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A COMPARISON OF LINEAR AND NONLINEAR UNIVARIATE MODELS FOR FORECASTING MACROECONOMIC TIME SERIES

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ABSTRACT

A forecasting comparison is undertaken in which 49 univariate forecasting methods, plus various forecast pooling procedures, are used to forecast 215 U.S. monthly macroeconomic time series at three forecasting horizons over the period 1959 - 1996. All forecasts simulate real time implementation, that is, they are fully recursive. The forecasting methods are based on four classes of models: autoregressions (with and without unit root pretests), exponential smoothing, artificial neural networks, and smooth transition autoregressions. The best overall performance of a single method is achieved by autoregressions with unit root pretests, but this performance can be improved when it is combined with the forecasts from other methods.

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1. Introduction

This paper addresses five specific questions in the context of forecasting U.S. macroeconomic time series. First, do nonlinear time series models produce forecasts that improve upon linear models in real time? Second, if there are benefits to using nonlinear models, are the benefits greatest for relatively tightly parameterized models or for more nonparametric approaches? Third, can forecasts at the six month or one year horizon be improved by using preliminary evidence on the persistence of the time series to select the forecasting model? Fourth, do combination forecasts outperform forecasts based on a single method across a range of time series, and if so how heavily should these combination forecasts weight the currently-best performing forecasting methods? Finally, are the gains from using these advanced methods over simple autoregressive forecasts large enough to justify their use, even by a risk-averse forecaster?

We conduct an experiment designed to answer these questions. In this experiment, various forecasts are compared at the one, six and twelve month horizons for 215 monthly U.S. economic time series. The experiment simulates real-time implementation of these methods, that is, all forecasts (including all parameter estimates, all model selection rules, all pretests, all forecast combining weights, etc.) are based exclusively on data through the date of each forecast. The parameter estimates, model selection statistics, pretests, and forecast combining weights, for all models are updated each month, and these updated statistics are used to make that month's simulated out of sample forecasts.

The forecasts studied here are produced by 49 forecasting methods. We refer to these as "methods" because many of these forecasts are based not on a single estimated model, but on results from multiple models that are subject to model selection criteria or pretests. We shall refer to the underlying individual models used by these forecasting methods as primitive models, of which there are a total of 121. For example, one of our forecasting methods is an autoregression in levels with a constant term and lag order selection based on the Akaike Information Criterion (AIC), with lag length ranging from zero to twelve; in our terminology this forecasting method combines information from thirteen primitive models. The primitive models fall into four classes: autoregressions (AR), exponential smoothing (EX), artificial neural networks (ANN), and logistic smooth transition autoregressions (LSTAR). As an additional benchmark, a "no change" forecast was also considered.

We also consider various procedures to combine information from these 49 forecasting methods. We refer to these as forecast pooling procedures. Bates and Granger (1969), Granger and Newbold (1977), and Granger and Ramanathan (1984) demonstrated that averaging forecasts from different models can improve forecast performance when all the models are approximations. The pooling procedures considered here differ by the amount of weight placed on the model with the currently best performance, including weighting all the forecasts equally, weighting the forecasts in inverse proportion to their current mean squared error (MSE), using median forecasts, and placing all weight on the forecasting method that currently has the lowest simulated real-time MSE; this final pooling procedure is simulated real-time model selection by predictive least squares (PLS).

The forecasting methods used in this study have been chosen in part to facilitate comparison with other large-scale "horse races" among time series models. Makridakis et. al. (1982) studied performance of univariate methods in many series, some of which were economic time series, and concluded that exponential smoothing was often successful. Meese and Geweke (1984) compared various linear models using 150 macroeconomic time series and found that AR models with lag lengths selected by the AIC generally worked well. Interestingly, they also found that that linear combination forecasts did not appreciably improve forecast quality. More recently, in a model comparison exercise conducted under the auspices of the Santa Fe Institute, Weigand and

Gershenfeld (1994) compared linear models with a large number of nonlinear models; although they detected nonlinear dynamics in several non-economic time series, the nonlinear forecasting models fared relatively poorly for the economic time series they considered (exchange rates). Swanson and White (1995, 1997) compared multivariate ANN models to linear vector autoregressions, and found that the vector autoregressions generally had lower MSEs than the ANN models in simulated real time (their models are all multivariate however so their study does not compare directly to the exercise here).[1] Relative to this literature, the contributions of our study include the use of a large number of macroeconomic time series, the use of a large number of nonlinear models, the investigation of unit root pretest methods, and an extensive investigation of forecast pooling procedures.

The remainder of this paper is organized as follows. The experimental design and forecasting models are given in section 2. The data are described briefly in section 3 and in more detail in the Appendix. The results are presented and discussed in section 4, and conclusions are summarized in section 5.

2. Forecasting Methods and Experimental Design

2.1. General considerations

Forecasting models. All the models investigated in this experiment are of the form,

$$y_{t+h} = f_i(Z_t;\theta_{ih}) + u_{it+h} \tag{2.1}$$

where y_t is the series being forecast, h is the forecast horizon, i indexes the forecasting model (i=1,...,121), θ_{ih} is a vector of unknown parameters, u_{it} is an error term, and Z_t is a vector of predictor variables. In general, $Z_t = (y_t,\ldots,y_{t-p},\Delta y_t,\ldots,\Delta y_{t-p},1,t)$, where p is the maximal lag lengths. Typically, individual forecasting models use only a subset of the elements of Z_t.

All forecasts are made fully recursively, that is, forecasts of y_{t+h} are made using information in time periods 1,2,...,t. For the forecast of y_{t+h}, the parameter vector θ_{ih} is estimated using the data $(y_1, y_2,..., y_t)$. In all models, the parameter vector is estimated by minimizing the sum of squared residuals of the h-step ahead forecast, that is, the estimate of θ_{ih} at time period t, $\hat{\theta}_{iht}$, solves, $\min_{\theta_{ih}} \sum_{s=t_0}^{t}[y_{t+h}-f_i(Z_t;\theta_{ih})]^2$, where t_0 denotes the first observation used for estimation for that model.

Note that in general each forecasting method, applied to a particular series, has different parameter values at different horizons (that is, the h-period ahead forecast is *not* computed by iterating forward for h periods the one-period ahead forecasting model). This has costs and benefits. If the one-period ahead forecasting model is correct, then estimating it at the one-period horizon and iterating forward is more efficient than estimating the h-period ahead model directly. On the other hand, to the extent that the models are mispecified, estimating the h-period ahead model directly permits the method to reduce the effects of the mispecification at the horizon at hand. From a practical perspective, forecasting the h-period ahead model directly requires more computer time for parameter estimation, but it simplifies considerably the computation of multistep forecasts from the nonlinear models.

The h-step ahead forecast and the forecast error are,

$$y_{t+h|t,ih} = f_i(Z_t;\hat{\theta}_{iht}) \tag{2.2}$$

$$e_{t+h,ih} = y_{t+h} - y_{t+h|t,ih}. \tag{2.3}$$

Forecast trimming. For our main results, all forecasts were automatically trimmed so that a forecasted change that exceeded in absolute value any change previously observed for that series was replaced by a no-change forecast. This adjustment was adopted to simulate the involvement of a human forecaster, who would be present in actual applications but is absent from our computerized experiment. Because the forecasts in this experiment are made automatically, some models could (and in fact do) make extreme forecasts. Possible sources of these extreme forecasts include parameter estimates that are local but not global maxima for the nonlinear models, parameter breaks, and errors arising from incorrect inclusion of deterministic trends. In true real time, such "crazy" forecasts arguably would be noticed and adjusted by human intervention. Accordingly, our forecast trimming algorithm can be thought of as a rule of thumb that a human forecaster might use in real time to detect and address such problems. Although we focus primarily on the trimmed forecasts, some results for the untrimmed forecasts are also presented for the purpose of comparison.

Startup and forecast periods. For each series, there are three separate periods: a startup period with which initial estimates of the model are produced; a intermediate period over which forecasts are produced by the 121 primitive models and 49 forecasting methods, but not by the pooling procedures; and the simulated real-time forecast period over which recursive forecasts are produced by all models, methods, and pooling procedures. Let T_0 be the date of the first observation used in this study. Then the startup estimation period is T_0 to T_1, where $T_1=T_0+120$. The intermediate period is T_1 to T_2-1, where $T_2=T_1+24$. The forecast period is T_2 to T_3, where T_3 is the date of the final observation (1996:12) minus the forecast horizon h.

All forecast performance results reported in the tables are from the simulated real-time forecast period, T_2 to T_3 (inclusive). For most series, the initial observation date is 1959:1, in which case T_0=1959:1, T_1=1970:1, T_2=1972:1, and T_3=1996:12-h.

2.2. Forecasting models and methods

The forecasting methods are listed in table 1.

Autoregressive (AR) models. Results are reported for eighteen different autoregressive forecasting methods. These differ in their treatment of lag lengths (3 variants); in whether a constant, or a constant and a time trend, were included (2 variants); and in their treatment of persistence in the form of large autoregressive roots (3 variants).

Three alternative treatments of lag lengths were considered: a fixed lag length of 4; lag length determination by the BIC ($0 \leq p \leq 12$); and lag length determination by the AIC ($0 \leq p \leq 12$).

The possibility of persistence in the time series was handled by considering three alternatives. In the first, the autoregression was specified in levels, that is, y_{t+h} was forecast using $y_t,\ldots,y_{t-p+1}$ with no restrictions on the coefficients. In the second, a unit root was imposed, so that the dependent variable was $y_{t+h}-y_t$ and the predictors were $\Delta y_t,\ldots,\Delta y_{t-p+1}$. In the third, a recursive unit root pretest was used to select between the levels or first differences specification. The unit root pretesting approach is widely used in practice, and many unit root tests statistics are available for this purpose. In a Monte Carlo study of unit root pretest autoregressive forecasts at moderate to long horizons, Stock (1996) compared several different pretest methods at various significance levels, and found that the best forecast performance across different values of the largest autoregressive root was obtained using the Elliott-Rothenberg-Stock (1996) DF-GLS test with a small signficance level. We therefore computed the unit root pretest using the DF-GLS$^{\mu}$ statistic for the selection between models that included a constant term only. For selection between models that included a linear time trend under the levels alternative, the DF-GLS$^{\tau}$ statistic was used.[2]

In all, a total of 52 primitive autoregressive models were estimated (2 specifications of deterministic terms, 13 lag choices, in either levels or differences). The 18 forecasting methods based on these 52 primitive models include recursive model selection using information criteria and/or recursive unit root pretests, as detailed in table 1.

For some of the results, it is useful to normalize the performance of the models by comparison to a naive method. Throughout, we use a simple autoregression as the naive method, specifically, an AR(4) (fixed lag length) in levels with a constant term.

Exponential Smoothing (EX). Two primitive exponential smoothing models are considered. Single or simple exponential smoothing forecasts are given by,

$$y_{t+h|t} = \alpha y_{t+h-1|t-1} + (1-\alpha)y_t. \tag{2.4}$$

Double exponential smoothing forecasts are given by,

$$f_t=\alpha_1(f_{t-1}+g_{t-1}) + (1-\alpha_1)y_t \tag{2.5a}$$

$$g_t=\alpha_2 g_{t-1} + (1-\alpha_2)(f_t-f_{t-1}) \tag{2.5b}$$

where the forecast is $y_{t+h|t} = f_t+hg_t$. The parameters α in (2.4) and (α_1,α_2) in (2.5) are estimated by recursive nonlinear least squares for each horizon.

Single exponential smoothing is conventionally intended for use with non-trending series, and double exponential smoothing is conventionally intended for trending series. We therefore considered a unit root pretest version of these two, in which either the single exponential smoothing forecast was used if the recursive DF-GLS$^{\mu}$ pretest (described above) rejected the null of a unit root, else the double exponential smoothing forecast was used. The three forecasting methods based on these two primitive models therefore include the I(0) specification (2.4), the I(1) specification (2.5), and the specification selected by a recursive unit root pretest.

Artificial neural networks (ANN). Neural network models with one and two hidden layers were considered. The single layer feedforward neural network models have the form, (2.6) $$\nu_{t+h} = \beta_0'\zeta_t + \Sigma_{i=1}^{n_1}\gamma_{1i}g(\beta_{1i}'\zeta_t) + u_{it+h}$$

where g(z) is the logistic function, $g(z) = 1/(1+e^z)$. When y_t is modeled in levels, $\nu_{t+h} = y_{t+h}$ and $\zeta_t = (1, y_t, y_{t-1},\ldots,y_{t-p+1})$. When y_t is modeled in first differences, $\nu_{t+h} = y_{t+h}-y_t$ and $\zeta_t = (1, \Delta y_t, \Delta y_{t-1},\ldots, \Delta y_{t-p+1})$. The neural network models with two hidden layers have the form,

(2.7) $$\nu_{t+h} = \beta_0'\zeta_t + \Sigma_{j=1}^{n_2}\gamma_{2j}g[\Sigma_{i=1}^{n_1}\beta_{2ji}g(\beta_{1i}'\zeta_t)] + u_{it+h}.$$

Note that all the neural nets are forced to include a linear component. We will refer to (2.6) as having n_1 hidden units, and to (2.7) as having n_1 and n_2 hidden units, after removing a linear component. Alternatively, (2.6) could be thought of as having n_1+1 hidden units, with one of the hidden units forced to be linear.

The variants of (2.6) and (2.7) that are considered include different lag lengths p; the number of hidden units; and specification in levels and differences. The choices for single hidden layer ANNs are $n_1=\{1,2,3,4\}$, $p=\{1,3,6\}$, and levels/differences specification, for a total of 24 primitive models. (The restricted lag length choice of $p=\{1,3,6\}$ was used to reduce computational requirements.) The choices for ANNs with two hidden layers are $n_1=2$, $n_2=\{1,2\}$, $p=\{1,3,6\}$, and levels/differences specification, comprising 12 primitive models. The 15 forecasting methods based on these 36 primitive models include recursive model selection using information criteria and/or recursive unit root pretests, as detailed in table 1.

In all models, coefficients were estimated by recursive nonlinear least squares. For these models, multiple local minima are an important concern, so the objective function was minimized using a combination of random search methods and local Gauss-Newton optimization. The initial parameter estimates at date T_1 were obtained as follows. The ANN models have a natural nesting from least complicated (fewest parameters) to most complicated. The most restrictive version of the model was estimated first. For the most restrictive versions of the models the objective function was evaluated using 5000 random draws of the parameter vector. The parameter vectors corresponding to the four smallest value of the objective function were then used as initial values for Gauss-Newton iterations, and the minimizer was chosen from the resulting set of parameters. This parameter vector together with 1000 additional random draws was used to evaluate the objective function associated with the next most complicated model; the parameter vectors associated with the two smallest values of the function were used to initialize the Gauss-Newton iterations. This procedure was repeated for each larger model in the nesting sequence. At subsequent dates ($T_1 < t \leq T_3$), with probability .99 the parameter values were updated by taking three Gauss-Newton steps, using the parameter estimates from the previous date as starting values; with probability .01 the parameters were updated by using the minimum of these results and results obtained by completely reoptimizing from a set of 500 randomly selected initial parameter values (using the same method as at time T_1).

