column Augment). The test regression was also applied with a set of seasonal dummies and a time trend, however the results were qualitatively similar (see Table A.1 in the appendix).

Table 3.2: Testing for Seasonal Unit Roots in Industrial Production Series

Country	t_0	t_6	F_1	F_2	F_3	F_4	F_5	$F_{1...6}$	$F_{0...6}$	Augment
Austria	0.71	-1.38	2.03	7.14*	6.11	8.04*	2.64	5.57*	5.17*	19
Canada	-0.84	-1.32	5.08	3.03	12.29*	4.79	4.14	6.54*	6.07*	24
Denmark	-1.64	-1.09	4.26	4.35	3.62	7.72*	7.62*	5.43*	5.22*	24
Finland	-0.74	-1.17	0.92	0.39	5.78	0.46	1.40	1.78	1.70	21
France	-0.38	-3.31*	5.28	8.77*	4.96	7.46*	2.80	7.98*	6.60*	18
Germany	-1.59	-0.68	2.19	8.79*	4.53	5.06	1.38	4.34	4.23	24
Greece	0.12	-2.23	6.25	5.90	2.89	4.21	0.85	4.38	4.02	24
Hungary	-1.08	-0.81	6.59	2.78	3.75	9.74*	2.44	5.19*	4.86	17
Italy	-1.67	-2.22	1.30	5.49	2.31	2.04	2.46	3.15	3.14	24
Japan	-2.51	-1.19	5.13	5.56	1.71	4.16	6.30	4.66	4.94	23
Luxembourg	-0.79	-2.28	14.96*	4.73	4.82	3.09	6.88	7.75*	7.17*	20
Netherlands	-0.07	-1.82	8.71*	6.65	6.71	5.06	1.83	6.04*	5.54*	12
Portugal	-1.35	-1.68	2.66	3.11	0.43	0.84	2.74	2.12	2.15	24
Spain	-0.78	-1.16	1.46	2.12	1.77	1.44	0.78	1.54	1.48	15
Sweden	0.24	-1.14	1.49	1.18	1.84	0.90	1.07	1.35	1.24	21
UK	-1.42	-2.96*	4.57	17.47*	7.74*	8.60*	1.37	9.59*	9.09*	20
USA	0.08	-2.50	11.94*	7.14*	12.76*	10.46*	17.48*	13.14*	12.05*	4
Euro Area	-1.03	-1.28	2.49	6.61	3.00	5.84	1.11	3.75	3.56	17

Note: * denotes significance at the 5% nominal level. The critical values considered were computed from a HEGY test regression such as (3.1) augmented with a set of seasonal dummies and a set of lags of the dependent variable (the maximum lag order considered for all cases was 24 lags), the data was generated from a monthly seasonal random walk and 50000 Monte Carlo replications used. t_0 and t_6, represent the one sided unit root t-test statistics at frequencies 0 and π, respectively; F_1, F_2, F_3, F_4 and F_5, correspond to the joint tests for seasonal unit roots at frequencies $\left(\frac{\pi}{2}, \frac{3\pi}{2}\right)$, $\left(\frac{5\pi}{3}, \frac{7\pi}{6}\right)$, $\left(\frac{\pi}{6}, \frac{11\pi}{6}\right)$, $\left(\frac{2\pi}{3}, \frac{4\pi}{3}\right)$ and $\left(\frac{\pi}{3}, \frac{5\pi}{6}\right)$, respectively; and $F_{1...6}$ and $F_{0...6}$

represent the joint tests for unit roots at all seasonal frequencies and at all frequencies, respectively. The column order identifies the order of the lag length considered in each test regression. The critical values considered were: -2.80 for the zero and Nyquist frequency unit roots; 5.04 and 4.98 for the $F_{1...6}$ and $F_{0...6}$ tests, respectively and 7.09 for the F_i, $i = 1, ..., 5$, tests.

The overall test statistics $F_{1...6}$ and $F_{0...6}$ of Table 3.2 reject the presence of the full set of seasonal unit roots for about half of the series. However, for a group of European countries (namely, Finland, Greece, Italy, Portugal and Spain, as well as the Euro area as a whole) the data does not reject the unit root at any frequency, providing relatively strong support in favour of seasonal integration. The strongest evidence against the presence of seasonal unit roots occurs for the UK and USA.

3.3. Nonlinearity

As an indicator of the potential value of SETAR models for our seasonal series, we test for the presence of threshold effects in the data by investigating whether the difference between the coefficients in the regimes is significant in (2.7).

Order selection for the autoregressive component of the seasonal SETAR model is also important. In this study, the order of the test regressions employed was determined following a general-to-specific procedure (see Ng and Perron, 1995) in a linear AR model, using a maximum lag of $p = 12$. The p-values for the linearity test are obtained using the bootstrap, as suggested by Hansen (1997) in this context. Our application uses 5000 bootstrap replications.

Table 3.3 presents the results of tests of linearity against SETAR type nonlinearity of the industrial production series. These results are obtained from a regression of the form of (2.7) where $q_{12n+s-d} = \Delta_{12} y_{12n+s-d}$ and the delay d and the threshold value γ are endogenously determined from a search over the central 70% of the empirical distribution of $\Delta_{12} y_{12n+s-d}$. The maximum delay considered for determining d was the effective order of the regression considered (as given in the column *AR order* in Table 3.3).

From Table 3.3, we observe that the linear structure is rejected for around half of the countries considered, with the strongest evidence of nonlinearity being for Germany, Sweden and the Euro Area.

Table 3.3: Testing for Linearity in Industrial Production Series

Country	γ	d	Linearity test (p-value)	AR order
Austria	-.005	4	.016	12
Canada	-.015	1	.121	10
Denmark	.052	4	.052	12
Finland	.030	12	.218	12
France	.019	8	.167	12
Germany	.037	5	.007	12
Greece	.027	5	.037	12
Hungary	.117	9	.023	12
Italy	.078	12	.112	12
Japan	-.026	2	.054	10
Luxembourg	.094	8	.024	12
Netherlands	-.065	6	.029	12
Portugal	-.003	7	.070	12
Spain	.014	6	.464	12
Sweden	.021	9	.001	12
UK	.045	1	.129	10
USA	-.051	2	.067	9
Euro Area	.014	10	.001	12

3.4. Periodicity

Given that monthly data are used in this paper, an obvious PAR model to consider is a $PAR(12, p)$, which identifies each month as a distinct "season". However, if used without restrictions, this model has the potential disadvantage of being highly parameterised. For instance, an unrestricted $PAR(12, 12)$, even with no deterministic terms, requires estimation of $12 \times 12 = 144$ coefficients. Hence, this raises interest in identifying more parsimonious models.

One strategy adopted below is based on the assumption that common behaviour is present for specific months, leading to the proposal of a $PAR(3, p)$ model. These $PAR(3, p)$ models are determined based on the classification of the monthly data into three distinct groups of months, with one group including all months with negative average monthly growth, another all months with relatively low monthly positive growth and the third group includes months with the strongest observed average monthly growth[1]. This grouping leads to three "seasons" with different numbers of observations.

In a similar way as for non-linearity, we also test the presence of periodic coefficient variation, to examine whether the data display this characteristic. The results are in Table 3.4.

[1] To be specific, the positive growth regime classifications generally used an average growth of less that 0.1% per month as low growth and monthly growth of 0.1% or more as high growth. However, different classification rules were used for the Canada and the US, for which low (positive) growth was defined in relation to thresholds of 0.03% and 0.05%, respectively.

[Insert Table 3.4 about here]

The test procedures denoted as F_{PeAR1_12} and F_{SH} are applied to the residuals of an AR model as described in (2.11) and (2.12) fitted to the annually differenced series. The $F_{PAR(.)}$ test is applied to the levels of the data. The maximum lag length of the AR considered is 12 in both cases, which was reduced where appropriate based on a testing down strategy.

Whether applied to the residuals or the levels of the data, Table 3.4 provides strong evidence in favour of the presence of periodic coefficient variation across the IPI series analysed. When directly applied to the coefficients, however, the $F_{PAR(3)}$ test rejects substantially less than does $F_{PAR(12)}$. Note, however, that the regression on which the latter test is based is highly parameterised, so the results may not be entirely reliable. The F_{SH} test provides only weak evidence of seasonal heterocedasticity across the series considered. Nevertheless, the other results point to the potential value of using periodic models for forecasting.

4. Forecast Accuracy

To evaluate forecast accuracy, consider the use of m post-sample observations to evaluate h-step ahead forecasts generated from models fitted to the first T observations.

Although many measures of forecast accuracy are available, we follow much of the literature in basing our evaluation on the Root Mean Squared Prediction Error ($RMSPE$), defined as

$$RMSPE(h) = \sqrt{\frac{1}{m-h+1} \sum_{j=h}^{T+m} \left(\widehat{y}_{T+j|T+j-h} - y_{T+j} \right)^2} \tag{4.1}$$

where $\widehat{y}_{T+j|T+j-h}$ is the h-step ahead forecast made for period $T+j$ based on data available at $T+j-h$. In order to focus on the role of seasonality, which may be anticipated to be most marked for short-term forecasts of less than a year, results are computed for horizons $h = 1, 3, 8$.

In this paper, nonlinear time series models are compared with linear and periodic models. To reflect the different approaches to treating seasonality in linear models, we consider specifications based on various levels of differencing, namely no differences, together with models after application of the filters Δ_{12}, Δ_1 and $\Delta_{12}\Delta_1$. All forecasts are considered in relation to the level of the IPI series using RMSPE as defined in (4.1).

There is growing empirical evidence that nonlinear models perform relatively well for long term forecasting and that linear models dominate in the short run (see, *inter alia*, Terui and van Dijk, 1999). Clements *et al.* (2003) compare linear autoregressive and SETAR models and study the degree of non-linearity that needs to be present in the data before forecasts from non-linear models outperform linear rivals. For interesting overviews on comparing forecast accuracy see, *inter alia*, Franses and van Dijk (2000) and Diebold and Mariano (1995).

4.1. Nonlinear Model Forecasts

The nonlinear (seasonal) SETAR models we employ are based on (2.7). For such models, computing point forcasts is considerably more involved than computing forcasts from linear models. To illustrate this, consider the case where the variable y_{Sn+s} is described by a first order nonlinear autoregressive model which is summarised as,

$$y_{Sn+s} = F\left(y_{Sn+s-1}; \theta\right) + \varepsilon_{Sn+s}. \tag{4.2}$$

In this context, when the forecast horizon is longer than 1 period, the linear conditional expectation operator can not be interchanged with the nonlinear operator F, since

$$E\left[F\left(.\right)\right] \neq F\left(E\left[.\right]\right).$$

Since the expected value of a nonlinear function is not equal to the function evaluated at the expected value of its argument, then for a given parameter vector θ and horizon h

$$E\left[F\left(y_{Sn+s+h-1}; \theta\right) |\Omega_{Sn+s}\right] \neq F\left(E\left[\left(y_{Sn+s+h-1|Sn+s}\right) |\Omega_{Sn+s}\right]; \theta\right), \qquad h > 1$$

where Ω_{Sn+s} indicates information available at time $Sn + s$. However, an unbiased point forecast based on (4.2) requires estimation of the left-hand side of this expression.

The distribution of the white noise disturbance ε_{Sn+s} in (4.2) is never known with certainty. However, to overcome this difficulty, forecasts can be computed using Monte Carlo or Bootstrap methods. Lin and Granger (1994) and Clements and Smith (1997) compare various methods to obtain multiple-step-ahead forecasts for SETAR models and conclude that the bootstrap method compares favourably to the other methods. This is the method also adopted in this paper, where we use 500 bootstrap replications in order to approximate $E\left[F\left(y_{Sn+s+h-1}; \theta\right) |\Omega_{Sn+s}\right]$. For interesting reviews see, *inter alia*, Franses and Van Dijk (2001, pp. 119-121), Lin and Granger (1994) and Clements and Smith (1997).