Logistic smooth transition autoregressions (LSTAR). The LSTAR models that were considered had the form,

$$\nu_{t+h} = \alpha'\zeta_t + d_t\beta'\zeta_t + u_{t+h} \qquad (2.8)$$

where ν_{t+h} and ζ_t are defined following (2.7) and $d_t = 1/(1+\exp[\gamma_0+\gamma_1\xi_t])$, where ξ_t is a function of current and past y_t and is the variable used to define the smooth threshold.

The variants of the LSTAR models differ by the variable used to define the threshold; the specification in levels or differences or unit root pretest; and the lag length p. For models specified in levels, the following five alternatives were used for the threshold variable: $\xi_t=y_t$;

$\xi_t=y_{t-2}$; $\xi_t=y_{t-5}$; $\xi_t=y_t-y_{t-6}$; and $\xi_t=y_t-y_{t-12}$. For models specified in first differences, the following five alternatives were used for the threshold variable: $\xi_t=\Delta y_t$; $\xi_t=\Delta y_{t-2}$; $\xi_t=\Delta y_{t-5}$; $\xi_t=y_t-y_{t-6}$; and $\xi_t=y_t-y_{t-12}$. In each case, lag lengths of $p=\{1,3,6\}$ were considered, for a total of 30 primitive models (15 in levels, 15 in differences). The 12 forecasting methods based on these 30 primitive models include recursive model selection using information criteria and/or recursive unit root pretests, as detailed in table 1.

The parameters α, β and γ were estimated using the same random search/recursive Gauss-Newton optimization method as the artificial neural network models.

No change forecast. The no change forecast is $y_{t+h|t} = y_t$.

2.3. Forecast Pooling Procedures

Linear combination forecasts. Pooled forecasts were computed as weighted averages of the forecasts produced by the 49 forecasting methods. These combination forecasts have the form,

(2.9) $$\Sigma_{i=1}^{M}\kappa_{iht}y_{t+h|t,ih}, \text{ where } \kappa_{iht} = (1/MSE_{iht})^{\omega}/\Sigma_{j=1}^{M}(1/MSE_{jht})^{\omega}$$

where where i runs over the M methods and $\{\kappa_{iht}\}$ are the weights. The weighting schemes differ in the choice of ω, how the MSE is computed, and the sets of methods that are combined. The simplest scheme places equal weight on all the forecasts, which corresponds to setting $\omega=0$ (in which case the MSE does not enter). As ω is increased, an increasing amount of emphasis is placed on those models that have been performing relatively well.

As shown by Bates and Granger (1969), if forecast error variances are finite then the optimal linear weighting scheme under quadratic loss involves the entire covariance matrix of forecast errors (see Granger and Newbold [1977]). With the large number of forecasts at hand, this scheme is impractical and would be unreliable because of the large number of covariances that would need to be estimated. Instead, we follow Bates and Granger's (1969) suggestion and drop the covariance term from our weighting expressions. Accordingly, the weights on the constituent forecasts are inversely proportional to their out-of-sample MSE, raised to the power ω. The weights with $\omega=1$ correspond to Bates and Granger's (1969) suggestion. We also explore the possibility that more weight should be placed on the best performing models than would be indicated by inverse MSE weights, and this is achieved by considering $\omega>1$. Note that when $\omega \neq 0$ the weights $\{\kappa_{iht}\}$ differ from series to series.

Bates and Granger (1969) also stress that the relative performance of different models can change over time. This suggests computing MSEs over rolling windows. The MSEs were therefore computed in three ways: over 60 and 120 period rolling windows (more precisely, over the past $\min(t\text{-}T_1+1,60)$ or $\min(t\text{-}T_1+1,120)$ periods, respectively), and recursively (over the past $t\text{-}T_1+1$ periods).

The averages were computed over three different sets of forecasts: the linear methods (AR and EX); the nonlinear methods (ANN and LSTAR); and all the methods discussed above (linear, nonlinear, and no change).

Median combination forecasts. If forecast errors are nonGaussian then linear combinations are no longer optimal. We therefore consider combination forecasts constructed as the median from a group of methods. In practice this guards against placing weight on forecasts that are badly wrong for method-specific reasons such as parameter breaks or parameter estimates achieving local but not global optima. The medians were computed over three different sets of forecasts: linear (AR and EX); nonlinear (ANN and LSTAR); and all the methods discussed above (linear, nonlinear, and no change). This median forecasts can be thought of as a consensus forecasts obtained by a vote of a panel of experts, where each expert (forecasting method) gets one vote: the consensus forecast is achieved when half the experts are on each side of the forecast.

Predictive least squares (PLS) forecasts. An alternative approach to pooling forecast information is to select the model that has produced the best forecasts (as measured by the lowest out-of-sample MSE) up to the forecast date. This constitutes selection across these models by predictive least squares. The PLS forecasts differ by the period over which the PLS criterion is computed and the sets of models for which it is computed.

The periods for which the PLS forecast were computed are the same as for the combination forecasts, specifically, over the past min($t-T_1+1$,60) periods; over the past min($t-T_1+1$,120) periods; and over the past $t-T_1+1$ periods.

The PLS forecasts were computed for five sets of models: all 49 models listed in Table 1 under the categories AR, EX, ANN, LSTAR, NOCHANGE; all linear models listed in table 1 (AR and EX); all nonlinear models listed in table 1 (ANN and LSTAR); all 121 primitive models; and all 49 methods plus all other linear combination, median, and PLS pooling forecasts. The purpose of examining this final group is to see whether the potential optimality of pooled forecasts could have been ascertained empirically in (simulated) real time.

3. Data

The data are monthly U.S. macroeconomic time series. The series fall into the following general categories: production (including personal income), employment and unemployment, wages (hours and earnings), construction (including housing starts), trade (wholesale and retail), inventories, orders, money and credit, stock returns, stock market dividends and volume, interest rates, exchange rates, producer price inflation, consumer price inflation, consumption, and miscellaneous (e.g. consumer confidence).

Some of these series were subjected to preliminary transformations. The series in dollars, real quantities and price deflators were transformed to their logarithms. Most other series (interest rates, the unemployment rate, exchange rates, etc.) were left in their native units.

In general, the first date used is either the first date for which the series is available or 1959:1, whichever is later. The exception to this rule is exchange rates; because exchange rates are essentially flat in the fixed exchange rate period, following Meese and Rogoff (1983) the first observation used for exchange rates is 1973:1.

A complete list of the series, their sources, the initial observation date used, and the transformation used are given in the Appendix.

4. Results

4.1. Description of Tables

Table 2 contains statistics summarizing the performance of each forecasting method, relative to the naive method (an AR(4) specified with a constant term in levels). For each series, forecast method and horizon, the mean square of the T_3-T_2+1 simulated out-of-sample forecast errors was computed; for forecasting method i, denote this $MSE_{ij,h}$, j=1,...,215 and h=1, 6, 12. The relative mean square forecast error of the i-th forecasting method is $MSE_{ij,h}/MSE_{1j,h}$, where i=1 corresponds to the naive AR(4) forecast. Table 2 contains the averages and empirical quantiles of the distribution (across series) of this relative MSE, for each of 49 AR, EX, No change, ANN, and LSTAR methods listed in table 1, and for various pooled forecasts. If, for example, the median of this distribution exceeds one for a candidate forecasting model and horizon, then for at least half the series the naive method had a lower simulated out-of-sample MSE at that horizon than the candidate forecasting model.

Table 3 compares forecasting methods by presenting the fraction of series for which each forecasting method is among the top N methods for various values of N. The forecasts compared in this table consist of the 49 methods in groups A, B and C in table 1, plus the 14 pooling procedures for which results are reported in table 3. For example, at horizon $h=1$, for 4% of the series, the ARFC04 method (which is the naive method used in table 2) had the lowest simulated out-of-sample MSE of all the forecasting methods; for 17% of the series, its MSE was among the lowest five.

A natural question to ask in this comparison is which forecasting method is best overall. The answer to this question depends, among other things, on the attitude towards risk of the forecaster, that is, on the forecaster's loss function. Table 4 therefore reports rankings of the different methods for different loss functions. The loss functions are all of the form,

$$\text{(4.1)} \qquad \text{Loss}_{i,h} = (1/215)\Sigma_{\text{series }\{y\}}(T_3-T_2+1)^{-1}\Sigma_{i=T_2}^{T_3}|(y_{t+h}-\hat{y}_{t+h|t,ih})/\sigma_h|^{\rho}$$

where σ_h is the estimated standard deviation of $y_{t+h}-y_t$.

4.2. Discussion of Results

We now turn to a summary of some of the main features of the results.

Unit root pretests. Pretesting for unit roots generally improves performance at all horizons, as measured by mean or median relative MSEs in table 2. Among AR models, this improvement is most pronounced when the levels specification includes a time trend. This improvement is also pronounced for the EX and ANN models. Evidently both ARs in levels with time trends and the ANN models in levels can produce forecasts that are quite poor, and pretesting to identify situations in which a unit root can be imposed reduces the frequency of extreme errors.

AIC- and BIC-based model selection. The performance of automatic lag length selection methods depends on the family of models being used, and it does not seem possible to reach general conclusions. Among autoregressions, average automatic order selection yields only marginal improvements over the naive imposition of 4 lags. Comparisons of AIC and BIC lag length choice for comparable autoregressive models indicates that BIC lag choice has somewhat lower MSEs than AIC-based methods. Among ANNs forecast performance was also best when the BIC was used. Among LSTARs, neither the AIC nor the BIC methods have mean, median, or extreme relative MSEs as good as some of the fixed methods (in particular the LS1063 and LSP063 methods).

On average, the MSE improvement over the naive method from using data-based model selection methods are modest. For example, adopting BIC lag selection and unit root pretesting in an autoregression with a constant results in a mean relative MSE of 1.00 for h=1, 0.96 for h=6, and 0.98 for h=12. However, for some series, large MSE gains are possible, relative to the naive forecast. For example, in 2% of series, MSE reductions of amost two-thirds were achieved at the 12 month horizon by introducing BIC lag selection and unit root pretests to the naive method. Comparison of the ARFC04, ARFC0b, ARFCP4, and ARFCPb results in table 2 clearly show that most of these gains are achieved by the unit root pretest rather than AIC lag selection.

Performance of simple methods. The simplest methods performed poorly relative to the naive AR(4) method. For example, for approximately 75% of series, the no change forecast was worse than the naive forecast at all three horizons. The exponential smoothing method EX1 was badly wrong for some series, and on average all exponential smoothing methods have relative MSEs exceeding one at all horizons.

ANN methods. Generally speaking, the ANN methods all performed poorly. The ANN methods are rarely among the top ten methods for a given series (table 3). All have mean and median relative MSEs exceeding one at all horizons. Although improvements are obtained for some series, all the ANN methods perform quite poorly for a small fraction of the series: for all ANN methods the 98% percentile of the relative MSE exceeds 2 for some horizon. The performance varies among ANN methods. The ANN methods specified in levels generally perform quite poorly. Interestingly, adding a second hidden layer generally results in worse performance, as measured by the relative MSEs. This generally poor performance of feedforward ANN methods for economic data is consistent with the findings in Swanson and White (1995, 1997) and Weigand and Gershenfeld (1994).

LSTAR methods. Although the LSTAR methods were rarely best for any series, in some cases they provided MSE improvements, relative to the naive method. The best-performing LSTAR methods were the LS1063 and its pretest variant LSP063. Although both have mean relative MSEs exceeding one, their median relative MSEs are less than one at the six month horizon. The LSTAR methods generally outperformed the ANN methods.

Forecast pooling. One of the striking features in tables 2-4 is the strong performance of various forecast pooling procedures Simple average forecasts, forecasts weighted by inverse MSEs, and the median forecasts outperform the naive method. Indeed, based on the loss function comparisons in table 4, the most attractive forecast is the simple average of the forecasts from all methods. Among the various weighting schemes, simple averaging and weighting by inverse MSEs produce similar performance. Performance, as measured by mean relative MSE, deterioriates as ω increases, especially at long horizons. In fact, performance of the PLS forecasts, which are the limit as $\omega \to \infty$ of the weighted average forecasts, is worse than all weighted average forecasts and the median forecast. As measured by average relative MSEs, the PLS forecasts are never better than the naive forecast. Use of a shortened window (60 or 120 months) seems to have little effect on the combination forecasts based on inverse MSE weights; although the relative MSE is least for the 120 month rolling window, the reduction is small.

The pooling procedures that combine forecasts from all 49 methods have a slight edge over these procedures applied to only the linear, or only the nonlinear, methods. Indeed, for at least one-half of the series at all three horizons, the equal-weighted linear combination forecast that averages the forecasts from all 49 methods produces forecasts that are among the top ten in table 3.

Sensitivity to forecaster attitudes towards risk. A wide range of risk parameters ρ are presented in table 4, ranging from mean absolute error loss to mean cubic absolute error loss. Mean absolute error loss characterizes a forecaster who is equally concerned about small and large errors; cubic loss most heavily penalizes large errors.

The rankings among the various methods are surprisingly insensitive to the choice of risk parameter ρ. Linear combination procedures minimize average loss for all values of ρ considered. Indeed, for all values of ρ and for all horizons, the loss minimizing forecast is produced by the simple average computed over all 49 methods.

Table 4 establishes a clear ranking of classes of models and procedures, with combination forecasts first, followed by AR forecasts, followed by LSTAR forecasts, followed by ANN forecasts, followed by EX and No Change. If pooling procedures are excluded, the best method is an autoregression based on a unit root pretest; whether fixed lags or data-dependent lag lengths are preferable depends on the forecast horizon.

Effect of forecast trimming. All results discussed so far are based on trimmed forecasts. The results for some methods are very different when the forecasts are not trimmed. The effects of trimming are most important for the nonlinear methods, which for some series produce forecasts that are off by two or more orders of magnitude. The trimming also considerably improves AR forecasts in levels with a time trend.

For comparison purposes, the rankings for the various forecasting methods based on the untrimmed forecasts are given in table 5. The differences between the rankings based on the trimmed (table 4) and untrimmed (table 5) forecasts are attributable to the relatively few extremely large forecast errors made by the nonlinear methods and, to a lesser degree, by the AR methods in levels with time trends. Because of the few large errors, the median pooled forecasts are optimal for the untrimmed forecasts, and because the large errors are concentrated in the nonlinear methods, the linear combination forecasts perform well only when computed over just the linear methods.

The rankings of the individual methods change somewhat for the untrimmed forecasts. Autoregressive methods work well if the series is specified in levels with a constant, in first differences with a constant and/or time trend, or if a pretest is used, but they work poorly for the levels/time trend specification. Exponential smoothing and No Change methods rank relatively higher because they produce fewer extreme errors. Among nonlinear methods, the best ranking at any horizon is for ANFPb, which is twenty-first for the least risk averse value of ρ ($\rho=1$) at $h=12$.

Nonlinearities across groups of series. The relative performance of linear and nonlinear methods is explored in table 6. The first three columns compare the relative performance of the best AR, the best ANN, and the best LSTAR methods (where best is determined by recursive PLS within that class of methods) by reporting the fraction of times that this forecast is best for the category of series specified in that row, by horizon. The final two columns contain a similar comparison, computed for the two linear combination forecasts respectively based on the linear and nonlinear methods (in both cases, weights are recursive inverse MSE).

The results suggest that the importance of nonlinearities differs across series. The nonlinear methods have the greatest relative success for wages, employment, and exchange rates especially at long horizons, and the least success for inventories, trade, consumption, stock prices. Exchange rates are interesting because the nonlinear combination forecast outperforms the linear combination forecast at the longer horizons for four of the six exchange rates. This is in some contrast to previous studies which have found limited ability of nonlinear models to forecast exchange rates (Brooks [1997]). There seems to be no apparent pattern in the relative performance of nonlinear and linear methods over horizons. Consistent with the previous findings, the ANN methods generally are not the best; of the nonlinear methods, the LSTAR forecasts are first much more often.

5. Conclusion

Several caveats are in order prior to drawing conclusions from this study. Although a large number of methods have been considered, we have only considered two classes of nonlinear methods, and within artificial neural networks we have only considered feedforward neural nets. It is possible that other nonlinear methods, for example recurrent neural nets, could perform better than those considered here. Also, these results are subject to sampling error. Although the design has carefully adhered to a recursive (simulated real time) structure, because there are many forecasting methods considered, the estimated performance of the best-performing single method for these data arguably overstates the population counterpart of this performance measure. This criticism is less likely to be a concern, however, for the combination forecasts. Finally, it is unlikely that the best performing forecasts could have been identified as such in real time. When PLS was applied to all forecasts (including all the combination forecasts), the resulting PLS forecasts (PA060, PA120 and PA999) performed considerably worse than the best combination forecast, and indeed on average it performed worse than the naive method as measured by its mean relative MSE.

One question is whether the limited evidence in favor of nonlinear methods found here is an artifact of seasonal adjustment. It is known that seasonal adjustment procedures are nonlinear filters, and Ghysels, Granger and Siklos (1996) showed that for Census X-11 these nonlinearities are sufficiently important that they can be detected with nontrivial power using various tests for nonlinearities. The focus here has been on forecast MSE reduction rather than tests for nonlinearities, but presumably some of the forecast MSE reduction of linear methods could be attributable to seasonal adjustment. It should be borne in mind that, were this the case, its implications are not self-evident. On the one hand, to the extent that we are interested in empirical evidence of nonlinear dynamics to guide theoretical macroeconomic modeling, then it is important to know if these nonlinearities are spuriously introduced by seasonal adjustment. On the other hand, if our interest is in forecasting seasonally adjusted series, the source of the nonlinearity is of only academic interest and the relevant question is which forecasting method best handles this nonlinearity.

Bearing these comments in mind, we turn to the implications of this forecasting experiment for the five questions raised in the introduction.

First, although some of the nonlinear forecasts improve upon the linear forecasts for some series, most of the nonlinear forecasting methods, and all of the neural network methods, produce worse forecasts than the linear methods. Overall, AR methods have lower average cost than the LSTAR or ANN methods.

Second, to the extent that the nonlinear forecasts improve upon the linear forecasts, the methods that do so are relatively tightly parameterized. In particular, the LSTAR methods generally outperform the feedforward ANN methods, either with one or two hidden layers. Interestingly, specification testing over LSTAR methods using the AIC or BIC does not seem to produce reliable improvements over the best fixed LSTAR method.

Third, forecasts at all horizons are improved by unit root pretests. Severe forecast errors are made in nonlinear methods specified in levels and in linear methods in levels with time trends, and these errors are reduced substantially by preliminary testing for a unit root.

Fourth, pooled forecasts, in particular linear combination and median forecasts, were found to outperform the forecasts from any single method. The pooling procedures that place weight on all forecasting methods (whether equal weighting, inverse MSE weighting, or median) proved most reliable, while those that emphasized the recently best performing methods (especially PLS) proved least reliable. At the twelve month horizon, the mean relative MSE of the pooled forecast, computed by simple averaging of all 49 methods is .89, and the 2% percentile relative MSE is .26. There was little effect (positive or negative) of using a reduced or rolling sample for computing the combination weights.

Fifth, the gains from using combination forecasts were sufficiently large to justify their use by a risk-averse forecaster. If, however, a macroeconomic forecaster is restricted to using a single method, then for the family of loss functions considered here she would be well advised to use an autoregression with a unit root pretest and data-dependent lag length selection.

Footnotes

1. It should be emphasized that, like the experiment reported in this paper, these studies are simulated real time exercises, not a comparison of true real time forecasts. True real-time forecasts are based on preliminary data and often contain significant judgmental adjustments; see for example McNees (1986, 1990) and the surveys in Granger and Newbold (1977, ch. 8.4 and 1986, ch. 9.4). Although true out of sample MSEs would differ from those reported here, the simulated real time nature of this experiment provides a controlled environment for comparing and ranking different forecasting methods.

2. A fixed lag length of six was used to compute the unit root test statistics. The unit root pretests were computed and applied recursively, that is, the forecast of y_{t+h} using data through time t were computed using the model selected at time t by the unit root pretest computed using data through time t. The critical values for the unit root tests were chosen so that the pretest constituted a consistent rule for selecting between the I(0) and I(1) specification. Specifically, for the DF-GLS$^{\mu}$ test, the critical value was ln(120/t)-1.95, and for the DF-GLS$^{\tau}$ test the critical value was ln(120/t)-2.89. When t=120, these correspond to 5% significance level unit root pretests, with lower significance levels as the sample size increases.

Appendix: Data Description

This appendix lists the time series used. The data were obtained from the DRI BASIC Economics Database (creation date 9/97). The format for each series is its DRI BASIC mnemonic; a brief description; and the first date used (in brackets). A series that was preliminarily transformed by taking its logarithm is denoted by "log" in parentheses; otherwise, the series was used without preliminary transformation. Abbreviations: sa=seasonally adjusted; saar=seassonally adjusted at an annual rate; nsa=not seasonally adjusted.

IP industrial production: total index (1992=100,sa) [1959:1] (log)
IPP industrial production: products, total (1992=100,sa) [1959:1] (log)
IPF industrial production: final products (1992=100,sa) [1959:1] (log)
IPC industrial production: consumer goods (1992=100,sa) [1959:1] (log)
IPCD industrial production: durable consumer goods (1992=100,sa) [1959:1] (log)
IPCN industrial production: nondurable condsumer goods (1992=100,sa) [1959:1] (log)
IPE industrial production: business equipment (1992=100,sa) [1959:1] (log)
IPI industrial production: intermediate products (1992=100,sa) [1959:1] (log)
IPM industrial production: materials (1992=100,sa) [1959:1] (log)
IPMD industrial production: durable goods materials (1992=100,sa) [1959:1] (log)
IPMND industrial production: nondurable goods materials (1992=100,sa) [1959:1] (log)
IPMFG industrial production: manufacturing (1992=100,sa) [1959:1] (log)
IPD industrial production: durable manufacturing (1992=100,sa) [1959:1] (log)
IPN industrial production: nondurable manufacturing (1992=100,sa) [1959:1] (log)
IPMIN industrial production: mining (1992=100,sa) [1959:1] (log)
IPUT industrial production: utilities (1992-=100,sa) [1959:1] (log)
IPX capacity util rate: total industry (% of capacity,sa)(frb) [1967:1]
IPXMCA capacity util rate: manufacturing,total(% of capacity,sa)(frb) [1959:1]
IPXDCA capacity util rate: durable mfg (% of capacity,sa)(frb) [1967:1]
IPXNCA capacity util rate: nondurable mfg (% of capacity,sa)(frb) [1967:1]
IPXMIN capacity util rate: mining (% of capacity,sa)(frb) [1967:1]
IPXUT capacity util rate: utilities (% of capacity,sa)(frb) [1967:1]
LHEL index of help-wanted advertising in newspapers (1967=100;sa) [1959:1]
LHELX employment: ratio; help-wanted ads:no. unemployed clf [1959:1]
LHEM civilian labor force: employed, total (thous.,sa) [1959:1] (log)
LHNAG civilian labor force: employed, nonagric.industries (thous.,sa) [1959:1] (log)
LHUR unemployment rate: all workers, 16 years & over (%,sa) [1959:1]
LHU680 unemploy.by duration: average(mean)duration in weeks (sa) [1959:1]
LHU5 unemploy.by duration: persons unempl.less than 5 wks (thous.,sa) [1959:1] (log)
LHU14 unemploy.by duration: persons unempl.5 to 14 wks (thous.,sa) [1959:1] (log)
LHU15 unemploy.by duration: persons unempl.15 wks + (thous.,sa) [1959:1] (log)
LHU26 unemploy.by duration: persons unempl.15 to 26 wks (thous.,sa) [1959:1] (log)
LHU27 unemploy.by duration: persons unempl.27 wks + (thous,sa) [1959:1] (log)

LHCH average hours of work per week (household data)(sa) [1959:1]
LPNAG employees on nonag. payrolls: total (thous.,sa) [1959:1] (log)
LP employees on nonag payrolls: total, private (thous,sa) [1959:1] (log)
LPGD employees on nonag. payrolls: goods-producing (thous.,sa) [1959:1] (log)
LPMI employees on nonag. payrolls: mining (thous.,sa) [1959:1] (log)
LPCC employees on nonag. payrolls: contract construction (thous.,sa) [1959:1] (log)
LPEM employees on nonag. payrolls: manufacturing (thous.,sa) [1959:1] (log)
LPED employees on nonag. payrolls: durable goods (thous.,sa) [1959:1] (log)
LPEN employees on nonag. payrolls: nondurable goods (thous.,sa) [1959:1] (log)
LPSP employees on nonag. payrolls: service-producing (thous.,sa) [1959:1] (log)
LPTU employees on nonag. payrolls: trans. & public utilities (thous.,sa) [1959:1] (log)
LPT employees on nonag. payrolls: wholesale & retail trade (thous.,sa) [1959:1] (log)
LPFR employees on nonag. payrolls: finance,insur.&real estate (thous.,sa [1959:1] (log)
LPS employees on nonag. payrolls: services (thous.,sa) [1959:1] (log)
LPGOV employees on nonag. payrolls: government (thous.,sa) [1959:1] (log)
LW avg. weekly hrs. of prod. wkrs.: total private (sa) [1964:1]
LPHRM avg. weekly hrs. of production wkrs.: manufacturing (sa) [1959:1]
LPMOSA avg. [1959:1]
LEH avg hr earnings of prod wkrs: total private nonagric ($,sa) [1964:1] (log)
LEHCC avg hr earnings of constr wkrs: construction ($,sa) [1959:1] (log)
LEHM avg hr earnings of prod wkrs: manufacturing ($,sa) [1959:1] (log)
LEHTU avg hr earnings of nonsupv wkrs: trans & public util($,sa) [1964:1] (log)
LEHTT avg hr earnings of prod wkrs:wholesale & retail trade(sa) [1964:1] (log)
LEHFR avg hr earnings of nonsupv wkrs: finance,insur,real est($,sa) [1964:1] (log)
LEHS avg hr earnings of nonsupv wkrs: services ($,sa) [1964:1] (log)
HSFR housing starts:nonfarm(1947-58);total farm&nonfarm(1959-)(thous.,sa [1959:1] (log)
HSNE housing starts:northeast (thous.u.)s.a. [1959:1] (log)
HSMW housing starts:midwest(thous.u.)s.a. [1959:1] (log)
HSSOU housing starts:south (thous.u.)s.a. [1959:1] (log)
HSWST housing starts:west (thous.u.)s.a. [1959:1] (log)
HSBR housing authorized: total new priv housing units (thous.,saar) [1959:1] (log)
HSBNE houses authorized by build. permits:northeast(thou.u.)s.a [1960:1] (log)
HSBMW houses authorized by build. permits:midwest(thou.u.)s.a. [1960:1] (log)
HSBSOU houses authorized by build. permits:south(thou.u.)s.a. [1960:1] (log)
HSBWST houses authorized by build. permits:west(thou.u.)s.a. [1960:1] (log)
HNS new 1-family houses sold during month (thous,saar) [1963:1] (log)
HNSNE one-family houses sold:northeast(thou.u.,s.a.) [1973:1] (log)
HNSMW one-family houses sold:midwest(thou.u.,s.a.) [1973:1] (log)
HNSSOU one-family houses sold:south(thou.u.,s.a.) [1973:1] (log)
HNSWST one-family houses sold:west(thou.u.,s.a.) [1973:1] (log)
HNR new 1-family houses, month's supply @ current sales rate(ratio) [1963:1]
HMOB mobile homes: manufacturers' shipments (thous.of units,saar) [1959:1] (log)
CONTC construct.put in place:total priv & public 1987$(mil$,saar) [1964:1] (log)
CONPC construct.put in place:total private 1987$(mil$,saar) [1964:1] (log)
CONQC construct.put in place:public construction 87$(mil$,saar) [1964:1] (log)
CONDO9 construct.contracts: comm'l & indus.bldgs(mil.sq.ft.floor sp.;sa) [1959:1] (log)
MSMTQ manufacturing & trade: total (mil of chained 1992 dollars)(sa) [1959:1] (log)
MSMQ manufacturing & trade:manufacturing;total(mil of chained 1992 dollars)(sa) [1959 (log):1]
MSDQ manufacturing & trade:mfg; durable goods (mil of chained 1992 dollars)(sa) [1959 (log):1]
MSNQ manufact. & trade:mfg;nondurable goods (mil of chained 1992 dollars)(sa) [1959:1 (log)]