4.2. Methods for Forecast Combinations

Combining forecasts, as introduced by Bates and Granger (1969), has often been found to improve forecast accuracy compared with using an individual forecasting method. The effectiveness of simple averaging is demonstrated by, among others, Bates and Granger (1969), Granger and Newbold (1977) and Granger and Ramanathan (1984), while other articles demonstrate the usefulness of other approaches to combining multiple individual forecasts; see, *inter alia*, Armstrong (1989, 2001); Clemen (1989), Diebold and Lopez (1996), Hendry and Clements (2002), Markridakis and Winkler (1983); Markridakis *et al.* (1982), Newbold and Harvey (2002), Stock and Watson (1999), Terui and van Dijk (2002).

The remainder of this section briefly introduces the forecast combination methods that we employ in our empirical analysis. In addition to simple averages (mean or median), methods for combining forecasts can be classified as being based on historical RMSPE or derived from regression methods. We devote separate subsections to each of these approaches.

4.3. Historical RMSPE Forecasts

The historical RMSPE forecasts consider the forecast combination as a weighted average of the individual forecasts, with the weights varying with the historical performance of each individual forecast; see, *inter alia*, Diebold and Pauly (1987) and Stock and Watson (1999).

For k separate h-step forecasts, namely $\widehat{y}^i_{Sn+s+h|Sn+s}$ $(i = 1, ..., k)$, the forecast combination is given by

$$\widehat{y}^c_{Sn+s+h|Sn+s} = \sum_{i=1}^{k} w_i^h \widehat{y}^i_{Sn+s+h|Sn+s}$$

where the weight w_i^h is

$$w_i^h = [1/RMSPE(h)_i]^\lambda / \sum_{j=1}^{k} [1/RMSPE(h)_i]^\lambda \tag{4.3}$$

and $RMSPE(h)_i$ the Root Mean Square Predictor Error for method i at horizon h. Since the relative performance of different models can change over time, following Bates and Granger (1969) we compute RMSPE at the end of the sample T using information relating to forecasts for the final three years of the estimation sample, namely $T - 35$ to T.

As implied by (4.3), the weights on the constituent forecasts are inversely related to their RMSPE values (note that the weights are initially based on RMSPE calculated using within-sample observations). A simple average which places equal weight on all forecasts corresponds to $\lambda = 0$. As λ increases, a weight is placed on those models that have been performing relatively well. In this paper we consider $\lambda \in \{0, 1, 1.25, 1.5, 2\}$, with $\lambda = 2$ implying that the weights are inversely proportional to the mean square prediction error.

In addition to weighting as in (4.3), we consider also weights that discount historical forecast accuracy based on RMSPE (see Stock and Watson, 2003). For an h-step forecast, the combination weight in this case has the form

$$w_i^h = \left(m_i^h\right)^{-1} / \sum_{j=1}^{k} \left(m_j^h\right)^{-1} \tag{4.4}$$

where

$$m_i^h = \sqrt{\sum_{j=1}^{T-h} \delta^{j-1} \left(\widehat{y}^i_{T-j+1|T-j+1-h} - y_{T-j+1}\right)^2} \tag{4.5}$$

and δ is the discount factor. In this paper, we consider three values for the discount factor $\delta \in \{1, 0.95, 0.90\}$. Note that for $\delta = 1$ (4.5) operates as a window with no discounting and this weighting scheme is then equivalent to (4.3) with $\lambda = 2$ when the latter uses all observations to time T.

4.4. Regression Methods

Granger and Ramanathan (1984), Diebold (1988) and others, suggest combining forecasts using regression methods. Following Diebold (1988), we consider a framework where relaxation of the zero constant and the weights summing to unity is allowed. Following Diebold (2001, p.297) it is preferable not to force the weigths to add to unity, or to exclude an intercept. Indeed, inclusion of an intercept facilitates bias correction and allows biased forecasts to be combined. Therefore, the regression used can be expressed as

$$y_{Sn+s+h} = \beta_0 + \sum_{j=1}^{k} \beta_j \widehat{y}^j_{Sn+s+h|Sn+s} + \varepsilon_{Sn+s+h} \quad (4.6)$$

with $j = 1, 2, ..., k$, and where k represents the number of individual forecast methods. The weights in (4.6) for the observation at T are estimated using the final 36 observations in the estimation period, namely corresponding to h-step ahead forecasts for periods $T - 35$ to T inclusive.

However, with $k = 17$ in our case, (4.6) implies an excessive parameterisation. Therefore, in implementing (4.6) we use only the five methods producing the most accurate forecasts over the latest available 36 observations.

5. Forecast Performance

5.1. Methods Employed

Table 5.1 presents the individual forecasting models that we apply, while the 18 forecast combination procedures used are summarised in Table 5.2.

As evident from Table 5.1, the models of Section 2 are generally applied to data after differencing. Since the appropriate level of differencing is often unclear in empirical analyses, we reflect this uncertainty by applying the same models to data differenced to different levels. For example, low-order ARMA models are applied to data after annual differencing, and to data after both first and annual differences are applied; PAR and SETAR models are estimated for levels and first differenced data. In each case these choices reflect the type of data to which these models are applied in practice, in conjunction with the indicated deterministic terms. For the $AR(p)$ models of Table 5.1, a maximum order of 24 is considered, while the $SETAR(p_1, p_2)$ considers a maximum order of 12. In both cases, insignificant lags are eliminated (starting with the minimum $t - statistic$) prior to using the models for forecasting.

Table 5.1 - Forecast Models

Code	Individual Models	Filter	Deterministic terms
M1	*Airline Model*	$\Delta_1\Delta_{12}$	None
M2	$ARMA(1,1)$	Δ_{12}	Intercept
M3	$ARMA(2,2)$	Δ_{12}	Intercept
M4	$AR(p)$	Δ_{12}	Intercept
M5	$SSETAR\ (p_1,p_2)$	Δ_{12}	Intercept
M6	$AR\ (p)$	*levels*	Seasonal intercepts + trend
M7	$PAR(12,3)$	*levels*	Seasonal intercepts + trend
M8	$PAR(3,3)$	*levels*	Seasonal intercepts & seasonal trends
M9	$SSETAR(p_1,p_2)$	*levels*	Seasonal intercepts & seasonal trends
M10	$AR\ (p)$	Δ_1	Seasonal intercepts
M11	$PAR(3,3)$	Δ_1	Seasonal intercepts + trend
M12	$PAR(12,3)$	Δ_1	Seasonal intercepts & seasonal trends
M13	$SSETAR(p_1,p_2)$	Δ_1	Seasonal intercepts
M14	$ARMA(1,1)$	$\Delta_1\Delta_{12}$	None
M15	$ARMA(2,2)$	$\Delta_1\Delta_{12}$	None
M16	$ARMA(3,3)$	$\Delta_1\Delta_{12}$	None
M17	$AR(p)$	$\Delta_1\Delta_{12}$	None

The combination methods that we consider are based i) on the weight function, (4.3) with $S = 12$ and $\lambda \in (0, 1, 1.25, 1.5, 2)$; ii) on the mean and median of the best 5, 10 and 15 models which are chosen based on the historical RMSPE across the 17 models considered; iii) on the discounted RMSPE weights as given in (4.4) and (4.5) with $S = 12$ and $\delta \in \{1, 0.95, 0.90\}$; iv) based on the regression method as described in (4.6); v) and finally, on the mean or median of all combinations. Table 5.2 summarizes the individual combination methods used in the empirical analysis.

Table 5.2 - Combination Methods

Code	Combination method	parameters
C1	mean of M1 to M17	
C2	median of M1 to M17	
C3	(4.3)	$\lambda = 0$
C4	(4.3)	$\lambda = 1$
C5	(4.3)	$\lambda = 1.25$
C6	(4.3)	$\lambda = 1.5$
C7	(4.3)	$\lambda = 2$
C8	mean of best 5 models (RMSPE criteria)	
C9	mean of best 10 models (RMSPE criteria)	
C10	mean of best 15 models (RMSPE criteria)	
C11	median of best 5 models (RMSPE criteria)	
C12	median of best 10 models (RMSPE criteria)	
C13	median of best 15 models (RMSPE criteria)	
C14	mean of combinations	
C15	(4.4) and (4.5)	$\delta = 1$
C16	(4.4) and (4.5)	$\delta = 0.95$
C17	(4.4) and (4.5)	$\delta = 0.9$
C18	regression method of (4.6)	

5.2. Forecasting Results

Forecast accuracy is evaluated by employing the final 36 observations (January 2003 to December 2005, inclusive) to provide post-sample actual values. All forecasting models are recursively re-estimated over this forecasting period. In addition, models that require specification of the appropriate AR order are also recursively re-specified during the forecast period, while the weights required in (4.3), (4.4) and (4.6) are also updated using the most recently available observations and the corresponding forecast values.

Tables 5.3a to 5.3e contain the individual results for each of the countries considered (including the Euro Area). Not surprisingly, the best performing methods differ over both the horizon ($h = 1, 3, 8, 12$) considered and the country. However, two cases of particular interest might be the US and Euro Area. For the former, the simple $AR(p)$ model M6 estimated in levels does well at short horizons ($h = 1$, 3), but thi smodel is relatively poor at longer horizons. On the other hand, the PAR(3,3) model M11 in first differences is the most accurate method at a horizon of $h = 8$.months and provides relatively good performance at $h = 3, 12$ but not at one month ahead. These last results are compatible with the evidence against the seasonal integration for this series in Table 3.2 and that in favour of the periodic model in Table 3.4. Nevertheless, the best overall results for the US are given by combining forecasts using the median forecast from the most accurate 5 models. This combination yields the most accurate US forecasts at horizons of one and 12 months, a close competitor to the best at $h = 3$ and the fifth most accurate at $h = 8$.

For the Euro Area, a good performance of the $PAR(3,3)$ model M11 at $h = 1, 3$ and 8 is observed, although this does not carry over to the longer horizon of $h = 12$ where seasonality is not expected to play a strong role. The closest competitor at very short horizons is another PAR model in levels, namely M12. For the Euro Area, however, it is striking that combinations perform well at $h = 8$, and a variety of combined forecasts are more accurate than any individual model at $h = 12$. In common with the US, the median of the best 5 forecasts is the most accurate of all considered at the one year horizon.

Across all the sub-tables in Table 5.3 it is easier to pick out consistently poor forecasting models than consistently good ones. Indeed, the SETAR models M9 and M13 are frequently the worst performing individual models. This may be a consequence of the nonlinearity often evident in Table 3.3 not being repeated during the forecast period.

[Insert Tables 5.3a to 5.3e about here]

From the detailed results of Tables 5.3a to 5.3e, we observe that the top five forecasting models across all countries considered can be classified as follows: for $h = 1$, combinations occupy 72% of the top five positions compared with only 28% from the individual models; for $h = 3$, forecast combinations take 57% of the top five positions; for $h = 8$, the distribution becomes slightly more symmetric in that combinations represent 54% of the top five positions and finally for $h = 12$ combinations account for only 44% of the top five positions. In this sense, the result for the US and the Euro Area that combinations do best at this one year horizon is not typical of all countries considered.