WTQ merchant wholesalers: total (mil of chained 1992 dollars)(sa) [1959:1] (log)
WTDQ merchant wholesalers:durable goods total (mil of chained 1992 dollars)(sa) [1959 (log):1]
WTNQ merchant wholesalers:nondurable goods (mil of chained 1992 dollars)(sa) [1959:1] (log)
RTQ retail trade: total (mil of chained 1992 dollars)(sa) [1959:1] (log)
RTDQ retail trade:durable goods total (mil.87$)(s.a.) [1959:1] (log)
RTNQ retail trade:nondurable goods (mil of 1992 dollars)(sa) [1959:1] (log)
IVMTQ manufacturing & trade inventories:total (mil of chained 1992)(sa) [1959:1] (log)
IVMFGQ inventories, business, mfg (mil of chained 1992 dollars, sa) [1959:1] (log)
IVMFDQ inventories, business durables (mil of chained 1992 dollars, sa) [1959:1] (log)
IVMFNQ inventories, business, nondurables (mil of chained 1992 dollars, sa) [1959:1] (log)
IVWRQ manufacturing & trade inv:merchant wholesalers (mil of chained 1992 dollars)(s (log)[1959:1]
IVRRQ manufacturing & trade inv:retail trade (mil of chained 1992 dollars)(sa) [1959: (log)1]
IVSRQ ratio for mfg & trade: inventory/sales (chained 1992 dollars, sa) [1959:1]
IVSRMQ ratio for mfg & trade:mfg;inventory/sales (87$)(s.a.) [1959:1]
IVSRWQ ratio for mfg & trade:wholesaler;inventory/sales(87$)(s.a.) [1959:1]
IVSRRQ ratio for mfg & trade:retail trade;inventory/sales(87$)(s.a.) [1959:1]
PMI purchasing managers' index (sa) [1959:1]
PMP napm production index (percent) [1959:1]
PMNO napm new orders index (percent) [1959:1]
PMDEL napm vendor deliveries index (percent) [1959:1]
PMNV napm inventories index (percent) [1959:1]
PMEMP napm employment index (percent) [1959:1]
PMCP napm commodity prices index (percent) [1959:1]
MOCMQ new orders (net) - consumer goods & materials, 1992 dollars (bci) [1959:1] (log)
MDOQ new orders, durable goods industries, 1992 dollars (bci) [1959:1] (log)
MSONDQ new orders, nondefense capital goods, in 1992 dollars (bci) [1959:1] (log)
MO mfg new orders: all manufacturing industries, total (mil$,sa) [1959:1] (log)
MOWU mfg new orders: mfg industries with unfilled orders(mil$,sa) [1959:1] (log)
MDO mfg new orders: durable goods industries, total (mil$,sa) [1959:1] (log)
MDUWU mfg new orders:durable goods indust with unfilled orders(mil$,sa) [1959:1] (log)
MNO mfg new orders: nondurable goods industries, total (mil$,sa) [1959:1] (log)
MNOU mfg new orders: nondurable gds ind.with unfilled orders(mil$,sa) [1959:1] (log)
MU mfg unfilled orders: all manufacturing industries, total (mil$,sa) [1959:1] (log)
MDU mfg unfilled orders: durable goods industries, total (mil$,sa) [1959:1] (log)
MNU mfg unfilled orders: nondurable goods industries, total (mil$,sa) [1959:1] (log)
MPCON contracts & orders for plant & equipment (bil$,sa) [1959:1] (log)
MPCONQ contracts & orders for plant & equipment in 1992 dollars (bci) [1959:1] (log)
FM1 money stock: m1(curr,trav.cks,dem dep,other ck'able dep)(bil$,sa) [1959:1] (log)
FM2 money stock:m2(m1+o'nite rps,euro$,g/p&b/d mmmfs&sav&sm time dep(bil$, [1959:1] (log)
FM3 money stock: m3(m2+lg time dep,term rp's&inst only mmmfs)(bil$,sa) [1959:1] (log)
FML money stock:l(m3 + other liquid assets) (bil$,sa) [1959:1] (log)
FM2DQ money supply - m2 in 1992 dollars (bci) [1959:1] (log)
FMFBA monetary base, adj for reserve requirement changes(mil$,sa) [1959:1] (log)
FMBASE monetary base, adj for reserve req chgs(frb of st.louis)(bil$,sa) [1959:1] (log)
FMRRA depository inst reserves:total,adj for reserve req chgs(mil$,sa) [1959:1] (log)
FMRNBA depository inst reserves:nonborrowed,adj res req chgs(mil$,sa) [1959:1] (log)
FMRNBC depository inst reserves:nonborrow+ext cr,adj res req cgs(mil$,sa) [1959:1] (log)
FMFBA monetary base, adj for reserve requirement changes(mil$,sa) [1959:1] (log)
FCLS loans & sec @ all coml banks: total (bils,sa) [1973:1] (log)
FCSGV loans & sec @ all coml banks: U.S.govt securities (bil$,sa) [1973:1] (log)

FCLRE loans & sec @ all coml banks: real estate loans (bil$,sa) [1973:1] (log)
FCLIN loans & sec @ all coml banks: loans to individuals (bil$,sa) [1973:1] (log)
FCLNBF loans & sec @ all coml banks: loans to nonbank fin inst(bil$,sa) [1973:1] (log)
FCLNQ commercial & industrial loans oustanding in 1992 dollars (bci) [1959:1] (log)
FCLBMC wkly rp lg com'l banks:net change com'l & indus loans(bil$,saar) [1959:1]
CCI30M consumer instal.loans: delinquency rate,30 days & over, (%,sa) [1959:1]
CCINT net change in consumer instal cr: total (mil$,sa) [1975:1]
CCINV net change in consumer instal cr: automobile (mil$,sa) [1975:1]
FSNCOM nyse common stock price index: composite (12/31/65=50) [1959:1] (log)
FSNIN nyse common stock price index: industrial (12/31/65=50) [1966:1] (log)
FSNTR nyse common stock price index: transportation (12/31/65=50) [1966:1] (log)
FSNUT nyse common stock price index: utility (12/31/65=50) [1966:1] (log)
FSNFI nyse common stock price index: finance (12/31/65=50) [1966:1] (log)
FSPCOM s&p's common stock price index: composite (1941-43=10) [1959:1] (log)
FSPIN s&p's common stock price index: industrials (1941-43=10) [1959:1] (log)
FSPCAP s&p's common stock price index: capital goods (1941-43=10) [1959:1] (log)
FSPTR s&p's common stock price index: transportation (1970=10) [1970:1] (log)
FSPUT s&p's common stock price index: utilities (1941-43=10) [1959:1] (log)
FSPFI s&p's common stock price index: financial (1970=10) [1970:1] (log)
FSDXP s&p's composite common stock: dividend yield (% per annum) [1959:1] (log)
FSPXE s&p's composite common stock: price-earnings ratio (%,nsa) [1959:1] (log)
FSNVV3 nyse mkt composition:reptd share vol by size,5000+ shrs,% [1959:1] (log)
FYFF interest rate: federal funds (effective) (% per annum,nsa) [1959:1]
FYCP interest rate: commercial paper, 6-month (% per annum,nsa) [1959:1]
FYGM3 interest rate: U.S.treasury bills,sec mkt,3-mo.(% per ann,nsa) [1959:1]
FYGM6 interest rate: U.S.treasury bills,sec mkt,6-mo.(% per ann,nsa) [1959:1]
FYGT1 interest rate: U.S.treasury const maturities,1-yr.(% per ann,nsa) [1959:1]
FYGT5 interest rate: U.S.treasury const maturities,5-yr.(% per ann,nsa) [1959:1]
FYGT10 interest rate: U.S.treasury const maturities,10-yr.(% per ann,nsa) [1959:1]
FYAAAC bond yield: moody's aaa corporate (% per annum) [1959:1]
FYBAAC bond yield: moody's baa corporate (% per annum) [1959:1]
FWAFIT weighted avg foreign interest rate(%,sa) [1959:1]
FYFHA secondary market yields on fha mortgages (% per annum) [1959:1]
EXRUS united states;effective exchange rate(merm)(index no.) [1973:1] (log)
EXRGER foreign exchange rate: germany (deutsche mark per U.S.$) [1973:1] (log)
EXRSW foreign exchange rate: switzerland (swiss franc per U.S.$) [1973:1] (log)
EXRJAN foreign exchange rate: japan (yen per U.S.$) [1973:1] (log)
EXRUK foreign exchange rate: united kingdom (cents per pound) [1973:1] (log)
EXRCAN foreign exchange rate: canada (canadian $ per U.S.$) [1973:1] (log)
HHSNTN u. of mich. index of consumer expectations(bcd-83) [1959:1]
F6EDM U.S.mdse exports: [1964:1] (log)
FTMC6 U.S.mdse imports: crude materials & fuels (mil$,nsa) [1964:1] (log)
FTMM6 U.S.mdse imports: manufactured goods (mil$,nsa) [1964:1] (log)
PWFSA producer price index: finished goods (82=100,sa) [1959:1] (log)
PWFCSA producer price index:finished consumer goods (82=100,sa) [1959:1] (log)
PWIMSA producer price index:intermed mat.supplies & components(82=100,sa) [1959:1] (log)
PWCMSA producer price index:crude materials (82=100,sa) [1959:1] (log)
PWFXSA producer price index: finished goods,excl. foods (82=100,sa) [1967:1] (log)
PW160A producer price index: crude materials less energy (82=100,sa) [1974:1] (log)
PW150A producer price index: crude nonfood mat less energy (82=100,sa) [1974:1] (log)

PW561 producer price index: crude petroleum (82=100,nsa) [1959:1] (log)
PWCM producer price index: construction materials (82=100,nsa) [1959:1] (log)
PWXFA producer price index: all commodities ex.farm prod (82=100,nsa) [1959:1] (log)
PSM99Q index of sensitive materials prices (1990=100)(bci-99a) [1959:1] (log)
PUNEW cpi-u: all items (82-84=100,sa) [1959:1] (log)
PU81 cpi-u: food & beverages (82-84=100,sa) [1967:1] (log)
PUH cpi-u: housing (82-84=100,sa) [1967:1] (log)
PU83 cpi-u: apparel & upkeep (82-84=100,sa) [1959:1] (log)
PU84 cpi-u: transportation (82-84=100,sa) [1959:1] (log)
PU85 cpi-u: medical care (82-84=100,sa) [1959:1] (log)
PUC cpi-u: commodities (82-84=100,sa) [1959:1] (log)
PUCD cpi-u: durables (82-84=100,sa) [1959:1] (log)
PUS cpi-u: services (82-84=100,sa) [1959:1] (log)
PUXF cpi-u: all items less food (82-84=100,sa) [1959:1] (log)
PUXHS cpi-u: all items less shelter (82-84=100,sa) [1959:1] (log)
PUXM cpi-u: all items less midical care (82-84=100,sa) [1959:1] (log)
PSCCOM spot market price index:bls & crb: all commodities(67=100,nsa) [1959:1] (log)
PSCFOO spot market price index:bls & crb: foodstuffs (67=100,nsa) [1959:1] (log)
PSCMAT spot market price index:bls & crb: raw industrials(67=100,nsa) [1959:1] (log)
PZFR prices received by farmers: all farm products (1977=100,nsa) [1975:1] (log)
PCGOLD commodities price:gold,london noon fix,avg of daily rate,$ per oz [1975:1] (log)
GMDC pce,impl pr defl:pce (1987=100) [1959:1] (log)
GMDCD pce,impl pr defl:pce; durables (1987=100) [1959:1] (log)
GMDCN pce,impl pr defl:pce; nondurables (1987=100) [1959:1] (log)
GMDCS pce,impl pr defl:pce; services (1987=100) [1959:1] (log)
GMPYQ personal income (chained) (series #52) (bil 92$,saar) [1959:1] (log)
GMYXPQ personal income less transfer payments (chained) (#51) (bil 92$,saar) [1959:1] (log)
GMCQ personal consumption expend (chained) - total (bil 92$,saar) [1959:1] (log)
GMCDQ personal consumption expend (chained) - total durables (bil 92$,saar) [1959:1] (log)
GMCNQ personal consumption expend (chained) - nondurables (bil 92$,saar) [1959:1] (log)
GMCSQ personal consumption expend (chained) - services (bil 92$,saar) [1959:1] (log)
GMCANQ personal cons expend (chained) - new cars (bil 92$,saar) (log)

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Table 1

Summary of Forecasting Methods

Mnemonic	Description
A. Linear Methods	
AR	
ARFC04	levels; constant; 4 lags
ARFT04	levels; constant and time trend; 4 lags
ARFC14	differences; constant; 4 lags
ARFT14	differences; constant and time trend; 4 lags
ARFCP4	DF-GLS$^{\mu}$ pretest between ARFC14 and ARFC04
ARFTP4	DF-GLS$^{\tau}$ pretest between ARFC14 and ARFT04
ARFC0a	levels; constant; AIC lag choice ($0 \le p \le 12$)
ARFT0a	levels; constant and time trend; AIC lag choice ($0 \le p \le 12$)
ARFC1a	differences; constant; AIC lag choice ($0 \le p \le 12$)
ARFT1a	differences; constant and time trend; AIC lag choice ($0 \le p \le 12$)
ARFCPa	DF-GLS$^{\mu}$ pretest between ARFC1a and ARFC0a
ARFTPa	DF-GLS$^{\tau}$ pretest between ARFC1a and ARFT0a
ARFC0b	levels; constant; BIC lag choice ($0 \le p \le 12$)
ARFT0b	levels; constant and time trend; BIC lag choice ($0 \le p \le 12$)
ARFC1b	differences; constant; BIC lag choice ($0 \le p \le 12$)
ARFT1b	differences; constant and time trend; BIC lag choice ($0 \le p \le 12$)
ARFCPb	DF-GLS$^{\mu}$ pretest between ARFC1b and ARFC0b
ARFTPb	DF-GLS$^{\tau}$ pretest between ARFC1b and ARFT0b
EX	
EX1	Single exponential smoothing
EX2	Double exponential smoothing
EXP	DF-GLS$^{\tau}$ pretest between EX1 and EX2
B. Nonlinear Methods	
ANN	
AN0203	levels; single layer, 2 hidden units, 3 lags ($p=3$)
AN1203	differences; single layer, 2 hidden units, 3 lags ($p=3$)
ANP203	DF-GLS$^{\mu}$ pretest between AN0203 and AN1203
AN0213	levels; two layers, $n_1=2$, $n_2=1$, 3 lags ($p=3$)
AN1213	differences; two layers, $n_1=2$, $n_2=1$, 3 lags ($p=3$)
ANP213	DF-GLS$^{\mu}$ pretest between AN0213 and AN1213
AN0223	levels; two layers, $n_1=2$, $n_2=2$, 3 lags ($p=3$)($p=3$)
AN1223	differences; two layers, $n_1=2$, $n_2=2$, 3 lags ($p=3$)($p=3$)
ANP223	DF-GLS$^{\mu}$ pretest between AN0223 and AN1223
ANF0a	levels; single layer; AIC choice of n_1, p ($1 \le n_1 \le 4$, $p=1,3,6$)
ANF1a	differences; single layer; AIC choice of n_1, p ($1 \le n_1 \le 4$, $p=1,3,6$)
ANFPa	DF-GLS$^{\mu}$ pretest between ANF0a and ANF1a
ANF0b	levels; single layer; BIC choice of n_1, p ($1 \le n_1 \le 4$, $p=1,3,6$)
ANF1b	differences; single layer; BIC choice of n_1, p ($1 \le n_1 \le 4$, $p=1,3,6$)
ANFPb	DF-GLS$^{\mu}$ pretest between ANF0b and ANF1b
LSTAR	
LS0103	levels; $\xi_t=y_t$; 3 lags ($p=3$)
LS1103	differences; $\xi_t=\Delta y_t$; 3 lags ($p=3$)

LSP103	DF-GLS$^{\mu}$ pretest between LS0103 and LS1103
LS0063	levels; $\xi_t = y_t - y_{t-6}$; 3 lags (p=3)
LS1063	differences; $\xi_t = y_t - y_{t-6}$; 3 lags (p=3)
LSP063	DF-GLS$^{\mu}$ pretest between LS0063 and LS1063
LSF0a	levels; AIC choice of ξ_t and lag length (p=1,3,6)
LSF1a	differences; AIC choice of ξ_t and lag length (p=1,3,6)
LSFPa	DF-GLS$^{\mu}$ pretest between LSF0a and LSF1a
LSF0b	levels; BIC choice of ξ_t and lag length (p=1,3,6)
LSF1b	differences; BIC choice of ξ_t and lag length (p=1,3,6)
LSFPb	DF-GLS$^{\mu}$ pretest between LSF0b and LSF1b

C. No Change

NOCHANGE

D. Pooling Procedures

Linear Combination

C1rrr060	Avg, groups A, B & C, MSE wts based on 60 period rolling avg, ω=rrr
C1rrr120	Avg, groups A, B & C, MSE wts based on 120 period rolling avg, ω=rrr
C1rrr999	Avg, groups A, B & C, MSE wts based on recursive avg, ω=rrr
C2rrr060	Avg, group A, MSE wts based on 60 period rolling avg, ω=rrr
C2rrr120	Avg, group A, MSE wts based on 120 period rolling avg, ω=rrr
C2rrr999	Avg, group A, MSE wts based on recursive avg, ω=rrr
C3rrr060	Avg, group B, MSE wts based on 60 period rolling avg, ω=rrr
C3rrr120	Avg, group B, MSE wts based on 120 period rolling avg, ω=rrr
C3rrr999	Avg, group B, MSE wts based on recursive avg, ω=rrr

Median

M1	Median, groups A, B & C
M2	Median, group A
M2	Median, group B

PLS

P0060	PLS, all primitive fcsts, MSEs computed over 60 period rolling window
P0120	PLS, all primitive fcsts, MSEs computed over 120 period rolling window
P0999	PLS, all primitive fcsts, MSEs computed recursively (expanding window)
P1060	PLS, groups A, B & C, MSEs computed over 60 period rolling window
P1120	PLS, groups A, B & C, MSEs computed over 120 period rolling window
P1999	PLS, groups A, B & C, MSEs computed recursively (expanding window)
P2060	PLS, group A, MSEs computed over 60 period rolling window
P2120	PLS, group A, MSEs computed over 120 period rolling window
P2999	PLS, group A, MSEs computed recursively (expanding window)
P3060	PLS, group B, MSEs computed over 60 period rolling window
P3120	PLS, group B, MSEs computed over 120 period rolling window
P3999	PLS, group B, MSEs computed recursively (expanding window)

E. Pooled Over All Groups

PA060	PLS, groups A-D, MSEs computed over 60 period rolling window
PA120	PLS, groups A-D, MSEs computed over 120 period rolling window
PA999	PLS, groups A-D, MSEs computed recursively (expanding window)

Table 2

Mean and percentiles of relative MSEs of various forecasting methods

relative MSE = MSE of method i/MSE of naive model

naive model = ARFC04 (AR(4) in levels with a constant term)

For each forecast, the first row corresponds to one-step ahead forecasts; the second row, to 6-step ahead forecasts; the third row, to 12-step ahead forecasts.

Method	mean	2%	10%	25%	50%	75%	90%	98%
AR								
ARFC04	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ARFT04	1.02	0.96	0.99	1.00	1.01	1.03	1.04	1.10
	1.10	0.78	0.88	0.99	1.08	1.17	1.27	1.56
	1.26	0.44	0.77	1.02	1.19	1.38	1.76	2.55
ARFC14	1.00	0.90	0.95	0.98	1.00	1.02	1.04	1.08
	0.98	0.59	0.77	0.90	0.97	1.05	1.17	1.36
	0.99	0.35	0.64	0.81	0.94	1.15	1.36	1.76
ARFT14	1.01	0.95	0.97	0.99	1.01	1.02	1.04	1.09
	1.06	0.74	0.89	0.99	1.03	1.11	1.25	1.46
	1.15	0.52	0.83	0.97	1.06	1.18	1.42	1.89
ARFCP4	1.00	0.90	0.95	0.98	1.00	1.01	1.03	1.07
	0.98	0.59	0.77	0.91	0.97	1.05	1.15	1.34
	0.98	0.35	0.64	0.81	0.94	1.11	1.33	1.76
ARFTP4	1.00	0.90	0.95	0.98	1.00	1.02	1.04	1.07
	0.98	0.59	0.77	0.91	0.97	1.06	1.16	1.34
	0.99	0.35	0.64	0.81	0.95	1.14	1.36	1.76
ARFC0a	1.02	0.83	0.95	1.00	1.02	1.04	1.07	1.14
	1.00	0.61	0.86	0.99	1.01	1.06	1.13	1.24
	0.98	0.63	0.87	0.98	1.00	1.02	1.08	1.18
ARFT0a	1.03	0.85	0.96	1.00	1.04	1.06	1.10	1.16
	1.12	0.66	0.81	0.96	1.10	1.25	1.37	1.82
	1.29	0.45	0.75	0.95	1.20	1.41	1.82	3.13
ARFC1a	1.01	0.77	0.94	0.98	1.02	1.05	1.09	1.15
	0.97	0.43	0.72	0.88	0.99	1.09	1.18	1.42
	0.98	0.33	0.58	0.83	0.95	1.15	1.36	1.74
ARFT1a	1.03	0.84	0.96	1.00	1.03	1.06	1.10	1.17
	1.07	0.60	0.80	0.96	1.06	1.16	1.31	1.53

	1.16	0.46	0.72	0.96	1.07	1.23	1.49	1.97
ARFCPa	1.01	0.77	0.94	0.98	1.02	1.05	1.08	1.15
	0.97	0.43	0.72	0.89	0.99	1.09	1.15	1.40
	0.97	0.33	0.58	0.83	0.95	1.13	1.35	1.74
ARFTPa	1.02	0.77	0.94	0.98	1.02	1.05	1.09	1.15
	0.98	0.43	0.72	0.89	0.99	1.09	1.18	1.41
	0.98	0.33	0.58	0.83	0.95	1.15	1.35	1.74
ARFC0b	1.01	0.91	0.97	0.99	1.01	1.02	1.04	1.12
	0.99	0.68	0.87	0.98	1.01	1.03	1.07	1.20
	0.99	0.71	0.93	0.99	1.00	1.02	1.05	1.11
ARFT0b	1.02	0.93	0.97	1.00	1.02	1.05	1.08	1.14
	1.11	0.67	0.83	0.96	1.09	1.23	1.36	1.67
	1.27	0.48	0.75	0.98	1.20	1.42	1.74	2.99
ARFC1b	1.00	0.83	0.94	0.98	1.01	1.03	1.07	1.13
	0.97	0.43	0.73	0.90	0.98	1.07	1.17	1.42
	0.99	0.33	0.58	0.83	0.94	1.15	1.37	1.66
ARFT1b	1.02	0.89	0.96	1.00	1.02	1.04	1.08	1.14
	1.06	0.64	0.79	0.99	1.05	1.12	1.26	1.57
	1.16	0.62	0.76	0.99	1.07	1.19	1.43	1.93
ARFCPb	1.00	0.83	0.94	0.98	1.00	1.03	1.06	1.12
	0.96	0.43	0.73	0.90	0.98	1.07	1.16	1.36
	0.98	0.33	0.58	0.83	0.94	1.14	1.31	1.66
ARFTPb	1.00	0.83	0.94	0.98	1.01	1.03	1.07	1.13
	0.97	0.43	0.73	0.90	0.99	1.08	1.16	1.36
	0.99	0.33	0.58	0.83	0.95	1.15	1.36	1.66
Exponential Smoothing								
EX1	1.73	0.90	0.98	1.01	1.09	1.47	2.82	8.42
	2.12	0.81	0.90	0.97	1.20	1.78	4.61	11.47
	1.83	0.69	0.81	0.95	1.17	1.87	3.02	9.18
EX2	1.06	0.82	0.94	1.00	1.04	1.10	1.18	1.37
	1.16	0.37	0.76	0.94	1.11	1.32	1.64	2.30
	1.26	0.30	0.63	0.91	1.15	1.47	2.14	3.02
EXP	1.06	0.82	0.94	1.00	1.04	1.09	1.18	1.37
	1.15	0.37	0.76	0.94	1.11	1.30	1.55	2.30
	1.23	0.30	0.63	0.91	1.14	1.40	1.92	2.79
Artificial Neural Networks								
AN0203	1.26	0.96	1.01	1.05	1.11	1.18	1.31	1.57
	1.62	0.78	1.04	1.16	1.37	2.00	2.45	3.43
	1.72	0.88	1.02	1.15	1.47	2.04	2.64	4.34
AN1203	1.09	0.88	0.98	1.02	1.08	1.15	1.23	1.46
	1.07	0.65	0.82	0.94	1.04	1.16	1.29	1.77

	1.09	0.40	0.68	0.86	1.02	1.24	1.51	2.25
ANP203	1.09	0.88	0.98	1.02	1.07	1.13	1.23	1.46
	1.06	0.65	0.82	0.94	1.04	1.15	1.27	1.77
	1.07	0.40	0.68	0.86	1.02	1.23	1.48	2.25
AN0213	1.30	0.98	1.06	1.13	1.20	1.34	1.50	2.27
	2.16	0.94	1.11	1.24	1.67	2.55	3.74	6.49
	2.28	0.72	1.09	1.24	1.77	2.74	4.28	7.70
AN1213	1.16	0.94	1.02	1.08	1.15	1.21	1.32	1.56
	1.14	0.73	0.85	0.98	1.11	1.22	1.40	1.99
	1.15	0.41	0.70	0.89	1.06	1.34	1.67	2.49
ANP213	1.16	0.94	1.01	1.08	1.14	1.21	1.32	1.56
	1.14	0.73	0.85	0.98	1.11	1.21	1.39	2.00
	1.13	0.41	0.70	0.89	1.06	1.29	1.62	2.49
AN0223	1.16	0.94	1.02	1.06	1.12	1.20	1.34	1.69
	1.78	0.82	1.04	1.16	1.45	2.15	2.90	4.31
	1.90	0.83	1.07	1.20	1.48	2.20	3.12	6.20
AN1223	1.15	0.94	1.01	1.05	1.11	1.21	1.31	1.63
	1.11	0.73	0.87	0.99	1.09	1.21	1.38	1.70
	1.11	0.43	0.70	0.89	1.03	1.24	1.56	2.35
ANP223	1.15	0.94	1.01	1.05	1.11	1.21	1.32	1.63
	1.11	0.73	0.87	0.99	1.10	1.21	1.34	1.70
	1.10	0.43	0.70	0.90	1.03	1.24	1.50	2.35
ANF0a	1.27	0.85	1.05	1.14	1.22	1.37	1.55	1.86
	1.99	0.90	1.13	1.34	1.68	2.32	3.16	5.64
	2.13	0.76	1.12	1.33	1.73	2.44	3.76	5.43
ANF1a	1.28	0.96	1.06	1.14	1.23	1.38	1.51	1.92
	1.23	0.67	0.84	1.08	1.19	1.33	1.58	2.27
	1.22	0.39	0.68	0.95	1.14	1.48	1.77	2.59
ANFPa	1.28	0.97	1.06	1.14	1.23	1.38	1.51	1.88
	1.23	0.67	0.84	1.08	1.19	1.33	1.56	2.06
	1.20	0.39	0.68	0.95	1.14	1.40	1.72	2.59
ANF0b	1.16	0.90	1.01	1.06	1.11	1.21	1.36	1.72
	1.83	0.82	1.08	1.23	1.50	2.15	2.78	5.03
	2.08	0.75	1.05	1.26	1.63	2.38	3.75	6.49
ANF1b	1.15	0.92	0.98	1.04	1.09	1.20	1.37	1.72
	1.07	0.56	0.80	0.94	1.05	1.19	1.34	1.80
	1.07	0.38	0.64	0.82	1.03	1.24	1.58	2.24
ANFPb	1.15	0.92	0.98	1.03	1.09	1.22	1.37	1.72
	1.07	0.56	0.80	0.94	1.05	1.18	1.33	1.80
	1.06	0.38	0.64	0.83	1.03	1.24	1.51	2.24