Table 5.4 allows general comparisons across rankings and RMSPE. Note that in Table 5.4 results for the RMSPE of the models and combinations considered are scaled by that of M1 at each horizon in order to facilitate comparisons. Here some individual linear models perform reasonably well, including the Airline model (M1) and the PAR models M7, M8, M11 and M12 as well as the $SARIMA$ model M17. It should be noted that the Airline and the AR models, M1 and M17 take account of seasonality only in the naive fashion of largely removing it through the application of annual (in addition to first) differences. Although a number of individual models provide more accurate forecasts than the Airline model in terms of average relative RMSPE at $h = 1$, the robust performance of this model becomes notable at longer horizons in Table 5.4, with no individual model providing more accurate average relative RMSPE at either $h = 8$ or 12.

[Insert Table 5.4 about here]

The poor performance of the $SETAR$ model in levels (M9) and first differences (M13) is particularly marked in Table 5.4. These results are also not favourable overall to the use of $ARMA$ specifications after first and annual differences (M14, M15, M16) for forecasting these IPI series. Thus, at least for this period, these are not favoured for forecasting seasonal IPI at short horizons.

The average rankings in Table 5.4 are, however, quite explicit as to the quality of the forecast combinations, with the overall average rankings for the forecast combinations being in general superior to the forecast models considered. Indeed, in terms of rankings, combinations always occupy the top places.

For $h = 1$, the best average performance is given by the combinations C17 (discounted RMSPE forecast weights based on (4.4) and (4.5) with $\delta = 0.90$), followed by C4, C15, C16.. For $h = 3$ the best overall average performance is C15 (undiscounted RMSPE forecasts based on (4.4) and (4.5) with $\delta = 1$) and C4 and C5. For $h = 8$, the best performance is C16 (discounted RMSPE forecasts based on (4.4) and (4.5) with $\delta = 0.95$), followed by C4, C10 and C17. Finally, for $h = 12$, the best average ranking is observed for C8 (mean of best 5 models) followed by C17, C6, C7 and C16. Overall, therefore, rankings point to the use of forecast combination methods that use previous RMSPE performance as weights.

Table 5.4 also indicates that almost all combination methods considered give average RMSPE gains compared to even the best of the individual models for the short horizons $h = 1, 3$. The only exceptions to this are C1 (mean of all models) and C3 ((4.3) with $\lambda = 0$) and C18 (regression method of (4.6)).

6. Conclusion

This study reinforces evidence that combining forecasts from individual models improves post-sample forcast accuracy. Our conclusion is based on forecasts from a large set of individual models and methods of combination of forecasts, whose performance is evaluated using monthly seasonally unadjusted Industrial Production data from 17 individual countries (Austria, Canada, Denmark, Finland, France, Germany, Greece, Hungary, Italy, Japan, Luxembourg, Netherlands, Portugal, Spain, Sweden, United Kingdom and USA) and an aggregate series for the Euro Area.

The potential of forecast combinations is even more attractive in the context of seasonal data than data after seasonal adjustment, due to the number of questions that arise in the analysis of seasonal data. For instance, there are questions as to the stationarity or otherwise of seasonal dynamics, whether capturing seasonality requires the use of periodic (seasonally-varying coefficient) models and whether there are nonlinear seasonal/business cycle interactions. According to our results, almost all forecast combination methods deliver improved forecast performance over individual methods. Nevertheless, the combination methods that produce the most accurate forecasts in our study identify the best forecasting models and base the combination on these. Indeed, a simple average of the best five forecasting models for a particular horizon is a robust method that reasonably performs well, especially when forecastiong one month ahead. Nevertheless, we find that better combinations can usually be found by weighting the forecasts using information from the root mean-square prediction error for earlier periods.

Our results relating to the use of more complex methods of handling seasonality are mixed, in the sense that nonlinear models here deliver poor forecast performance, whereas a parsiminous parameterisation of a periodic model performs relatively well at very short horizons of one and three months. However, relatively high parameterisations are typically implied by these complex methods, and future research may examine further the extent to which the imposition of restrictions can improve this performance.

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Appendix

Table A.1. - Testing for Seasonal Unit Roots in Industrial Production Series

(Results from HEGY Test Regression with Seasonal Dummies and Time Trend)

Country	t_0	t_6	F_1	F_2	F_3	F_4	F_5	$F_{1...6}$	$F_{0...6}$	Augment'n
Austria	-1.92	-1.37	1.98	7.07	6.23	7.94*	2.47	5.51*	5.50*	19
Canada	-1.89	-1.33	5.15	3.03	12.47*	4.81	4.03	6.59*	6.40*	24
Denmark	-2.72	-1.10	4.42	4.31	3.82	7.96*	8.27*	5.65*	5.79*	24
Finland	-2.81	-0.99	0.74	0.15	4.87	0.34	1.47	1.48	2.12	18
France	-2.89	-3.34*	5.20	8.82*	5.31	7.25*	3.03	7.29*	7.57*	18
Germany	-1.73	-0.69	2.25	8.85*	4.61	5.10	1.41	4.39	4.28	24
Greece	-1.19	-2.23	6.25	5.94	2.87	4.21	0.84	4.37	4.12	24
Hungary	-1.72	-0.81	6.57	2.72	3.76	9.80*	2.42	5.19*	5.05	17
Italy	-1.96	-2.45	1.78	7.22*	2.78	2.08	2.57	3.85	3.92	18
Japan	-2.33	-1.18	5.08	5.50	1.70	4.08	6.55	4.67	4.52	23
Luxembourg	-2.65	-2.31	14.90*	4.64	4.90	3.01	6.69	7.69*	7.95*	20
Netherlands	-2.90	-1.85	8.87*	6.76	6.96	5.11	1.75	6.15*	6.46*	12
Portugal	-1.54	-1.68	2.76	3.10	0.41	0.84	2.81	2.15	2.18	24
Spain	-2.54	-1.15	1.44	2.21	1.56	1.45	1.01	1.56	2.05	15
Sweden	-2.54	-1.12	1.56	1.26	1.77	0.86	1.16	1.36	1.87	21
UK	-1.75	-2.99*	4.54	17.20*	7.69*	8.49*	1.28	9.50*	9.18*	20
USA	-2.61	-1.19	10.75*	3.99	5.45	6.45	7.84*	7.06*	7.29*	17
Euro Area	-2.96	-1.12	2.89	7.03	3.46	6.47	0.79	4.01	4.71	16

Note: * denotes significance at the 5% nominal level. The critical values considered were computed from a HEGY test regression such as (3.1) augmented with a set of seasonal dummies and a time trend, and a set of lags of the dependent variable (the maximum lag order considered for all cases was 24 lags) and the data was generated from a monthly seasonal random walk. t_0 and t_6, represent the one sided unit root t-test statistics at frequencies 0 and π, respectively; F_1, F_2, F_3, F_4 and F_5, correspond to the joint tests for seasonal unit roots at frequencies $\left(\frac{\pi}{2}, \frac{3\pi}{2}\right)$, $\left(\frac{5\pi}{3}, \frac{7\pi}{6}\right)$, $\left(\frac{\pi}{6}, \frac{11\pi}{6}\right)$, $\left(\frac{2\pi}{3}, \frac{4\pi}{3}\right)$ and $\left(\frac{\pi}{3}, \frac{5\pi}{6}\right)$, respectively; and $F_{1...6}$ and $F_{0...6}$ represent the joint tests for unit roots at all seasonal frequencies and at all frequencies, respectively. The column order identifies the order of the lag length considered in each test regression. The critical values considered were: -3.38 for the zero frequecy, -2.80 for the Nyquist frequency; 5.03 and 5.27 for the $F_{1...6}$ and $F_{0...6}$ tests, respectively and 7.08 for the F_i, $i = 1, ..., 5$, tests.

Table 3.4: Testing for Periodicity

	F_{PeAR1_12}		F_{SH}			
	PAR(3)[a)]	PAR(12)[b)]	PAR(3)[a)]	PAR(12)[b)]	$F_{PAR(3)}$	$F_{PAR(12)}$
Austria	1.83* (36,191)	1.37* (144,83)	3.69* (2,227)	3.50* (11,227)	2.05* (24,235)	1.52* (132,118)
Canada	2.73* (36,195)	1.55* (144,87)	0.08 (2,231)	1.50 (11,231)	8.24* (8,259)	3.07* (44,214)
Denmark	3.35* (36,191)	2.79* (144,83)	3.14* (2,227)	1.66 (11,227)	0.64 (24,235)	1.92* (132,118)
Finland	1.59* (36,191)	1.66* (144,83)	3.08* (2,227)	1.79 (11,227)	1.14 (24,235)	4.51* (132,118)
France	1.85* (36,191)	2.00* (144,83)	1.84 (2,227)	1.42 (11,227)	4.94* (24,235)	3.15* (132,118)
Germany	2.64* (36,191)	1.89* (144,83)	2.60 (2,227)	1.59 (11,227)	1.71 (24,235)	2.22* (132,118)
Greece	3.50* (36,191)	1.88* (144,83)	1.82 (2,227)	1.63 (11,227)	3.69* (24,235)	1.89* (132,118)
Hungary	2.46* (36,191)	2.02* (144,83)	0.46 (2,227)	0.36 (11,227)	1.02 (24,235)	2.87* (132,118)
Italy	1.84* (36,191)	1.91* (144,83)	3.69* (2,227)	6.80* (11,227)	1.06 (24,235)	2.62* (132,118)
Japan	3.80* (36,195)	1.88* (144,87)	0.17 (2,231)	1.59 (11,231)	3.73* (24,235)	2.60* (132,118)
Luxembourg	1.80* (36,191)	1.75* (144,83)	2.41 (2,227)	1.35 (11,227)	1.55 (24,235)	1.76* (132,118)
Netherlands	2.84* (36,191)	2.84* (144,83)	0.32 (2,227)	0.97 (11,227)	1.10 (24,235)	2.95* (132,118)
Portugal	2.45* (36,191)	1.56* (144,83)	2.53 (2,227)	1.31 (11,227)	1.56 (24,235)	2.10* (132,118)
Spain	2.23* (36,191)	2.05* (144,83)	0.48 (2,227)	0.97 (11,227)	4.61* (24,235)	4.44* (132,118)
Sweden	3.15* (36,207)	2.24* (144,99)	3.57* (2,243)	2.73* (11,243)	3.02* (24,235)	5.82* (132,118)
UK	2.46* (36,195)	2.35* (144,87)	0.92 (2,231)	1.72 (11,231)	1.41 (24,235)	3.21* (132,118)
USA	1.76* (36,197)	1.74* (144,89)	1.12 (2,233)	1.21 (11,233)	7.37* (24,235)	1.30* (132,118)
Euro Area	2.81* (36,191)	1.99* (144,83)	1.72 (2,227)	1.33 (11,227)	0.88 (24,235)	4.26* (132,118)

Note: * denotes significant at the 5 % level; and F_{PeAR1_12} and F_{SH} represent the results of the Periodic residual autocorrelation tests of order 1 to 12, and the Seasonal heterocedasticity tests respectively. $F_{PAR(.)}$ denotes the F-test for H_0 in (2.10) presented in Section 2.3. The values in brackets, (., .), indicate the degrees of freedom of the F-statistics.

Table 5.3a: Forecasts of Industrial Production

Austria

	h=1		h=3		h=8		h=12	
Ranking		RMSPE		RMSPE		RMSPE		RMSPE
1	M11	0,0361	M12	0,0447	M6	0,0564	M6	0,0568
2	C1	0,0365	M11	0,0454	M7	0,0608	M7	0,0592
3	C3	0,0366	M6	0,0459	M12	0,0641	M8	0,0665
4	C17	0,0371	M7	0,0464	M8	0,0669	M12	0,0696
5	M12	0,0372	C17	0,0468	C10	0,0689	C8	0,0721
6	M6	0,0373	C16	0,0471	C16	0,0692	M10	0,0743
7	C16	0,0373	C4	0,0474	C4	0,0692	C18	0,0761
8	C15	0,0375	C15	0,0474	C15	0,0692	C2	0,0764
9	C4	0,0375	C5	0,0475	C17	0,0693	M4	0,0765
10	C14	0,0376	C14	0,0476	C5	0,0695	C11	0,0766
11	C10	0,0377	C10	0,0476	C6	0,0697	C15	0,0766
12	C5	0,0377	C6	0,0476	M10	0,0699	C4	0,0766
13	C6	0,0378	C7	0,0478	C2	0,0700	C16	0,0767
14	C7	0,0380	C2	0,0483	C7	0,0701	C17	0,0767
15	C2	0,0382	C9	0,0486	C14	0,0705	C5	0,0767
16	C13	0,0385	C13	0,0489	M4	0,0705	C10	0,0769
17	M2	0,0385	C12	0,0494	M3	0,0710	M3	0,0769
18	M3	0,0386	M3	0,0497	C11	0,0711	C6	0,0769
19	C8	0,0387	C11	0,0497	M2	0,0712	C7	0,0771
20	C11	0,0387	M2	0,0497	C13	0,0712	M2	0,0771
21	C9	0,0388	C8	0,0499	C18	0,0713	C14	0,0781
22	C12	0,0390	M4	0,0502	C9	0,0719	C13	0,0789
23	M7	0,0392	M5	0,0504	C8	0,0720	C9	0,0803
24	M4	0,0394	M17	0,0505	C12	0,0726	C12	0,0835
25	M17	0,0398	C3	0,0508	M11	0,0726	M11	0,0844
26	M14	0,0398	C1	0,0519	M5	0,0728	M5	0,0864
27	M16	0,0399	M16	0,0522	M17	0,0779	M17	0,0908
28	M15	0,0401	M14	0,0525	M16	0,0791	M14	0,0912
29	M1	0,0403	M1	0,0530	M14	0,0792	M16	0,0913
30	M10	0,0406	C18	0,0531	M15	0,0798	M15	0,0915
31	C18	0,0417	M15	0,0534	M1	0,0810	M1	0,0928
32	M5	0,0438	M8	0,0535	C3	0,1065	C3	0,1375
33	M8	0,0455	M10	0,0539	C1	0,1126	C1	0,1474
34	M9	0,0612	M9	0,1834	M9	0,8138	M9	1,1111
35	M13	0,0791	M13	0,3021	M13	0,8378	M13	1,3664

Canada

	h=1		h=3		h=8		h=12	
Ranking		RMSPE		RMSPE		RMSPE		RMSPE
1	M1	0,0133	C11	0,0159	M1	0,0221	M1	0,0271
2	C1	0,0133	C8	0,0164	C14	0,0224	M7	0,0280
3	C3	0,0133	M7	0,0171	C12	0,0229	C12	0,0283
4	M11	0,0133	M12	0,0171	C17	0,0230	C9	0,0289
5	C17	0,0134	M1	0,0171	C7	0,0231	C17	0,0292
6	C16	0,0135	C14	0,0171	C16	0,0231	C10	0,0295
7	C14	0,0135	C9	0,0171	C6	0,0232	C7	0,0295
8	C4	0,0135	C12	0,0173	C9	0,0232	C16	0,0296
9	C15	0,0135	C7	0,0175	C5	0,0233	M6	0,0297
10	C8	0,0136	C16	0,0176	C15	0,0234	C14	0,0297
11	C5	0,0136	C6	0,0176	C4	0,0234	C6	0,0298
12	C6	0,0136	C5	0,0176	C13	0,0239	M8	0,0298
13	C7	0,0136	C4	0,0176	C11	0,0239	C13	0,0298
14	C12	0,0136	C15	0,0176	C10	0,0240	C5	0,0299
15	C9	0,0136	C13	0,0176	C2	0,0242	C8	0,0300
16	C11	0,0136	C17	0,0176	C8	0,0244	C4	0,0301
17	C13	0,0137	C10	0,0177	M6	0,0255	C15	0,0301
18	C10	0,0137	C2	0,0178	M11	0,0255	M3	0,0305
19	M7	0,0137	M11	0,0182	M8	0,0255	C2	0,0307
20	C2	0,0139	M6	0,0183	M7	0,0256	C11	0,0309
21	M6	0,0143	M17	0,0192	M12	0,0256	M11	0,0323
22	M12	0,0143	M10	0,0195	M17	0,0282	M2	0,0326
23	M17	0,0145	M8	0,0197	M3	0,0283	M4	0,0346
24	M10	0,0148	C3	0,0204	M2	0,0287	M17	0,0349
25	M4	0,0149	C1	0,0210	M4	0,0288	M12	0,0358
26	C18	0,0155	M4	0,0214	C18	0,0303	M14	0,0389
27	M8	0,0157	M2	0,0214	M10	0,0307	M10	0,0393
28	M3	0,0159	M3	0,0223	M14	0,0324	M5	0,0417
29	M2	0,0162	M14	0,0225	C3	0,0334	M16	0,0463
30	M14	0,0163	M5	0,0234	M5	0,0336	M15	0,0487
31	M15	0,0165	C18	0,0243	C1	0,0352	C3	0,0496
32	M16	0,0169	M16	0,0251	M16	0,0378	M9	0,0519
33	M5	0,0179	M15	0,0251	M15	0,0386	C1	0,0531
34	M9	0,0218	M9	0,0636	M9	0,0453	C18	0,0542
35	M13	0,0244	M13	0,1536	M13	0,4048	M13	0,6554

Germany

	h=1		h=3		h=8		h=12	
Ranking		RMSPE		RMSPE		RMSPE		RMSPE
1	M17	0,0158	M11	0,0203	M11	0,0331	M12	0,0340
2	C3	0,0162	M7	0,0203	C9	0,0349	M11	0,0341
3	C8	0,0162	C11	0,0219	M7	0,0351	C8	0,0351
4	C17	0,0163	C15	0,0222	C17	0,0358	C7	0,0356
5	C16	0,0163	C4	0,0222	C16	0,0359	C12	0,0356
6	C1	0,0163	C16	0,0222	C7	0,0360	C9	0,0357
7	C4	0,0163	C17	0,0222	M12	0,0360	C6	0,0359
8	C15	0,0163	C10	0,0222	C6	0,0360	C14	0,0361
9	C5	0,0164	C5	0,0222	C5	0,0360	C5	0,0361
10	C14	0,0164	C8	0,0223	C14	0,0360	C17	0,0362
11	C6	0,0164	C6	0,0223	C4	0,0360	C16	0,0363
12	C10	0,0164	C7	0,0223	C15	0,0360	C4	0,0364
13	C7	0,0164	C14	0,0224	C10	0,0361	C15	0,0364
14	C11	0,0166	M4	0,0227	C12	0,0362	C10	0,0367
15	M4	0,0166	C12	0,0227	C8	0,0364	M4	0,0367
16	C9	0,0167	C13	0,0227	M1	0,0367	C11	0,0369
17	C13	0,0168	C9	0,0228	M4	0,0370	C13	0,0370
18	C2	0,0168	C2	0,0229	C2	0,0375	C2	0,0374
19	C12	0,0169	M17	0,0229	M8	0,0375	M2	0,0380
20	C18	0,0171	M1	0,0231	C13	0,0379	M1	0,0383
21	M10	0,0176	M3	0,0234	M2	0,0380	M6	0,0384
22	M5	0,0177	M6	0,0238	M6	0,0390	M8	0,0384
23	M3	0,0178	M10	0,0242	C11	0,0390	M7	0,0397
24	M1	0,0178	M16	0,0247	M17	0,0405	M3	0,0416
25	M2	0,0181	M2	0,0256	M3	0,0405	M17	0,0441
26	M11	0,0181	M15	0,0256	M10	0,0415	M14	0,0450
27	M16	0,0184	M14	0,0257	M14	0,0427	M10	0,0450
28	M15	0,0186	C3	0,0258	M16	0,0436	M16	0,0470
29	M14	0,0186	C1	0,0266	M5	0,0459	M5	0,0477
30	M6	0,0186	M12	0,0266	C3	0,0463	M15	0,0526
31	M7	0,0186	C18	0,0271	M15	0,0471	C3	0,0603
32	M12	0,0197	M5	0,0276	C1	0,0483	C1	0,0644
33	M8	0,0218	M8	0,0304	C18	0,0637	C18	0,0749
34	M9	0,0248	M9	0,0874	M9	0,0755	M9	0,0826
35	M13	0,0264	M13	0,1828	M13	0,4735	M13	0,7469

Denmark

	h=1		h=3		h=8		h=12	
Ranking		RMSPE		RMSPE		RMSPE		RMSPE
1	C10	0,0306	C9	0,0306	C10	0,0307	C18	0,0303
2	C9	0,0308	C10	0,0308	C5	0,0313	M4	0,0316
3	C7	0,0311	M4	0,0308	C4	0,0313	C10	0,0319
4	C8	0,0312	C17	0,0308	C15	0,0313	C12	0,0323
5	C6	0,0313	C7	0,0309	C6	0,0313	C17	0,0323
6	C5	0,0314	C6	0,0309	C7	0,0313	C13	0,0324
7	C11	0,0316	C16	0,0309	C16	0,0315	C16	0,0324
8	C15	0,0316	C5	0,0309	C17	0,0317	C6	0,0324
9	C4	0,0316	C4	0,0310	C14	0,0323	C5	0,0324
10	C16	0,0316	C15	0,0310	M4	0,0323	C7	0,0324
11	C17	0,0317	C14	0,0318	C8	0,0324	C15	0,0325
12	C13	0,0318	C8	0,0318	C9	0,0326	C4	0,0325
13	M4	0,0321	M17	0,0321	C13	0,0333	C9	0,0326
14	C14	0,0326	C12	0,0325	M17	0,0343	C14	0,0330
15	C12	0,0326	C13	0,0327	C12	0,0344	C11	0,0334
16	C2	0,0327	C11	0,0330	C11	0,0344	M17	0,0335
17	M17	0,0339	C2	0,0336	C2	0,0345	C2	0,0336
18	M12	0,0353	C18	0,0357	C18	0,0362	C8	0,0344
19	C18	0,0356	M3	0,0367	M3	0,0366	M10	0,0358
20	M8	0,0357	M2	0,0369	M2	0,0367	M11	0,0365
21	M5	0,0359	M15	0,0373	M16	0,0383	M3	0,0372
22	M15	0,0379	M14	0,0380	M6	0,0385	M2	0,0373
23	M3	0,0379	M16	0,0380	M15	0,0388	M6	0,0388
24	M16	0,0381	M10	0,0387	M14	0,0393	M16	0,0399
25	M2	0,0389	M12	0,0389	M11	0,0395	M14	0,0403
26	M14	0,0391	M6	0,0391	M7	0,0399	M15	0,0413
27	M7	0,0393	M8	0,0392	M10	0,0404	M8	0,0414
28	M10	0,0395	M1	0,0395	M8	0,0406	M7	0,0447
29	M6	0,0402	M7	0,0408	M12	0,0431	M5	0,0464
30	M1	0,0415	M11	0,0430	M1	0,0434	M1	0,0494
31	M11	0,0417	M5	0,0464	M5	0,0502	M12	0,0538
32	M13	0,0848	C3	0,0841	C3	0,0887	C3	0,1062
33	C3	0,0857	C1	0,0928	C1	0,0976	C1	0,1175
34	C1	0,0942	M13	0,2025	M13	0,6171	M13	1,0681
35	M9	1,3640	M9	1,3648	M9	1,3377	M9	1,3468