LSTAR								
LS0103	1.07	0.91	0.98	1.01	1.05	1.10	1.17	1.31
	1.24	0.80	1.00	1.06	1.15	1.34	1.72	2.00
	1.34	0.56	0.92	1.07	1.19	1.45	1.95	2.89
LS1103	1.06	0.90	0.95	1.00	1.04	1.09	1.16	1.38
	1.04	0.69	0.82	0.93	1.02	1.11	1.26	1.60
	1.05	0.40	0.67	0.84	0.98	1.20	1.44	2.21
LSP103	1.05	0.90	0.96	1.00	1.04	1.08	1.15	1.33
	1.03	0.69	0.82	0.93	1.02	1.11	1.22	1.60
	1.04	0.40	0.67	0.85	0.98	1.18	1.41	2.21
LS0063	1.04	0.93	0.97	1.00	1.03	1.07	1.12	1.25
	1.09	0.75	0.92	1.00	1.06	1.14	1.28	1.52
	1.10	0.74	0.92	1.01	1.06	1.16	1.26	1.61
LS1063	1.03	0.85	0.95	0.99	1.02	1.06	1.11	1.27
	1.01	0.52	0.72	0.91	1.00	1.12	1.24	1.46
	1.04	0.34	0.60	0.83	0.96	1.20	1.45	1.99
LSP063	1.03	0.85	0.95	0.99	1.02	1.06	1.11	1.24
	1.00	0.52	0.72	0.91	1.00	1.11	1.22	1.42
	1.03	0.34	0.60	0.84	0.96	1.17	1.45	1.99
LSF0a	1.13	0.92	0.98	1.04	1.08	1.18	1.33	1.68
	1.42	0.77	0.96	1.11	1.29	1.57	2.10	2.99
	1.47	0.73	0.92	1.12	1.34	1.70	2.13	3.27
LSF1a	1.11	0.83	0.97	1.01	1.08	1.16	1.29	1.72
	1.07	0.47	0.80	0.95	1.06	1.18	1.35	1.61
	1.06	0.31	0.60	0.82	1.00	1.25	1.56	2.35
LSFPa	1.11	0.83	0.97	1.01	1.07	1.16	1.29	1.61
	1.07	0.47	0.80	0.96	1.06	1.17	1.33	1.58
	1.05	0.31	0.60	0.83	1.00	1.24	1.57	2.36
LSF0b	1.11	0.89	0.97	1.02	1.07	1.15	1.27	1.70
	1.41	0.74	0.96	1.11	1.26	1.59	1.97	3.02
	1.46	0.72	0.90	1.11	1.32	1.71	2.09	3.19
LSF1b	1.07	0.81	0.96	1.00	1.05	1.11	1.19	1.46
	1.04	0.47	0.77	0.92	1.03	1.15	1.31	1.61
	1.06	0.31	0.60	0.84	0.99	1.20	1.52	2.31
LSFPb	1.06	0.81	0.96	1.00	1.04	1.11	1.19	1.44
	1.03	0.47	0.77	0.92	1.03	1.15	1.29	1.61
	1.05	0.31	0.60	0.84	0.99	1.19	1.52	2.31
No Change								
NOCHANGE	1.76	0.89	0.99	1.04	1.12	1.49	2.82	8.42
	2.14	0.81	0.90	1.00	1.22	1.78	4.61	11.47
	1.83	0.69	0.82	0.97	1.21	1.77	2.93	9.18

Combination forecasts (weighted averages with weights $1/MSE_i^{\omega}$)

C1000999	0.97	0.78	0.89	0.96	0.98	1.00	1.01	1.05
	0.91	0.42	0.69	0.87	0.95	1.00	1.06	1.12
	0.89	0.26	0.55	0.79	0.91	1.02	1.10	1.34
C2000999	0.98	0.81	0.91	0.96	0.99	1.01	1.02	1.06
	0.92	0.46	0.68	0.88	0.96	1.01	1.08	1.15
	0.90	0.37	0.57	0.81	0.93	1.05	1.16	1.33
C3000999	0.98	0.79	0.89	0.96	0.99	1.01	1.04	1.09
	0.94	0.45	0.77	0.88	0.96	1.03	1.10	1.21
	0.91	0.28	0.60	0.82	0.92	1.05	1.16	1.39
C1001999	0.97	0.76	0.90	0.96	0.98	1.00	1.01	1.05
	0.91	0.47	0.72	0.88	0.95	1.00	1.05	1.11
	0.89	0.37	0.58	0.80	0.92	1.03	1.12	1.35
C2001999	0.98	0.82	0.91	0.97	0.99	1.01	1.02	1.05
	0.93	0.48	0.71	0.90	0.96	1.01	1.08	1.15
	0.91	0.43	0.57	0.81	0.94	1.07	1.15	1.40
C3001999	0.98	0.79	0.89	0.96	0.99	1.01	1.04	1.08
	0.93	0.50	0.72	0.88	0.96	1.02	1.08	1.17
	0.91	0.33	0.59	0.81	0.92	1.05	1.16	1.40
C1001060	0.97	0.76	0.90	0.96	0.98	1.00	1.01	1.05
	0.91	0.45	0.70	0.88	0.95	1.00	1.06	1.12
	0.90	0.35	0.59	0.79	0.93	1.04	1.12	1.35
C1001120	0.97	0.76	0.90	0.96	0.98	1.00	1.01	1.05
	0.91	0.46	0.71	0.88	0.95	0.99	1.05	1.12
	0.89	0.37	0.58	0.79	0.92	1.03	1.11	1.35
C1005060	0.97	0.76	0.90	0.95	0.98	1.00	1.01	1.04
	0.93	0.47	0.72	0.88	0.97	1.02	1.08	1.13
	0.97	0.38	0.64	0.83	0.98	1.12	1.26	1.45
C1005120	0.97	0.76	0.90	0.96	0.98	1.00	1.01	1.04
	0.92	0.49	0.73	0.88	0.95	1.01	1.06	1.12
	0.92	0.37	0.60	0.81	0.93	1.06	1.18	1.50
C1005999	0.97	0.76	0.91	0.96	0.98	1.00	1.01	1.04
	0.92	0.51	0.75	0.87	0.95	1.01	1.05	1.11
	0.92	0.37	0.60	0.81	0.93	1.06	1.17	1.42
C1010060	0.97	0.76	0.91	0.96	0.99	1.01	1.02	1.07
	0.96	0.49	0.74	0.91	0.99	1.07	1.13	1.23
	1.05	0.40	0.64	0.87	1.05	1.24	1.40	1.78
C1010120	0.97	0.76	0.91	0.96	0.99	1.01	1.02	1.06
	0.93	0.51	0.72	0.89	0.97	1.02	1.08	1.19
	0.96	0.37	0.60	0.83	0.97	1.08	1.23	1.77
C1010999	0.97	0.76	0.91	0.96	0.99	1.00	1.02	1.04

	0.93	0.51	0.72	0.89	0.96	1.01	1.08	1.14
	0.95	0.37	0.61	0.83	0.96	1.07	1.21	1.84
C1050060	1.02	0.76	0.93	0.98	1.02	1.05	1.10	1.33
	1.07	0.49	0.77	0.94	1.08	1.21	1.36	1.61
	1.17	0.35	0.64	0.90	1.13	1.41	1.68	2.10
C1050120	1.00	0.76	0.93	0.97	1.01	1.03	1.07	1.23
	1.02	0.48	0.74	0.94	1.03	1.12	1.23	1.45
	1.07	0.38	0.65	0.88	1.07	1.21	1.44	1.89
C1050999	1.00	0.76	0.93	0.97	1.00	1.02	1.06	1.24
	1.00	0.48	0.73	0.93	1.02	1.08	1.20	1.45
	1.05	0.37	0.63	0.88	1.05	1.16	1.36	1.96
C1100060	1.04	0.78	0.94	0.99	1.03	1.07	1.12	1.38
	1.10	0.51	0.80	0.95	1.10	1.25	1.41	1.63
	1.19	0.37	0.67	0.90	1.13	1.45	1.74	2.14
C1100120	1.02	0.76	0.93	0.98	1.02	1.05	1.09	1.24
	1.04	0.48	0.77	0.96	1.04	1.14	1.29	1.51
	1.10	0.39	0.66	0.89	1.08	1.25	1.50	1.97
C1100999	1.01	0.76	0.93	0.98	1.02	1.04	1.07	1.28
	1.02	0.48	0.76	0.95	1.03	1.12	1.24	1.55
	1.07	0.37	0.64	0.89	1.06	1.18	1.42	2.04
C1500060	1.05	0.81	0.95	1.00	1.05	1.09	1.15	1.42
	1.12	0.52	0.81	0.97	1.12	1.27	1.44	1.65
	1.21	0.38	0.68	0.91	1.15	1.47	1.76	2.17
C1500120	1.03	0.76	0.94	0.99	1.04	1.07	1.12	1.27
	1.06	0.50	0.80	0.97	1.05	1.17	1.31	1.60
	1.11	0.43	0.67	0.90	1.11	1.28	1.49	2.16
C1500999	1.03	0.77	0.94	0.99	1.03	1.07	1.10	1.30
	1.04	0.50	0.76	0.95	1.04	1.15	1.25	1.60
	1.09	0.38	0.66	0.90	1.08	1.22	1.49	2.10
C2001060	0.98	0.82	0.91	0.97	0.99	1.01	1.02	1.05
	0.93	0.47	0.71	0.90	0.96	1.01	1.08	1.15
	0.92	0.37	0.57	0.81	0.95	1.07	1.17	1.40
C2001120	0.98	0.82	0.91	0.97	0.99	1.01	1.02	1.05
	0.93	0.48	0.71	0.90	0.96	1.01	1.08	1.15
	0.91	0.43	0.57	0.80	0.94	1.05	1.15	1.40
C2005060	0.98	0.81	0.92	0.97	0.99	1.01	1.02	1.04
	0.94	0.48	0.73	0.90	0.98	1.03	1.08	1.18
	0.98	0.40	0.64	0.87	1.01	1.14	1.27	1.50
C2005120	0.98	0.82	0.91	0.97	1.00	1.01	1.02	1.04
	0.93	0.51	0.72	0.89	0.97	1.01	1.07	1.16
	0.93	0.43	0.60	0.82	0.96	1.06	1.14	1.52

C2005999	0.98	0.82	0.91	0.97	1.00	1.01	1.02	1.04
	0.93	0.52	0.72	0.89	0.97	1.02	1.07	1.16
	0.93	0.42	0.61	0.82	0.96	1.06	1.16	1.52
C2010060	0.98	0.80	0.92	0.97	1.00	1.01	1.02	1.04
	0.97	0.48	0.73	0.92	1.00	1.07	1.11	1.23
	1.03	0.43	0.61	0.88	1.04	1.19	1.34	1.62
C2010120	0.98	0.81	0.92	0.97	1.00	1.01	1.02	1.04
	0.94	0.51	0.71	0.90	0.98	1.03	1.08	1.19
	0.96	0.44	0.60	0.84	0.98	1.09	1.17	1.72
C2010999	0.98	0.81	0.92	0.97	1.00	1.01	1.02	1.04
	0.94	0.51	0.70	0.89	0.97	1.02	1.08	1.18
	0.96	0.43	0.60	0.84	0.97	1.08	1.18	1.82
C2050060	0.99	0.77	0.93	0.98	1.00	1.02	1.05	1.08
	1.03	0.46	0.76	0.94	1.06	1.15	1.23	1.40
	1.09	0.43	0.65	0.92	1.09	1.30	1.48	1.73
C2050120	0.99	0.79	0.93	0.98	1.00	1.02	1.03	1.07
	0.99	0.49	0.74	0.93	1.02	1.08	1.18	1.32
	1.03	0.44	0.60	0.86	1.03	1.16	1.35	1.87
C2050999	0.99	0.80	0.93	0.98	1.00	1.02	1.03	1.07
	0.98	0.48	0.73	0.92	1.01	1.07	1.14	1.31
	1.02	0.47	0.63	0.90	1.02	1.13	1.30	1.91
C2100060	1.00	0.77	0.94	0.98	1.01	1.03	1.06	1.09
	1.04	0.46	0.76	0.95	1.07	1.18	1.25	1.45
	1.11	0.43	0.65	0.93	1.10	1.31	1.50	1.73
C2100120	0.99	0.80	0.93	0.98	1.01	1.02	1.04	1.09
	1.00	0.49	0.74	0.94	1.03	1.11	1.20	1.34
	1.04	0.44	0.62	0.88	1.04	1.18	1.36	1.89
C2100999	0.99	0.80	0.94	0.98	1.01	1.02	1.04	1.08
	0.99	0.48	0.74	0.92	1.02	1.08	1.16	1.32
	1.04	0.47	0.64	0.91	1.03	1.16	1.34	1.91
C2500060	1.01	0.78	0.94	0.99	1.02	1.04	1.07	1.11
	1.05	0.47	0.78	0.96	1.07	1.18	1.28	1.47
	1.11	0.43	0.65	0.92	1.11	1.33	1.51	1.73
C2500120	1.00	0.79	0.93	0.98	1.01	1.03	1.05	1.11
	1.01	0.49	0.75	0.94	1.03	1.11	1.22	1.36
	1.05	0.44	0.63	0.89	1.05	1.19	1.40	1.91
C2500999	1.00	0.81	0.94	0.99	1.01	1.03	1.05	1.10
	1.00	0.48	0.75	0.93	1.03	1.09	1.18	1.36
	1.05	0.49	0.65	0.92	1.04	1.20	1.38	1.91
C3001060	0.98	0.79	0.89	0.96	0.99	1.01	1.04	1.08

	0.93	0.48	0.71	0.87	0.96	1.02	1.09	1.18
	0.91	0.33	0.62	0.81	0.93	1.06	1.17	1.35
C3001120	0.98	0.79	0.89	0.96	0.99	1.01	1.04	1.08
	0.93	0.49	0.72	0.88	0.96	1.02	1.08	1.17
	0.91	0.33	0.58	0.81	0.92	1.05	1.14	1.38
C3005060	0.98	0.79	0.90	0.96	0.99	1.01	1.04	1.09
	0.95	0.58	0.72	0.89	0.97	1.04	1.11	1.26
	0.97	0.30	0.62	0.83	0.96	1.14	1.31	1.53
C3005120	0.98	0.79	0.90	0.95	0.99	1.01	1.04	1.07
	0.93	0.52	0.73	0.89	0.95	1.02	1.09	1.22
	0.94	0.32	0.60	0.82	0.94	1.08	1.21	1.55
C3005999	0.98	0.79	0.90	0.95	0.99	1.01	1.04	1.07
	0.94	0.54	0.75	0.89	0.95	1.02	1.08	1.23
	0.94	0.34	0.59	0.82	0.93	1.07	1.24	1.52
C3010060	0.99	0.80	0.90	0.96	0.99	1.02	1.05	1.17
	0.99	0.62	0.74	0.91	1.00	1.07	1.19	1.40
	1.04	0.28	0.67	0.86	1.00	1.22	1.42	1.77
C3010120	0.98	0.79	0.90	0.95	0.99	1.02	1.04	1.14
	0.96	0.56	0.77	0.90	0.97	1.03	1.12	1.28
	0.97	0.29	0.61	0.83	0.96	1.10	1.27	1.76
C3010999	0.98	0.80	0.91	0.95	0.99	1.02	1.04	1.11
	0.95	0.56	0.78	0.90	0.96	1.03	1.11	1.26
	0.96	0.33	0.60	0.84	0.95	1.09	1.25	1.64
C3050060	1.04	0.86	0.94	0.99	1.03	1.08	1.15	1.38
	1.10	0.63	0.83	0.97	1.08	1.20	1.41	1.67
	1.16	0.28	0.72	0.91	1.10	1.38	1.62	2.11
C3050120	1.03	0.87	0.94	0.99	1.02	1.06	1.12	1.25
	1.03	0.57	0.80	0.95	1.02	1.13	1.28	1.57
	1.06	0.33	0.63	0.89	1.03	1.21	1.43	1.91
C3050999	1.03	0.87	0.94	0.99	1.02	1.06	1.11	1.28
	1.02	0.57	0.80	0.95	1.02	1.12	1.23	1.45
	1.04	0.33	0.62	0.89	1.02	1.20	1.38	2.03
C3100060	1.06	0.90	0.95	1.00	1.05	1.10	1.16	1.41
	1.12	0.61	0.84	0.98	1.11	1.22	1.47	1.72
	1.18	0.28	0.73	0.92	1.12	1.38	1.69	2.14
C3100120	1.05	0.90	0.95	1.00	1.04	1.08	1.14	1.30
	1.06	0.57	0.82	0.95	1.04	1.16	1.31	1.60
	1.08	0.35	0.64	0.91	1.04	1.23	1.48	1.93
C3100999	1.04	0.88	0.95	1.00	1.04	1.07	1.14	1.31
	1.04	0.57	0.82	0.95	1.04	1.14	1.27	1.57
	1.06	0.33	0.62	0.90	1.04	1.23	1.41	2.21

C3500060	1.08	0.92	0.96	1.01	1.06	1.13	1.19	1.41
	1.15	0.61	0.85	1.00	1.12	1.25	1.51	1.77
	1.20	0.28	0.76	0.94	1.16	1.40	1.75	2.24
C3500120	1.07	0.91	0.96	1.00	1.06	1.11	1.17	1.29
	1.07	0.57	0.82	0.95	1.04	1.17	1.32	1.69
	1.10	0.34	0.65	0.91	1.06	1.27	1.52	2.01
C3500999	1.06	0.90	0.96	1.00	1.05	1.09	1.17	1.30
	1.06	0.57	0.83	0.96	1.04	1.17	1.31	1.70
	1.08	0.33	0.62	0.91	1.05	1.25	1.44	2.36
Combination forecasts (Medians)								
M1	0.97	0.80	0.91	0.96	0.98	1.00	1.01	1.04
	0.92	0.48	0.73	0.87	0.95	1.01	1.07	1.17
	0.91	0.35	0.58	0.80	0.92	1.05	1.17	1.43
M2	0.99	0.82	0.93	0.97	1.00	1.01	1.03	1.07
	0.94	0.44	0.73	0.89	0.97	1.03	1.11	1.19
	0.94	0.37	0.59	0.83	0.93	1.11	1.22	1.54
M3	0.98	0.79	0.90	0.95	0.99	1.01	1.04	1.10
	0.93	0.51	0.74	0.88	0.95	1.01	1.11	1.25
	0.93	0.33	0.58	0.80	0.91	1.06	1.20	1.60
Predictive Least Squares								
P0999	1.05	0.81	0.96	1.01	1.04	1.08	1.14	1.32
	1.06	0.50	0.76	0.97	1.06	1.16	1.30	1.61
	1.13	0.41	0.65	0.92	1.09	1.33	1.60	2.20
P1999	1.03	0.77	0.94	0.99	1.03	1.07	1.12	1.32
	1.05	0.50	0.76	0.95	1.04	1.16	1.27	1.61
	1.09	0.38	0.65	0.91	1.08	1.23	1.50	2.12
P2999	1.00	0.81	0.94	0.99	1.01	1.03	1.06	1.12
	1.01	0.49	0.75	0.94	1.03	1.10	1.21	1.36
	1.05	0.48	0.65	0.92	1.04	1.19	1.38	1.92
P3999	1.06	0.90	0.96	1.00	1.05	1.10	1.19	1.34
	1.07	0.57	0.84	0.95	1.05	1.17	1.32	1.74
	1.09	0.33	0.62	0.91	1.06	1.25	1.46	2.36
PA999	1.04	0.77	0.93	0.99	1.03	1.08	1.15	1.29
	1.08	0.48	0.76	0.95	1.07	1.20	1.39	1.89
	1.16	0.44	0.64	0.94	1.13	1.36	1.68	2.34
P0060	1.07	0.83	0.96	1.02	1.06	1.11	1.17	1.35
	1.17	0.54	0.83	0.99	1.15	1.36	1.55	1.77
	1.28	0.45	0.70	0.98	1.24	1.51	1.88	2.34
P0120	1.05	0.80	0.94	1.00	1.05	1.10	1.16	1.26
	1.08	0.57	0.81	0.97	1.08	1.18	1.34	1.59
	1.16	0.42	0.67	0.93	1.12	1.33	1.63	2.37

P1060	1.06	0.81	0.96	1.00	1.05	1.10	1.16	1.38
	1.12	0.51	0.81	0.97	1.12	1.28	1.46	1.65
	1.21	0.38	0.68	0.92	1.15	1.49	1.76	2.17
P1120	1.04	0.77	0.95	0.99	1.04	1.08	1.13	1.27
	1.06	0.50	0.80	0.97	1.07	1.17	1.32	1.60
	1.12	0.44	0.67	0.90	1.11	1.29	1.51	2.19
P2060	1.01	0.77	0.95	0.99	1.02	1.04	1.07	1.11
	1.06	0.47	0.79	0.96	1.07	1.19	1.28	1.48
	1.12	0.43	0.65	0.92	1.11	1.34	1.51	1.73
P2120	1.00	0.79	0.94	0.99	1.01	1.03	1.06	1.13
	1.02	0.50	0.75	0.94	1.03	1.12	1.23	1.36
	1.05	0.44	0.64	0.89	1.05	1.19	1.41	1.91
P3060	1.08	0.92	0.96	1.01	1.06	1.13	1.20	1.42
	1.15	0.61	0.85	1.01	1.12	1.28	1.52	1.78
	1.20	0.28	0.77	0.94	1.16	1.42	1.75	2.25
P3120	1.07	0.92	0.96	1.01	1.06	1.12	1.18	1.29
	1.08	0.58	0.82	0.95	1.05	1.17	1.34	1.74
	1.11	0.34	0.66	0.91	1.06	1.28	1.51	2.03
PA060	1.06	0.80	0.95	1.01	1.05	1.09	1.15	1.41
	1.16	0.51	0.81	0.98	1.12	1.31	1.54	1.92
	1.25	0.45	0.69	0.94	1.21	1.53	1.76	2.55
PA120	1.04	0.75	0.94	1.00	1.04	1.08	1.15	1.27
	1.09	0.47	0.76	0.96	1.08	1.19	1.39	1.88
	1.16	0.44	0.66	0.94	1.13	1.35	1.63	2.30

Table 3
Summary of rankings of various methods

Entries are fraction of series for which the indicated method performs in the top N

For each forecast, the first row corresponds to one-step ahead forecasts; the second row, to 6-step ahead forecasts; the third row, to 12-step ahead forecasts.

Method	N = 1	5	10	15	20
AR					
ARFC04	0.04	0.17	0.35	0.47	0.58
	0.07	0.18	0.28	0.37	0.43
	0.07	0.23	0.32	0.37	0.40
ARFT04	0.01	0.04	0.12	0.23	0.34
	0.00	0.07	0.13	0.17	0.22
	0.00	0.08	0.13	0.15	0.18
ARFC14	0.00	0.08	0.20	0.41	0.65
	0.00	0.07	0.26	0.36	0.53
	0.00	0.06	0.18	0.28	0.50
ARFT14	0.00	0.03	0.09	0.18	0.29
	0.00	0.02	0.05	0.09	0.16
	0.01	0.03	0.06	0.12	0.16
ARFCP4	0.01	0.08	0.22	0.47	0.71
	0.01	0.11	0.28	0.40	0.54
	0.00	0.07	0.18	0.33	0.52
ARFTP4	0.01	0.10	0.20	0.39	0.65
	0.01	0.11	0.20	0.35	0.52
	0.00	0.06	0.17	0.29	0.48
ARFC0a	0.02	0.06	0.10	0.16	0.27
	0.04	0.13	0.25	0.33	0.38
	0.02	0.17	0.26	0.34	0.39
ARFT0a	0.01	0.01	0.07	0.10	0.18
	0.05	0.07	0.10	0.13	0.17
	0.04	0.08	0.10	0.13	0.16
ARFC1a	0.00	0.08	0.13	0.22	0.33
	0.01	0.07	0.19	0.33	0.47
	0.01	0.09	0.24	0.32	0.47
ARFT1a	0.00	0.03	0.05	0.11	0.17
	0.00	0.03	0.05	0.08	0.13
	0.00	0.03	0.07	0.13	0.17
ARFCPa	0.02	0.08	0.14	0.21	0.34
	0.01	0.09	0.23	0.31	0.48

	0.01	0.12	0.22	0.33	0.46
ARFTPa	0.02	0.08	0.11	0.22	0.31
	0.03	0.09	0.18	0.31	0.45
	0.02	0.11	0.19	0.31	0.44
ARFC0b	0.02	0.08	0.15	0.31	0.46
	0.02	0.11	0.24	0.31	0.40
	0.03	0.19	0.29	0.34	0.39
ARFT0b	0.01	0.04	0.09	0.12	0.19
	0.01	0.08	0.13	0.16	0.19
	0.02	0.07	0.11	0.15	0.18
ARFC1b	0.01	0.08	0.20	0.34	0.47
	0.00	0.09	0.24	0.43	0.54
	0.00	0.05	0.18	0.37	0.52
ARFT1b	0.00	0.05	0.08	0.15	0.23
	0.01	0.02	0.05	0.09	0.15
	0.00	0.02	0.05	0.08	0.12
ARFCPb	0.00	0.08	0.23	0.33	0.47
	0.00	0.08	0.24	0.39	0.55
	0.00	0.04	0.23	0.35	0.51
ARFTPb	0.02	0.08	0.21	0.30	0.42
	0.01	0.09	0.24	0.39	0.53
	0.00	0.05	0.19	0.32	0.50
EX					
EX1	0.05	0.11	0.17	0.23	0.28
	0.06	0.16	0.22	0.25	0.27
	0.06	0.17	0.22	0.26	0.29
EX2	0.01	0.07	0.14	0.19	0.23
	0.01	0.10	0.14	0.19	0.26
	0.02	0.08	0.13	0.16	0.23
EXP	0.02	0.09	0.15	0.20	0.24
	0.04	0.11	0.15	0.20	0.26
	0.02	0.09	0.13	0.17	0.24
ANN					
AN0203	0.00	0.02	0.03	0.04	0.06
	0.00	0.02	0.03	0.05	0.07
	0.01	0.03	0.05	0.09	0.12
AN1203	0.00	0.02	0.04	0.06	0.10
	0.00	0.05	0.08	0.12	0.17
	0.00	0.04	0.09	0.12	0.15
ANP203	0.01	0.02	0.04	0.07	0.11
	0.01	0.05	0.08	0.14	0.19

	0.00	0.04	0.09	0.12	0.15
AN0213	0.00	0.00	0.01	0.01	0.01
	0.00	0.00	0.02	0.02	0.04
	0.01	0.02	0.04	0.05	0.07
AN1213	0.00	0.00	0.01	0.01	0.02
	0.00	0.01	0.02	0.05	0.07
	0.00	0.01	0.04	0.05	0.08
ANP213	0.00	0.00	0.01	0.02	0.03
	0.00	0.00	0.03	0.07	0.07
	0.00	0.01	0.03	0.05	0.08
AN0223	0.00	0.01	0.03	0.04	0.04
	0.00	0.02	0.03	0.03	0.03
	0.00	0.02	0.04	0.07	0.08
AN1223	0.00	0.01	0.01	0.03	0.06
	0.00	0.01	0.03	0.05	0.07
	0.00	0.02	0.06	0.11	0.15
ANP223	0.00	0.01	0.02	0.03	0.06
	0.01	0.01	0.03	0.05	0.07
	0.00	0.02	0.06	0.10	0.15
ANF0a	0.00	0.00	0.01	0.02	0.02
	0.00	0.00	0.01	0.01	0.02
	0.00	0.02	0.04	0.04	0.05
ANF1a	0.00	0.00	0.00	0.01	0.02
	0.00	0.01	0.01	0.01	0.03
	0.00	0.01	0.02	0.04	0.05
ANFPa	0.00	0.00	0.00	0.00	0.01
	0.00	0.00	0.01	0.01	0.03
	0.00	0.00	0.02	0.04	0.04
ANF0b	0.00	0.01	0.01	0.04	0.07
	0.00	0.02	0.04	0.06	0.07
	0.00	0.02	0.04	0.07	0.08
ANF1b	0.00	0.02	0.04	0.06	0.08
	0.00	0.01	0.05	0.10	0.17
	0.00	0.04	0.07	0.18	0.27
ANFPb	0.01	0.02	0.04	0.07	0.09
	0.00	0.02	0.06	0.10	0.17
	0.02	0.05	0.07	0.18	0.25
LSTAR					
LS0103	0.01	0.05	0.07	0.14	0.19
	0.01	0.03	0.06	0.09	0.10
	0.01	0.07	0.13	0.18	0.19

LS1103	0.02	0.06	0.11	0.15	0.20
	0.01	0.02	0.07	0.12	0.27
	0.00	0.03	0.07	0.14	0.25
LSP103	0.01	0.06	0.12	0.15	0.21
	0.00	0.02	0.07	0.14	0.27
	0.00	0.03	0.06	0.14	0.23
LS0063	0.00	0.06	0.13	0.20	0.27
	0.03	0.09	0.16	0.20	0.24
	0.03	0.08	0.18	0.24	0.26
LS1063	0.02	0.09	0.15	0.19	0.26
	0.02	0.08	0.17	0.28	0.35
	0.01	0.08	0.14	0.26	0.37
LSP063	0.03	0.08	0.14	0.20	0.28
	0.02	0.08	0.17	0.29	0.39
	0.03	0.08	0.16	0.27	0.37
LSF0a	0.01	0.03	0.06	0.09	0.10
	0.00	0.01	0.04	0.07	0.10
	0.01	0.04	0.07	0.11	0.13
LSF1a	0.02	0.04	0.07	0.10	0.15
	0.00	0.02	0.06	0.10	0.19
	0.02	0.07	0.13	0.19	0.28
LSFPa	0.00	0.04	0.08	0.11	0.16
	0.00	0.02	0.07	0.11	0.19
	0.01	0.07	0.14	0.20	0.28
LSF0b	0.02	0.06	0.08	0.12	0.13
	0.02	0.04	0.07	0.10	0.12
	0.01	0.04	0.07	0.09	0.13
LSF1b	0.00	0.04	0.10	0.13	0.18
	0.00	0.06	0.12	0.18	0.27
	0.00	0.09	0.18	0.23	0.33
LSFPb	0.02	0.04	0.10	0.15	0.20
	0.02	0.05	0.12	0.19	0.28
	0.03	0.08	0.19	0.24	0.35
No Change					
NOCHANGE	0.03	0.07	0.10	0.13	0.18
	0.04	0.13	0.17	0.21	0.21
	0.04	0.14	0.20	0.23	0.25
Combination					
C1000999	0.09	0.39	0.68	0.83	0.93
	0.06	0.31	0.52	0.70	0.81
	0.05	0.32	0.52	0.66	0.75