Table 5.3b: Forecasts of Industrial Production

Euro Area

Ranking	h=1	RMSPE	h=3	RMSPE	h=8	RMSPE	h=12	RMSPE
1	M11	0,0180	M11	0,0293	M11	0,0548	C11	0,0569
2	M7	0,0197	M7	0,0295	C9	0,0555	C8	0,0571
3	M12	0,0203	C10	0,0314	C14	0,0555	C7	0,0588
4	C16	0,0211	M12	0,0316	C7	0,0556	C14	0,0593
5	C15	0,0211	M10	0,0316	C6	0,0557	C6	0,0595
6	C4	0,0211	C15	0,0320	C16	0,0557	C9	0,0596
7	C17	0,0212	C4	0,0320	C5	0,0557	C17	0,0597
8	C5	0,0212	C16	0,0320	C4	0,0558	C5	0,0599
9	M10	0,0212	C17	0,0321	C15	0,0558	C16	0,0600
10	C10	0,0212	C5	0,0322	C17	0,0558	M3	0,0601
11	C6	0,0213	C2	0,0322	M7	0,0559	C4	0,0604
12	C7	0,0214	C11	0,0323	C8	0,0562	C15	0,0604
13	C11	0,0216	C6	0,0323	M3	0,0564	C10	0,0616
14	C2	0,0218	M3	0,0323	C10	0,0565	M2	0,0621
15	C13	0,0220	C14	0,0323	M12	0,0569	M8	0,0630
16	M17	0,0220	C7	0,0325	C2	0,0575	C12	0,0632
17	M3	0,0222	C13	0,0326	M10	0,0576	C2	0,0638
18	C8	0,0222	C8	0,0327	C11	0,0576	M12	0,0641
19	C9	0,0223	C9	0,0331	C12	0,0577	C13	0,0642
20	C12	0,0224	C12	0,0332	C13	0,0579	M7	0,0644
21	M4	0,0225	M4	0,0335	M2	0,0585	M1	0,0653
22	C14	0,0225	M17	0,0337	M1	0,0585	M4	0,0660
23	M1	0,0228	M1	0,0340	M8	0,0600	M11	0,0661
24	M2	0,0229	M15	0,0347	M4	0,0610	M10	0,0695
25	M15	0,0232	M16	0,0352	M17	0,0612	M17	0,0704
26	M14	0,0234	M2	0,0357	M6	0,0637	M6	0,0705
27	M16	0,0235	M14	0,0357	M14	0,0637	M14	0,0711
28	M5	0,0241	M6	0,0366	M15	0,0654	M5	0,0725
29	M6	0,0241	M5	0,0369	M5	0,0661	M15	0,0740
30	C18	0,0245	M8	0,0404	M16	0,0670	M16	0,0766
31	M8	0,0252	C18	0,0441	C18	0,1139	C3	0,1414
32	M13	0,0293	C3	0,0922	C3	0,1189	C18	0,1448
33	C3	0,1000	C1	0,1018	C1	0,1297	C1	0,1543
34	C1	0,1111	M13	0,2949	M13	0,8087	M13	1,2865
35	M9	1,7450	M9	1,5479	M9	1,7385	M9	1,9034

Spain

Ranking	h=1	RMSPE	h=3	RMSPE	h=8	RMSPE	h=12	RMSPE
1	C17	0,0178	C10	0,0204	C8	0,0252	M11	0,0229
2	C4	0,0178	C15	0,0206	C9	0,0256	C9	0,0243
3	C15	0,0178	C4	0,0206	C7	0,0261	C8	0,0245
4	C16	0,0178	C5	0,0206	M11	0,0262	C7	0,0249
5	C5	0,0179	C8	0,0206	C6	0,0262	C6	0,0252
6	C8	0,0179	C6	0,0207	C5	0,0262	C5	0,0253
7	C6	0,0179	C16	0,0207	C15	0,0262	C4	0,0254
8	C9	0,0179	C7	0,0207	C4	0,0262	C15	0,0254
9	C7	0,0179	C17	0,0207	C16	0,0265	C16	0,0255
10	C10	0,0180	C14	0,0207	C10	0,0268	C12	0,0256
11	C13	0,0180	C11	0,0208	C17	0,0268	C17	0,0258
12	C2	0,0181	C13	0,0210	C11	0,0269	C10	0,0258
13	C12	0,0181	C9	0,0212	M12	0,0269	C14	0,0264
14	C14	0,0181	C2	0,0212	C12	0,0274	C13	0,0265
15	C11	0,0182	C12	0,0213	M4	0,0277	C11	0,0266
16	M4	0,0187	M4	0,0219	C14	0,0277	C2	0,0266
17	M2	0,0189	M11	0,0221	C2	0,0279	M4	0,0267
18	M17	0,0190	M17	0,0221	C18	0,0279	M2	0,0271
19	M11	0,0190	M3	0,0225	C13	0,0281	M12	0,0277
20	M3	0,0192	M12	0,0225	M2	0,0282	M3	0,0279
21	M15	0,0194	M2	0,0226	M3	0,0287	M17	0,0295
22	M12	0,0194	C18	0,0233	M17	0,0290	M8	0,0296
23	C18	0,0194	M14	0,0233	M1	0,0309	M1	0,0313
24	M14	0,0194	M1	0,0235	M15	0,0326	M15	0,0333
25	M10	0,0200	M15	0,0236	M14	0,0326	M14	0,0336
26	M16	0,0201	M16	0,0240	M8	0,0329	M5	0,0346
27	M6	0,0206	M5	0,0262	M7	0,0330	C18	0,0349
28	M1	0,0207	M10	0,0263	M16	0,0333	M16	0,0351
29	M5	0,0209	M7	0,0263	M5	0,0356	M7	0,0362
30	M7	0,0215	M6	0,0267	M10	0,0365	M10	0,0371
31	M13	0,0226	M8	0,0300	M6	0,0396	M6	0,0456
32	M8	0,0233	C3	0,0794	C3	0,1372	C3	0,1498
33	C3	0,1053	C1	0,0884	C1	0,1526	C1	0,1669
34	C1	0,1177	M13	0,4257	M13	1,1458	M13	1,7746
35	M9	1,8962	M9	1,3304	M9	2,0633	M9	1,9024

Finland

Ranking	h=1	RMSPE	h=3	RMSPE	h=8	RMSPE	h=12	RMSPE
1	M17	0,0570	M17	0,0805	M17	0,1230	M3	0,1433
2	C10	0,0577	C15	0,0835	M1	0,1290	M2	0,1442
3	C13	0,0590	C4	0,0835	C4	0,1298	M17	0,1445
4	C11	0,0596	M1	0,0837	C15	0,1298	C8	0,1457
5	C7	0,0596	C16	0,0838	C5	0,1301	M1	0,1461
6	C9	0,0597	C17	0,0839	C6	0,1305	C7	0,1467
7	C8	0,0598	C5	0,0839	C14	0,1309	C6	0,1468
8	C2	0,0599	C14	0,0841	C16	0,1309	C5	0,1468
9	M4	0,0600	C6	0,0842	C7	0,1310	C4	0,1469
10	M10	0,0601	C7	0,0847	C17	0,1319	C15	0,1469
11	C12	0,0601	C18	0,0853	C10	0,1322	C14	0,1474
12	M5	0,0601	C10	0,0855	M3	0,1323	C16	0,1479
13	C14	0,0603	C11	0,0870	M12	0,1328	C9	0,1480
14	C6	0,0605	C2	0,0871	M2	0,1330	C17	0,1487
15	M1	0,0608	C13	0,0873	C8	0,1336	C10	0,1491
16	C17	0,0608	C12	0,0875	C11	0,1337	C2	0,1507
17	M2	0,0610	M3	0,0879	M4	0,1340	C11	0,1510
18	M3	0,0611	C9	0,0880	C13	0,1356	M8	0,1510
19	C5	0,0614	C8	0,0881	C18	0,1356	C12	0,1512
20	C16	0,0614	M16	0,0881	C2	0,1360	C13	0,1513
21	M16	0,0619	M2	0,0883	C9	0,1367	M4	0,1520
22	M15	0,0624	M4	0,0886	C12	0,1374	M11	0,1523
23	C4	0,0625	M12	0,0888	M11	0,1378	M12	0,1574
24	C15	0,0625	M10	0,0891	C3	0,1399	M16	0,1617
25	M14	0,0626	M15	0,0899	M16	0,1423	M5	0,1639
26	C18	0,0638	M11	0,0908	C1	0,1427	M7	0,1657
27	M12	0,0638	M14	0,0916	M10	0,1429	M14	0,1657
28	M13	0,0648	M5	0,0922	M15	0,1466	M15	0,1667
29	M11	0,0662	C3	0,0983	M14	0,1467	M10	0,1671
30	M6	0,0679	C1	0,1026	M5	0,1468	C3	0,1687
31	C3	0,0724	M6	0,1050	M7	0,1481	C18	0,1694
32	C1	0,0757	M7	0,1060	M8	0,1592	C1	0,1739
33	M7	0,0790	M8	0,1119	M6	0,1689	M6	0,1906
34	M8	0,0871	M13	0,2505	M13	0,7431	M9	0,8173
35	M9	0,7959	M9	1,1246	M9	0,8320	M13	1,2725

France

Ranking	h=1	RMSPE	h=3	RMSPE	h=8	RMSPE	h=12	RMSPE
1	M6	0,0255	C18	0,0227	C18	0,0268	M7	0,0295
2	C8	0,0264	M6	0,0260	M6	0,0278	C18	0,0298
3	C11	0,0267	C8	0,0264	C8	0,0281	M8	0,0316
4	C18	0,0269	M12	0,0276	C11	0,0282	C9	0,0316
5	C14	0,0269	C9	0,0276	M10	0,0288	M12	0,0323
6	C7	0,0274	C11	0,0277	M7	0,0291	C8	0,0325
7	C9	0,0274	C7	0,0280	C7	0,0296	C12	0,0325
8	C6	0,0275	C6	0,0282	C9	0,0298	M6	0,0327
9	C5	0,0275	C10	0,0282	C6	0,0298	C11	0,0333
10	C4	0,0275	C5	0,0283	C5	0,0300	C7	0,0337
11	C15	0,0275	C4	0,0284	C10	0,0300	C6	0,0340
12	C16	0,0276	C15	0,0284	C4	0,0302	C5	0,0341
13	C10	0,0277	C16	0,0285	C15	0,0302	C17	0,0341
14	C17	0,0277	C14	0,0285	C16	0,0302	C16	0,0341
15	C12	0,0279	C17	0,0286	C17	0,0302	C10	0,0342
16	M8	0,0282	M8	0,0287	M12	0,0304	C15	0,0343
17	M10	0,0282	C12	0,0289	C12	0,0309	C4	0,0343
18	M5	0,0285	C13	0,0293	M4	0,0309	M11	0,0344
19	C13	0,0286	M7	0,0294	M17	0,0314	C14	0,0352
20	C2	0,0286	C2	0,0294	C13	0,0314	C2	0,0357
21	M4	0,0288	M4	0,0300	C14	0,0318	C13	0,0358
22	M12	0,0297	M10	0,0302	C2	0,0321	M10	0,0361
23	M17	0,0298	M11	0,0309	M8	0,0322	M1	0,0368
24	M11	0,0300	M17	0,0313	M11	0,0333	M3	0,0383
25	M7	0,0303	M1	0,0326	M1	0,0340	M2	0,0388
26	M16	0,0326	M2	0,0328	M3	0,0341	M4	0,0395
27	M2	0,0331	M16	0,0334	M2	0,0355	M17	0,0402
28	M15	0,0335	M14	0,0345	M16	0,0371	M5	0,0425
29	M1	0,0336	M15	0,0346	M15	0,0373	M16	0,0447
30	M14	0,0345	M3	0,0346	M14	0,0379	M14	0,0459
31	M3	0,0349	M5	0,0421	M5	0,0417	M15	0,0469
32	M13	0,0435	C3	0,0871	C3	0,1183	C3	0,1514
33	C3	0,0772	C1	0,0960	C1	0,1305	C1	0,1677
34	C1	0,0856	M13	0,4034	M13	1,0732	M13	1,6941
35	M9	1,3537	M9	1,3534	M9	1,5323	M9	1,7474

Table 5.3c: Forecasts of Industrial Production

	UK								Greece							
	h=1		h=3		h=8		h=12		h=1		h=3		h=8		h=12	
Ranking		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE
1	C18	0,0220	C18	0,0233	M7	0,0286	M8	0,0274	M17	0,0299	M10	0,0343	M10	0,0403	C18	0,0411
2	M12	0,0228	M12	0,0239	M8	0,0293	M7	0,0291	C8	0,0302	C10	0,0346	C11	0,0414	M7	0,0417
3	M6	0,0230	M7	0,0242	M12	0,0316	M12	0,0329	C10	0,0303	C8	0,0346	C18	0,0415	M12	0,0434
4	C8	0,0237	M8	0,0247	M6	0,0329	C18	0,0373	C11	0,0304	C13	0,0346	C10	0,0417	M11	0,0439
5	M10	0,0238	C9	0,0247	C10	0,0333	M11	0,0393	M5	0,0305	C15	0,0347	C15	0,0420	M10	0,0444
6	M11	0,0240	C14	0,0251	M10	0,0334	M6	0,0401	C7	0,0306	C4	0,0347	C4	0,0420	M6	0,0449
7	C14	0,0241	C7	0,0251	C8	0,0336	C4	0,0416	C6	0,0307	C5	0,0347	C16	0,0420	M8	0,0457
8	C9	0,0242	C6	0,0252	C14	0,0339	C15	0,0416	C13	0,0307	C16	0,0347	C8	0,0420	M1	0,0457
9	C7	0,0244	C5	0,0253	C4	0,0342	C14	0,0417	C5	0,0307	C6	0,0348	C5	0,0421	C10	0,0457
10	C10	0,0245	C4	0,0253	C15	0,0342	C5	0,0418	C15	0,0308	C17	0,0348	C17	0,0421	C15	0,0460
11	M7	0,0245	C15	0,0253	C5	0,0342	C6	0,0419	C4	0,0308	M17	0,0349	M6	0,0421	C4	0,0460
12	C6	0,0245	C16	0,0254	C18	0,0342	C7	0,0422	C16	0,0308	C7	0,0349	C6	0,0422	C16	0,0461
13	C12	0,0246	C8	0,0254	C6	0,0343	C10	0,0425	C17	0,0308	C2	0,0350	C2	0,0422	C5	0,0462
14	C5	0,0246	C17	0,0255	C7	0,0344	C16	0,0426	M10	0,0308	C14	0,0353	C13	0,0422	C8	0,0462
15	C11	0,0246	M6	0,0255	C16	0,0346	C2	0,0428	M4	0,0311	C11	0,0354	M1	0,0423	M2	0,0463
16	C4	0,0247	C10	0,0257	C17	0,0347	C9	0,0429	C9	0,0312	C9	0,0358	C7	0,0423	C6	0,0463
17	C15	0,0247	C12	0,0258	C11	0,0350	C17	0,0431	C14	0,0313	M1	0,0359	M7	0,0428	C17	0,0464
18	C17	0,0247	C11	0,0258	M11	0,0355	M1	0,0434	C12	0,0316	C12	0,0360	C14	0,0430	C7	0,0466
19	C16	0,0247	M10	0,0259	C9	0,0358	C11	0,0443	M6	0,0316	M3	0,0360	M2	0,0430	C2	0,0468
20	C3	0,0250	M4	0,0266	C13	0,0365	C8	0,0443	M1	0,0318	M2	0,0364	M3	0,0433	C11	0,0469
21	C1	0,0250	C2	0,0269	C2	0,0365	M10	0,0446	C2	0,0319	M4	0,0365	C12	0,0437	M3	0,0471
22	C13	0,0252	C13	0,0269	C12	0,0374	C12	0,0447	C18	0,0320	M7	0,0367	C9	0,0438	C14	0,0472
23	M8	0,0252	M11	0,0269	M4	0,0376	M3	0,0451	M2	0,0331	M6	0,0368	M5	0,0440	C9	0,0480
24	C2	0,0259	C3	0,0277	M1	0,0384	C13	0,0453	M3	0,0341	C18	0,0373	M4	0,0441	C13	0,0480
25	M17	0,0261	M17	0,0279	M3	0,0385	M4	0,0463	M14	0,0346	M16	0,0389	M11	0,0442	C12	0,0494
26	M4	0,0267	C1	0,0281	M17	0,0424	M2	0,0485	M16	0,0351	M14	0,0390	M8	0,0453	M4	0,0495
27	M5	0,0281	M3	0,0313	C3	0,0427	M5	0,0539	M11	0,0352	M15	0,0394	M17	0,0457	M17	0,0515
28	M15	0,0313	M15	0,0315	M2	0,0431	M17	0,0563	M7	0,0353	M11	0,0402	M14	0,0485	M5	0,0537
29	M16	0,0321	M16	0,0317	C1	0,0443	M15	0,0575	M15	0,0354	M5	0,0412	M16	0,0487	M14	0,0546
30	M3	0,0323	M1	0,0338	M15	0,0449	M16	0,0576	M8	0,0414	M8	0,0466	M15	0,0495	M16	0,0562
31	M9	0,0334	M2	0,0344	M16	0,0451	M14	0,0583	M13	0,0415	M12	0,0528	M12	0,0556	M15	0,0564
32	M2	0,0337	M14	0,0347	M14	0,0470	C3	0,0852	M12	0,0419	C3	0,0944	C3	0,1211	C3	0,1318
33	M1	0,0339	M5	0,0448	M5	0,0503	C1	0,0923	C3	0,1005	C1	0,1039	C1	0,1334	C1	0,1450
34	M14	0,0343	M9	0,0717	M9	0,0950	M13	0,6647	C1	0,1114	M13	0,2298	M13	0,6041	M13	0,9579
35	M13	0,0386	M13	0,1648	M13	0,4439	M9	1,0902	M9	1,7149	M9	1,5379	M9	1,8892	M9	1,8908

	Hungary								Italy							
	h=1		h=3		h=8		h=12		h=1		h=3		h=8		h=12	
Ranking		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE
1	C10	0,0297	M1	0,0326	M1	0,0397	M1	0,0366	C18	0,0206	M1	0,0202	M3	0,0239	C2	0,0236
2	C3	0,0297	C6	0,0332	C9	0,0411	C8	0,0387	M5	0,0213	M17	0,0205	C2	0,0240	C13	0,0240
3	C17	0,0298	C2	0,0332	C10	0,0415	M8	0,0396	C14	0,0218	C8	0,0206	M2	0,0240	M3	0,0241
4	C15	0,0298	C5	0,0332	C15	0,0416	C7	0,0399	C11	0,0220	C11	0,0207	C13	0,0240	M2	0,0241
5	C4	0,0298	C10	0,0332	C4	0,0416	C6	0,0400	C8	0,0221	C2	0,0209	M1	0,0242	M1	0,0246
6	C16	0,0298	C7	0,0332	C5	0,0416	C4	0,0400	C4	0,0221	C13	0,0210	C14	0,0244	C12	0,0248
7	C5	0,0298	C15	0,0332	C6	0,0417	C15	0,0400	C15	0,0221	C12	0,0211	C12	0,0245	C17	0,0261
8	C1	0,0298	C4	0,0332	C7	0,0417	C5	0,0400	M4	0,0222	C7	0,0212	C17	0,0252	M10	0,0263
9	C6	0,0298	C17	0,0333	C17	0,0419	C9	0,0403	C16	0,0222	C10	0,0212	C16	0,0252	C10	0,0263
10	C7	0,0299	C16	0,0333	C16	0,0420	C10	0,0404	C5	0,0222	C6	0,0212	C9	0,0253	C16	0,0263
11	C2	0,0300	C13	0,0335	C11	0,0425	C16	0,0409	C17	0,0222	C5	0,0212	C4	0,0253	M12	0,0263
12	C13	0,0300	C8	0,0339	C8	0,0426	C14	0,0413	C6	0,0222	C15	0,0212	C15	0,0253	C15	0,0266
13	C12	0,0301	C12	0,0339	C12	0,0427	C17	0,0413	C7	0,0223	C4	0,0212	C10	0,0254	C4	0,0266
14	C11	0,0302	C14	0,0339	C2	0,0429	M10	0,0418	C10	0,0224	C16	0,0212	C5	0,0255	C5	0,0269
15	C9	0,0303	C9	0,0340	C13	0,0431	C11	0,0421	M1	0,0227	M3	0,0213	C6	0,0256	C6	0,0271
16	C8	0,0305	C11	0,0347	C14	0,0435	C2	0,0431	C2	0,0228	C17	0,0213	C7	0,0257	C14	0,0272
17	C14	0,0305	M14	0,0350	M10	0,0448	C13	0,0435	C13	0,0228	C9	0,0213	M12	0,0261	C7	0,0274
18	M11	0,0306	M17	0,0352	M8	0,0449	C12	0,0447	C9	0,0229	M16	0,0215	M17	0,0270	M5	0,0278
19	M17	0,0314	C3	0,0353	M14	0,0455	M7	0,0448	M12	0,0230	C14	0,0217	M14	0,0274	M4	0,0283
20	M10	0,0316	M16	0,0354	M16	0,0460	M14	0,0471	C12	0,0232	M2	0,0218	M10	0,0275	C9	0,0284
21	M1	0,0317	M15	0,0354	M15	0,0461	M17	0,0472	M16	0,0235	M4	0,0221	M16	0,0275	C18	0,0295
22	M2	0,0321	M2	0,0356	M2	0,0465	M16	0,0477	M17	0,0236	M14	0,0222	M15	0,0277	M17	0,0301
23	M14	0,0322	C1	0,0358	M17	0,0467	M15	0,0479	M2	0,0238	M15	0,0224	M5	0,0278	M14	0,0310
24	M16	0,0323	M11	0,0359	M11	0,0482	M2	0,0489	M3	0,0240	C18	0,0230	M4	0,0288	C11	0,0314
25	M15	0,0323	M10	0,0362	C3	0,0484	M11	0,0520	M15	0,0241	M12	0,0244	C8	0,0292	M15	0,0319
26	M4	0,0328	M4	0,0366	C1	0,0501	C3	0,0538	M14	0,0250	M10	0,0247	C11	0,0297	M16	0,0320
27	M6	0,0329	M12	0,0370	M12	0,0526	M5	0,0539	M8	0,0251	M5	0,0248	C18	0,0304	C8	0,0321
28	M3	0,0332	M3	0,0374	M7	0,0537	M12	0,0557	M10	0,0252	M11	0,0261	M11	0,0328	M11	0,0343
29	M12	0,0341	M6	0,0381	M6	0,0542	C1	0,0570	M11	0,0256	M8	0,0274	M8	0,0334	M8	0,0367
30	M7	0,0350	M7	0,0401	M3	0,0551	M3	0,0578	M13	0,0260	M6	0,0283	M6	0,0430	M7	0,0502
31	M5	0,0397	M8	0,0420	M4	0,0574	M4	0,0677	M7	0,0263	M7	0,0314	M7	0,0454	M6	0,0505
32	M8	0,0414	M5	0,0456	M5	0,0576	M6	0,0698	M6	0,0269	C3	0,0821	C3	0,1312	C3	0,2110
33	M13	0,0455	C18	0,0612	M9	0,0970	M9	0,0836	C3	0,1031	C1	0,0911	C1	0,1469	C1	0,2360
34	M9	0,0475	M9	0,1052	C18	0,1192	C18	0,1209	C1	0,1152	M13	0,7218	M9	1,1484	M9	1,5881
35	C18	0,0668	M13	0,1734	M13	0,4731	M13	0,7258	M9	1,8899	M9	1,1161	M13	1,9437	M13	3,1870

Table 5.3d: Forecasts of Industrial Production

	Japan								Luxembourg								The Netherlands								Portugal							
	h=1		h=3		h=8		h=12		h=1		h=3		h=8		h=12		h=1		h=3		h=8		h=12		h=1		h=3		h=8		h=12	
Ranking		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE
1	M12	0,0192	C2	0,0243	M1	0,0360	M7	0,0459	M9	0,0331	C15	0,0368	M16	0,0414	M16	0,0391	M11	0,0216	C2	0,0267	M4	0,0284	M4	0,0274	M5	0,0496	M4	0,0556	M4	0,0617	M12	0,0685
2	C5	0,0193	C11	0,0243	C10	0,0384	M1	0,0477	C1	0,0348	C4	0,0368	M14	0,0423	M1	0,0391	C17	0,0216	C13	0,0267	M3	0,0295	M3	0,0288	M17	0,0505	M1	0,0566	M1	0,0623	M11	0,0690
3	C6	0,0193	C5	0,0244	C17	0,0393	C17	0,0507	C3	0,0350	C14	0,0369	M1	0,0426	M17	0,0401	C16	0,0216	M11	0,0267	M2	0,0307	M2	0,0299	M4	0,0505	M11	0,0579	M12	0,0630	M8	0,0694
4	C15	0,0193	C6	0,0244	C16	0,0393	M6	0,0510	C15	0,0355	C16	0,0369	C13	0,0437	M14	0,0406	C4	0,0217	C12	0,0268	C9	0,0313	C14	0,0313	C10	0,0509	M12	0,0584	M11	0,0645	C18	0,0708
5	C4	0,0193	C4	0,0244	C15	0,0394	C16	0,0513	C4	0,0355	C9	0,0369	M17	0,0439	M15	0,0424	C15	0,0217	M3	0,0268	C8	0,0317	C9	0,0317	C15	0,0512	C10	0,0591	C10	0,0652	C8	0,0721
6	C7	0,0193	C15	0,0244	C4	0,0394	C6	0,0516	C18	0,0356	C5	0,0370	M15	0,0439	C17	0,0441	C3	0,0217	C9	0,0270	M11	0,0317	C17	0,0321	C4	0,0512	M17	0,0593	C13	0,0659	M4	0,0722
7	C16	0,0193	C14	0,0245	C5	0,0397	C5	0,0517	C16	0,0357	M16	0,0370	C2	0,0440	C13	0,0443	C10	0,0217	C8	0,0270	C11	0,0318	C16	0,0322	C16	0,0512	C4	0,0598	C2	0,0659	M7	0,0729
8	C10	0,0193	C16	0,0245	C2	0,0399	C10	0,0517	C5	0,0357	C6	0,0371	C17	0,0442	C10	0,0446	C5	0,0218	C14	0,0270	C7	0,0318	C12	0,0322	C13	0,0513	C15	0,0598	C14	0,0661	C9	0,0740
9	C17	0,0193	C7	0,0245	C6	0,0399	C7	0,0517	C17	0,0357	C17	0,0371	M5	0,0445	C16	0,0449	C13	0,0218	C7	0,0270	C17	0,0319	C7	0,0324	C17	0,0513	C17	0,0598	C17	0,0661	C11	0,0748
10	C8	0,0194	C17	0,0245	C14	0,0400	C4	0,0517	C6	0,0358	C10	0,0371	C10	0,0445	M5	0,0450	C1	0,0218	C6	0,0271	C16	0,0319	C4	0,0324	C2	0,0514	C16	0,0599	C16	0,0662	M1	0,0748
11	C13	0,0195	C9	0,0245	C7	0,0405	C15	0,0517	C7	0,0360	C7	0,0372	C16	0,0448	C4	0,0454	C6	0,0218	C5	0,0271	C6	0,0319	C15	0,0324	C5	0,0514	C5	0,0600	C4	0,0662	C2	0,0756
12	C9	0,0195	C8	0,0245	M7	0,0405	C14	0,0523	C14	0,0360	C3	0,0374	C15	0,0453	C15	0,0454	C14	0,0219	C15	0,0271	C5	0,0320	C6	0,0324	C14	0,0516	C6	0,0602	C15	0,0662	C14	0,0759
13	M5	0,0196	C10	0,0246	C13	0,0408	C9	0,0531	C11	0,0366	C2	0,0375	C4	0,0453	C14	0,0454	C7	0,0219	C4	0,0271	C4	0,0320	C5	0,0324	C6	0,0517	C13	0,0603	C9	0,0665	C12	0,0759
14	M8	0,0196	M8	0,0248	M2	0,0413	M2	0,0533	C8	0,0369	C12	0,0377	C5	0,0454	C8	0,0454	C2	0,0220	M1	0,0271	C15	0,0320	C10	0,0325	M10	0,0519	C2	0,0605	C5	0,0665	C7	0,0766
15	M17	0,0197	M11	0,0248	C9	0,0427	C8	0,0538	C10	0,0373	C11	0,0378	C6	0,0455	C11	0,0455	C9	0,0223	C16	0,0271	C12	0,0321	C2	0,0326	C7	0,0520	C7	0,0607	C6	0,0668	C6	0,0768
16	C11	0,0197	C13	0,0249	M6	0,0430	C12	0,0541	C12	0,0375	C1	0,0379	C7	0,0458	C5	0,0455	C12	0,0223	M4	0,0272	C14	0,0322	M16	0,0327	M6	0,0527	C14	0,0608	M8	0,0673	C5	0,0769
17	C2	0,0197	C12	0,0251	C8	0,0436	C11	0,0544	C2	0,0376	C13	0,0379	C14	0,0458	C6	0,0456	C8	0,0225	C17	0,0272	C10	0,0322	C13	0,0329	C9	0,0534	M7	0,0610	C7	0,0673	C4	0,0770
18	C12	0,0197	M12	0,0252	C11	0,0442	C2	0,0549	C13	0,0377	C8	0,0384	C8	0,0468	C2	0,0458	M4	0,0231	C10	0,0272	C13	0,0322	C18	0,0334	M7	0,0537	M6	0,0619	C12	0,0683	C15	0,0770
19	M6	0,0200	M7	0,0252	C12	0,0443	C13	0,0563	C9	0,0378	M14	0,0387	C18	0,0468	C7	0,0459	C11	0,0232	M2	0,0276	C2	0,0325	M15	0,0337	C8	0,0539	C8	0,0624	C18	0,0689	C17	0,0770
20	M11	0,0201	M6	0,0264	M8	0,0464	M8	0,0571	M16	0,0381	M1	0,0393	M2	0,0469	C12	0,0466	M10	0,0233	C11	0,0276	M16	0,0332	C8	0,0338	M12	0,0541	C9	0,0627	M7	0,0699	C16	0,0770
21	C18	0,0201	M4	0,0266	M14	0,0469	M4	0,0576	M14	0,0384	M3	0,0395	M3	0,0469	M10	0,0467	M1	0,0233	M17	0,0287	M7	0,0336	C11	0,0341	C12	0,0557	C18	0,0628	M17	0,0709	C10	0,0783
22	C14	0,0203	M17	0,0266	M4	0,0474	M3	0,0594	M2	0,0385	M2	0,0399	C9	0,0473	C9	0,0476	M17	0,0234	M16	0,0289	M15	0,0340	M11	0,0346	M11	0,0560	C12	0,0641	C11	0,0715	M6	0,0802
23	M4	0,0204	C18	0,0282	M11	0,0477	M14	0,0649	M1	0,0385	M15	0,0402	C12	0,0478	M2	0,0487	M2	0,0234	M15	0,0290	M12	0,0344	M7	0,0348	M1	0,0561	M10	0,0641	M3	0,0725	C13	0,0810
24	M7	0,0209	M2	0,0284	C18	0,0493	M5	0,0678	M15	0,0389	M5	0,0406	M10	0,0485	M3	0,0503	M12	0,0237	C3	0,0293	M17	0,0344	M1	0,0355	M2	0,0567	M8	0,0650	M2	0,0727	M3	0,0821
25	M10	0,0213	C3	0,0285	M5	0,0502	M17	0,0693	M3	0,0394	C18	0,0423	C11	0,0499	C18	0,0507	M3	0,0237	M10	0,0298	M1	0,0347	M17	0,0356	C11	0,0571	C11	0,0654	M6	0,0729	M2	0,0822
26	M2	0,0228	M1	0,0292	M17	0,0514	M10	0,0706	M17	0,0397	M17	0,0423	M4	0,0516	M8	0,0530	M7	0,0237	C1	0,0299	M10	0,0350	M10	0,0357	M3	0,0577	M2	0,0656	C8	0,0730	M10	0,0864
27	M3	0,0230	M10	0,0294	M12	0,0525	C18	0,0753	M4	0,0401	M10	0,0423	M8	0,0517	M11	0,0531	M16	0,0238	M14	0,0309	M8	0,0358	M12	0,0366	C18	0,0581	M3	0,0660	M10	0,0746	M17	0,0886
28	M14	0,0232	C1	0,0294	M3	0,0535	M11	0,0766	M10	0,0402	M4	0,0426	M11	0,0535	M12	0,0534	M15	0,0240	M12	0,0311	C18	0,0363	M8	0,0387	M15	0,0581	M14	0,0678	M16	0,0772	M5	0,0931
29	M15	0,0236	M14	0,0299	M10	0,0540	M16	0,0788	M6	0,0408	M12	0,0434	M12	0,0541	M4	0,0543	C18	0,0240	C18	0,0313	M6	0,0389	M6	0,0406	M14	0,0584	M15	0,0678	M5	0,0779	M14	0,0939
30	M16	0,0240	M5	0,0300	M16	0,0557	M12	0,0807	M12	0,0435	M11	0,0437	M6	0,0567	M7	0,0608	M14	0,0248	M7	0,0318	M14	0,0411	M14	0,0419	M8	0,0589	M5	0,0688	M15	0,0780	M15	0,0942
31	M1	0,0259	M3	0,0302	M15	0,0575	M15	0,0813	M8	0,0435	M6	0,0442	M7	0,0579	M6	0,0619	M5	0,0251	M6	0,0333	M5	0,0437	M5	0,0457	M16	0,0602	M16	0,0706	M14	0,0781	M16	0,1005
32	M13	0,0309	M15	0,0320	C3	0,0618	C3	0,0932	M11	0,0445	M8	0,0448	C3	0,0672	C3	0,0805	M6	0,0253	M5	0,0338	C3	0,0922	C3	0,0772	M13	0,0929	C3	0,0992	C3	0,1246	C3	0,1426
33	C3	0,0669	M16	0,0323	C1	0,0663	C1	0,1000	M5	0,0458	M7	0,0491	C1	0,0717	C1	0,0878	M8	0,0263	M8	0,0344	C1	0,1016	C1	0,0857	C3	0,1048	C1	0,1061	C1	0,1358	C1	0,1551
34	C1	0,0739	M9	0,0895	M13	0,4564	M13	0,6804	M7	0,0459	M9	0,1182	M9	0,1446	M9	0,1414	M9	0,0391	M9	0,0956	M13	0,3706	M13	0,5440	C1	0,1150	M13	0,2558	M13	0,8830	M13	1,3738
35	M9	1,0909	M13	0,2041	M9	0,7658	M9	1,1068	M13	0,0639	M13	0,2121	M13	0,7607	M13	1,1559	M13	0,0408	M13	0,1276	M9	1,5332	M9	1,3498	M9	1,7147	M9	1,3316	M9	1,7312	M9	1,7312

Table 5.3e: Forecasts of Industrial Production

	Sweden								USA							
	h=1		h=3		h=8		h=12		h=1		h=3		h=8		h=12	
Ranking		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE		RMSPE
1	M11	0,0361	M12	0,0447	M6	0,0564	M6	0,0568	C11	0,0085	M6	0,0134	M11	0,0288	C11	0,0323
2	C1	0,0365	M11	0,0454	M7	0,0608	M7	0,0592	M6	0,0085	M7	0,0135	C8	0,0289	M1	0,0352
3	C3	0,0366	M6	0,0459	M12	0,0641	M8	0,0665	C8	0,0085	C11	0,0135	M7	0,0292	M7	0,0356
4	C17	0,0371	M7	0,0464	M8	0,0669	M12	0,0696	C9	0,0086	M10	0,0136	M1	0,0294	M11	0,0364
5	M12	0,0372	C17	0,0468	C10	0,0689	C8	0,0721	C2	0,0086	M11	0,0138	C11	0,0298	C12	0,0377
6	M6	0,0373	C16	0,0471	C16	0,0692	M10	0,0743	C14	0,0086	C8	0,0139	C14	0,0307	C2	0,0381
7	C16	0,0373	C4	0,0474	C4	0,0692	C18	0,0761	C13	0,0086	C9	0,0139	C12	0,0307	C13	0,0381
8	C15	0,0375	C15	0,0474	C15	0,0692	C2	0,0764	M1	0,0086	C14	0,0140	C9	0,0309	C14	0,0387
9	C4	0,0375	C5	0,0475	C17	0,0693	M4	0,0765	C3	0,0086	C12	0,0140	C7	0,0313	M8	0,0389
10	C14	0,0376	C14	0,0476	C5	0,0695	C11	0,0766	C12	0,0086	C13	0,0141	C2	0,0313	M3	0,0397
11	C10	0,0377	C10	0,0476	C6	0,0697	C15	0,0766	C1	0,0086	C2	0,0142	M8	0,0314	M12	0,0403
12	C5	0,0377	C6	0,0476	M10	0,0699	C4	0,0766	C7	0,0087	C7	0,0142	C17	0,0316	M2	0,0410
13	C6	0,0378	C7	0,0478	C2	0,0700	C16	0,0767	C17	0,0087	C6	0,0143	C6	0,0316	M10	0,0432
14	C7	0,0380	C2	0,0483	C7	0,0701	C17	0,0767	C16	0,0087	C5	0,0143	M12	0,0317	M15	0,0459
15	C2	0,0382	C9	0,0486	C14	0,0705	C5	0,0767	C6	0,0087	C15	0,0144	C5	0,0318	M6	0,0473
16	C13	0,0385	C13	0,0489	M4	0,0705	C10	0,0769	C4	0,0087	C4	0,0144	C16	0,0318	M5	0,0475
17	M2	0,0385	C12	0,0494	M3	0,0710	M3	0,0769	C15	0,0087	C16	0,0144	C13	0,0318	M17	0,0491
18	M3	0,0386	M3	0,0497	C11	0,0711	C6	0,0769	C5	0,0087	C10	0,0144	M10	0,0320	M4	0,0509
19	C8	0,0387	C11	0,0497	M2	0,0712	C7	0,0771	C10	0,0087	M1	0,0144	C4	0,0320	M14	0,0543
20	C11	0,0387	M2	0,0497	C13	0,0712	M2	0,0771	M11	0,0089	C17	0,0145	C15	0,0320	M16	0,0544
21	C9	0,0388	C8	0,0499	C18	0,0713	C14	0,0781	M7	0,0089	C3	0,0147	C10	0,0322	C3	0,0601
22	C12	0,0390	M4	0,0502	C9	0,0719	C13	0,0789	M10	0,0089	C1	0,0147	M6	0,0348	C10	0,0636
23	M7	0,0392	M5	0,0504	C8	0,0720	C9	0,0803	M17	0,0090	M8	0,0149	C3	0,0350	C1	0,0641
24	M4	0,0394	M17	0,0505	C12	0,0726	C12	0,0835	M12	0,0092	M12	0,0151	C1	0,0352	C4	0,0681
25	M17	0,0398	C3	0,0508	M11	0,0726	M11	0,0844	C18	0,0093	C18	0,0159	C18	0,0357	C15	0,0681
26	M14	0,0398	C1	0,0519	M5	0,0728	M5	0,0864	M4	0,0094	M17	0,0163	M3	0,0362	C5	0,0708
27	M16	0,0399	M16	0,0522	M17	0,0779	M17	0,0908	M8	0,0097	M4	0,0171	M9	0,0372	C6	0,0737
28	M15	0,0401	M14	0,0525	M16	0,0791	M14	0,0912	M16	0,0099	M16	0,0178	M2	0,0372	C16	0,0754
29	M1	0,0403	M1	0,0530	M14	0,0792	M16	0,0913	M15	0,0102	M15	0,0178	M17	0,0388	C17	0,0791
30	M10	0,0406	C18	0,0531	M15	0,0798	M15	0,0915	M14	0,0108	M3	0,0190	M15	0,0392	C7	0,0795
31	C18	0,0417	M15	0,0534	M1	0,0810	M1	0,0928	M3	0,0108	M14	0,0192	M5	0,0419	C9	0,0859
32	M5	0,0438	M8	0,0535	C3	0,1065	C3	0,1375	M2	0,0109	M2	0,0194	M4	0,0425	C8	0,1529
33	M8	0,0455	M10	0,0539	C1	0,1126	C1	0,1474	M13	0,0114	M5	0,0205	M16	0,0433	M13	0,2470
34	M9	0,0612	M9	0,1834	M9	0,8138	M9	1,1111	M9	0,0140	M9	0,0239	M14	0,0444	C18	0,5860
35	M13	0,0791	M13	0,3021	M13	0,8378	M13	1,3664	M5	0,0147	M13	0,0524	M13	0,1552	M9	0,7627

Table 5.4: Average Ranking and Average RMSPE scaled by the RMSPE of M1

	h=1			h=3			h=8			h=12		
Model	**Ranking**	**RMSPE**	**A/M1**	**Ranking**	**RMSPE**	**A/M1**	**Ranking**	**RMSPE**	**A/M1**	**Ranking**	**RMSPE**	**A/M1**
M1	23,2	0,031	1,000	18,2	0,036	1,000	15,1	0,048	1,000	14,8	0,053	1,000
M2	24,6	0,031	1,014	24,4	0,037	1,055	20,1	0,049	1,053	17,5	0,053	1,031
M3	25,2	0,031	1,017	22,4	0,037	1,047	20,3	0,050	1,076	17,8	0,054	1,049
M4	19,6	0,029	0,948	20,2	0,036	1,000	19,7	0,050	1,077	18,3	0,055	1,098
M5	23,2	0,032	1,048	30,1	0,041	1,178	28,6	0,056	1,202	26,1	0,062	1,192
M6	20,6	0,030	0,972	20,9	0,038	1,030	20,2	0,052	1,111	18,8	0,058	1,164
M7	25,1	0,032	1,010	17,8	0,038	1,028	16,8	0,049	1,069	14,4	0,052	1,041
M8	29,0	0,034	1,092	27,4	0,041	1,119	20,4	0,050	1,062	14,4	0,051	0,999
M9	33,4	0,772	28,034	35,4	0,652	20,096	35,1	0,927	20,877	35,4	1,101	23,707
M10	21,3	0,030	0,965	22,6	0,037	1,028	20,2	0,050	1,078	20,2	0,057	1,094
M11	17,9	0,030	0,964	16,2	0,036	0,991	17,4	0,049	1,043	17,4	0,055	1,057
M12	19,4	0,030	0,979	17,3	0,036	1,012	16,9	0,049	1,050	15,7	0,055	1,062
M13	33,8	0,047	1,464	35,6	0,259	8,741	35,5	0,724	18,990	35,4	1,154	28,311
M14	28,1	0,032	1,035	27,1	0,039	1,082	26,7	0,054	1,152	25,9	0,062	1,189
M15	27,5	0,032	1,026	27,7	0,039	1,087	27,5	0,055	1,186	26,7	0,063	1,241
M16	27,2	0,032	1,025	25,6	0,038	1,077	26,5	0,054	1,176	26,2	0,063	1,236
M17	17,6	0,029	0,939	18,7	0,035	0,985	21,9	0,050	1,079	22,4	0,058	1,127
C1	21,2	0,062	2,205	29,2	0,062	1,874	32,3	0,097	2,273	33,1	0,123	2,785
C2	15,8	0,029	0,924	12,8	0,034	0,951	14,4	0,047	0,988	14,7	0,052	0,990
C3	19,9	0,058	2,033	27,7	0,058	1,743	31,1	0,090	2,096	31,8	0,113	2,545
C4	9,3	0,028	0,906	8,3	0,034	0,933	9,3	0,046	0,968	12,2	0,053	1,023
C5	10,4	0,028	0,906	8,8	0,034	0,934	9,7	0,046	0,969	12,3	0,053	1,027
C6	10,9	0,028	0,906	9,4	0,034	0,935	10,1	0,046	0,969	12,1	0,053	1,031
C7	10,8	0,028	0,906	10,6	0,034	0,936	10,6	0,046	0,971	12,1	0,053	1,041
C8	10,4	0,028	0,909	11,8	0,034	0,940	13,8	0,047	0,992	11,9	0,057	1,165
C9	13,8	0,029	0,919	12,3	0,034	0,944	12,4	0,047	0,982	13,8	0,054	1,059
C10	9,9	0,028	0,904	9,7	0,034	0,934	9,3	0,046	0,966	12,8	0,053	1,017
C11	12,9	0,029	0,916	12,7	0,035	0,944	15,7	0,048	1,010	14,4	0,052	0,987
C12	17,1	0,029	0,929	15,1	0,035	0,957	17,2	0,048	1,002	14,2	0,053	0,993
C13	13,9	0,029	0,918	13,9	0,034	0,951	15,7	0,047	0,991	16,9	0,053	0,999
C14	12,3	0,028	0,912	11,2	0,034	0,938	11,7	0,047	0,975	12,9	0,051	0,982
C15	9,3	0,028	0,906	8,2	0,034	0,933	9,6	0,046	0,968	12,6	0,053	1,023
C16	9,3	0,028	0,904	9,4	0,034	0,934	9,1	0,046	0,968	12,1	0,053	1,035
C17	9,0	0,028	0,904	10,8	0,034	0,935	9,3	0,046	0,968	12,0	0,053	1,040
C18	21,6	0,032	1,025	23,7	0,039	1,090	21,9	0,058	1,255	19,6	0,096	2,253

Note: A/M1 denotes the Average RMSPE of Models i, scaled by the RMSPE of M1