C2000999	0.03	0.26	0.53	0.74	0.87
	0.08	0.23	0.44	0.67	0.85
	0.07	0.18	0.37	0.60	0.74
C3000999	0.05	0.28	0.44	0.57	0.73
	0.07	0.23	0.36	0.46	0.58
	0.10	0.23	0.37	0.49	0.61
C1001999	0.03	0.38	0.67	0.86	0.96
	0.01	0.24	0.54	0.74	0.88
	0.01	0.18	0.44	0.65	0.81
C2001999	0.00	0.17	0.46	0.71	0.87
	0.00	0.14	0.35	0.58	0.81
	0.02	0.14	0.33	0.53	0.70
C3001999	0.03	0.27	0.50	0.62	0.75
	0.02	0.24	0.34	0.51	0.65
	0.00	0.18	0.36	0.50	0.67
M1	0.06	0.25	0.61	0.86	0.95
	0.03	0.23	0.52	0.77	0.93
	0.03	0.11	0.40	0.69	0.82
M2	0.01	0.07	0.24	0.57	0.80
	0.01	0.08	0.27	0.49	0.71
	0.01	0.06	0.19	0.43	0.64
M3	0.07	0.33	0.52	0.67	0.75
	0.09	0.26	0.43	0.58	0.73
	0.02	0.20	0.37	0.55	0.70
PLS					
P0999	0.01	0.03	0.09	0.14	0.20
	0.01	0.04	0.09	0.15	0.20
	0.02	0.05	0.11	0.14	0.19
P1999	0.00	0.04	0.08	0.13	0.23
	0.00	0.03	0.11	0.18	0.22
	0.00	0.05	0.11	0.19	0.23
P2999	0.01	0.05	0.15	0.26	0.40
	0.00	0.07	0.15	0.24	0.31
	0.01	0.08	0.15	0.23	0.29
P3999	0.01	0.04	0.08	0.15	0.21
	0.00	0.02	0.05	0.11	0.15
	0.01	0.06	0.11	0.14	0.20
PA999	0.00	0.04	0.12	0.17	0.26
	0.00	0.06	0.11	0.19	0.26
	0.00	0.02	0.08	0.11	0.17

Table 4

Rankings of various methods, combined over all series, for different cost functions: Trimmed forecasts

Cost function = $E|e_t|^{\rho}$, e_t=forecast error

For each forecast, the first row corresponds to one-step ahead forecasts; the second row, to 6-step ahead forecasts; the third row, to 12-step ahead forecasts.

Rank	ρ = 1.00	1.50	2.00	2.50	3.00
1	C1000999	C1000999	C1000999	C1001999	C1001999
	C1000999	C1000999	C1000999	C1000999	C1000999
	C1000999	C1000999	C1000999	C1000999	C1000999
2	C1001999	C1001999	C1001999	C1000999	C1000999
	C1001999	C1001999	C1001999	C1001999	C1001999
	C1001999	C1001999	C1001999	C1001999	C3000999
3	M1	M1	M1	M1	M1
	M1	M1	M1	M1	M1
	M1	M1	C3000999	C3000999	C1001999
4	M3	C3001999	C3001999	C3001999	C3001999
	C2000999	C2000999	C2000999	C2000999	C2000999
	C2000999	C2000999	M1	C3001999	C3001999
5	C3001999	M3	M3	C3000999	C3000999
	C2001999	C2001999	C3001999	C3001999	C3001999
	C3001999	C3001999	C2000999	M1	M1
6	C3000999	C3000999	C3000999	M3	C2000999
	M3	C3001999	C2001999	C2001999	C3000999
	M3	C3000999	C3001999	C2000999	C2000999
7	C2000999	C2000999	C2000999	C2000999	M3
	M2	M3	M3	C3000999	C2001999
	C2001999	M3	M3	M3	M3
8	C2001999	C2001999	C2001999	C2001999	C2001999
	C3001999	M2	C3000999	M3	M3
	C3000999	C2001999	C2001999	C2001999	C2001999
9	M2	M2	M2	M2	M2
	C3000999	C3000999	M2	M2	M2
	M2	M2	M2	M2	M2
10	ARFCP4	ARFCP4	ARFCP4	ARFCP4	ARFCP4
	ARFCPb	ARFCPb	ARFCPb	ARFCPb	ARFCPb
	ARFCPa	ARFCPa	ARFCPa	ARFCPa	ARFC1a

11	ARFC14	ARFTP4	ARFTP4	ARFTP4	ARFTP4
	ARFCPa	ARFTPb	ARFTPb	ARFTPb	ARFTPb
	ARFC1a	ARFC1a	ARFC1a	ARFC1a	ARFCPa
12	ARFTP4	ARFC14	ARFC14	ARFC14	ARFC04
	ARFTPb	ARFC1b	ARFC1b	ARFC1b	ARFC1b
	ARFTPa	ARFTPa	ARFTPa	ARFTPa	ARFTPa
13	P2999	ARFC04	ARFC04	ARFC04	ARFC14
	ARFC1a	ARFCPa	ARFCPa	ARFCPa	ARFCP4
	ARFCPb	ARFCPb	ARFCPb	ARFCPb	ARFCPb
14	ARFCPb	P2999	P2999	P2999	P2999
	ARFC1b	ARFC1a	ARFC1a	ARFC1a	ARFCPa
	ARFTPb	ARFC1b	ARFC1b	ARFC1b	ARFC1b
15	ARFC1b	ARFCPb	ARFCPb	ARFCPb	ARFCPb
	ARFTPa	ARFTPa	ARFTPa	ARFTPa	ARFC1a
	ARFC1b	ARFTPb	ARFTPb	ARFTPb	ARFTPb
16	ARFTPb	ARFTPb	ARFTPb	ARFC0b	ARFC0b
	ARFCP4	ARFCP4	ARFCP4	ARFCP4	ARFTPa
	ARFCP4	ARFCP4	ARFCP4	ARFCP4	ARFCP4
17	ARFC04	ARFC1b	ARFC1b	ARFTPb	ARFTPb
	ARFC14	ARFC14	ARFC14	ARFC14	ARFC14
	ARFC14	ARFC14	ARFC14	ARFC14	ARFC14
18	ARFC0b	ARFC0b	ARFC0b	ARFC1b	ARFC1b
	ARFTP4	ARFTP4	ARFTP4	ARFTP4	ARFTP4
	ARFTP4	ARFTP4	ARFTP4	ARFTP4	ARFTP4
19	ARFCPa	ARFT14	ARFT14	ARFT14	ARFT04
	LSP063	LSP063	LSP063	ARFC0b	LSP063
	LSP063	LSP063	LSP063	LSP063	LSP063
20	ARFC1a	ARFCPa	ARFCPa	ARFT04	ARFT14
	LS1063	ARFC0b	ARFC0b	LSP063	ARFC0b
	LSFPb	LS1063	LS1063	LS1063	LS1063
21	ARFTPa	ARFC1a	ARFT04	ARFC0a	ARFC0a
	ARFC0b	LS1063	LS1063	LS1063	P2999
	LS1063	LSFPb	LSFPb	LSF1b	LSF1b
22	ARFT14	ARFTPa	ARFC1a	ARFCPa	ARFT0b
	P2999	P2999	P2999	P2999	ARFC04
	LSF1b	LSF1b	LSF1b	LSFPb	LSFPb
23	P1999	ARFC0a	ARFC0a	ARFC1a	ARFT1b
	ARFC0a	ARFC0a	ARFC0a	ARFC04	LS1063
	LSFPa	LSFPa	LSFPa	LSFPa	LSFPa
24	ARFC0a	ARFT1b	ARFTPa	ARFT1b	ARFCPa
	LSFPb	LSFPb	ARFC04	ARFC0a	ARFC0a

	LSF1a	LSF1a	LSF1a	LSF1a	LSF1a
25	LSP063	ARFT04	ARFT1b	ARFTPa	ARFC1a
	LSF1b	LSF1b	LSFPb	LSFPb	LSP103
	ARFC0a	ARFC0a	ARFC0a	ARFC0a	ARFC0a
26	PA999	LSP063	ARFT0b	ARFT0b	ARFTPa
	P1999	ARFC04	LSF1b	LSF1b	ARFT14
	ANFPb	ANFPb	ANFPb	ANFPb	LSP103
27	LS1063	LS1063	LSP063	LSP063	ARFT0a
	ARFC04	LSP103	LSP103	LSP103	LSFPb
	ANF1b	ANF1b	ANF1b	LSP103	LS1103
28	ARFT1b	P1999	LS1063	ARFT1a	LSP063
	LSFPa	P1999	LS1103	LS1103	LSF1b
	LSP103	LSP103	LSP103	ANF1b	ANFPb
29	ARFT04	ARFT0b	ARFT1a	ARFT0a	ARFT1a
	LSP103	LS1103	P1999	ARFT1b	ARFT1b
	ARFC0b	ARFC0b	ARFC0b	LS1103	P2999
30	ARFT1a	ARFT1a	P1999	LS1063	LS1063
	LSF1a	LSFPa	ARFT1b	ARFT14	LS1103
	LS1103	LS1103	LS1103	ARFC0b	ARFC0b
31	ARFT0b	PA999	ARFT0a	LS0063	LS0063
	LS1103	LSF1a	ARFT14	P1999	ARFT1a
	P2999	ANP203	ANP203	P2999	P3999
32	LSP103	LS0063	LS0063	P1999	EXP
	P0999	P0999	LSF1a	ARFT1a	ANP203
	ANP203	P2999	P2999	ANP203	ANP203
33	LS0063	P0999	PA999	EXP	EX2
	P3999	ARFT1b	LSFPa	ANP203	P1999
	AN1203	AN1203	P3999	P3999	ANF1b
34	P0999	ARFT0a	P0999	P0999	P1999
	ANFPb	P3999	P0999	P0999	AN1203
	P3999	P3999	AN1203	AN1203	AN1203
35	LS1103	LSP103	EXP	EX2	P0999
	ANF1b	ANFPb	ANP203	AN1203	ARFT04
	P1999	P1999	P1999	P1999	P1999
36	LSFPb	LS1103	LSP103	LSP103	LS0103
	ARFT1b	ANF1b	ARFT1a	LSF1a	P0999
	ARFC04	ARFC04	ARFC04	ARFC04	ANP223
37	LSF1b	LSFPb	EX2	LS0103	LSP103
	PA999	ARFT1a	P3999	LSFPa	LSF1a
	ANP223	ANP223	ANP223	ANP223	ARFC04

38	ARFT0a	EXP	LS1103	LS1103	LS1103
	ARFT1a	ANP203	AN1203	P3999	ARFT0b
	AN1223	AN1223	AN1223	AN1223	AN1223
39	P3999	LSF1b	LSFPb	PA999	P3999
	ANP203	ARFT14	ANF1b	ANF1b	LSFPa
	ANP213	ANP213	ANP213	PA999	ARFT1a
40	EXP	EX2	LS0103	LSFPb	LSFPb
	ARFT14	AN1203	ANFPb	ANFPb	LS0063
	AN1213	P0999	P0999	ARFT1a	PA999
41	EX2	P3999	P3999	P3999	LSF1b
	AN1203	PA999	PA999	LS0063	ARFT0a
	P0999	AN1213	PA999	P0999	P0999
42	LSFPa	LS0103	LSF1b	LSF1b	PA999
	LS0063	LS0063	LS0063	ARFT04	P3999
	PA999	PA999	ARFT1a	ANP213	EXP
43	LS0103	ANP203	ANP203	ANP203	ANP203
	ANP223	ANP223	ARFT04	PA999	ANF1b
	LS0063	ARFT1a	AN1213	AN1213	ANP213
44	LSF1a	AN1203	AN1203	AN1203	AN1203
	EXP	AN1223	ANP223	ARFT0b	ANFPb
	ARFT1a	LS0063	EXP	EXP	EX2
45	ANP203	LSFPa	LSF0b	LSF0b	LSF0b
	AN1223	EXP	AN1223	ARFT0a	PA999
	ANFPa	ANFPa	ARFT1b	EX2	AN1213
46	AN1203	LSF1a	LSFPa	LSFPa	LSFPa
	EX2	ARFT04	ARFT0b	ANP223	EXP
	ANF1a	ARFT1b	ANFPa	ARFT1b	ARFT1b
47	LSF0b	LSF0b	LSF1a	LSF1a	LSF1a
	ANP213	ARFT0b	EXP	EXP	EX2
	ARFT1b	EXP	ARFT14	ARFT14	ARFT14
48	LSF0a	LSF0a	LSF0a	LSF0a	LSF0a
	AN1213	EX2	ARFT0a	AN1223	ANP223
	EXP	ARFT14	LS0063	ANFPa	ANFPa
49	ANF1b	ANF1b	AN1223	AN0223	ANP213
	ARFT0b	ANP213	EX2	EX2	AN1223
	ARFT14	ANF1a	ANF1a	ANF1a	ANF1a
50	ANFPb	ANFPb	ANP223	ANP213	AN1213
	ARFT04	ARFT0a	ANP213	AN1213	AN1213
	EX2	EX2	EX2	LS0063	LS0063
51	ANP223	AN1223	ANF1b	AN1213	AN0223
	ARFT0a	AN1213	AN1213	ANP213	ANP213

	ARFT0b	ARFT0b	ARFT0b	ARFT0b	ARFT0a
52	AN1223	ANP223	ANFPb	AN1223	AN1223
	ANFPa	ANFPa	ANFPa	LS0103	LS0103
	ARFT04	ARFT0a	ARFT0a	ARFT0a	ARFT0b
53	ANF0b	ANF0b	AN0223	ANP223	ANP223
	ANF1a	ANF1a	ANF1a	ANF1a	ANF1a
	ARFT0a	ARFT04	ARFT04	ARFT04	ARFT04
54	ANP213	ANP213	ANF0b	ANF0b	ANF0b
	LS0103	LS0103	LS0103	ANFPa	ANFPa
	LS0103	LS0103	LS0103	LS0103	LS0103
55	AN1213	AN1213	ANP213	ANF1b	ANF1b
	LSF0b	LSF0b	LSF0b	LSF0b	LSF0b
	LSF0b	LSF0b	LSF0b	LSF0b	LSF0b
56	AN0223	AN0223	AN1213	ANFPb	ANFPb
	LSF0a	LSF0a	LSF0a	LSF0a	LSF0a
	LSF0a	LSF0a	LSF0a	LSF0a	LSF0a
57	AN0203	AN0203	ANF0a	ANF0a	ANF0a
	AN0203	AN0203	AN0203	AN0203	AN0203
	AN0203	AN0203	AN0203	AN0203	AN0203
58	ANF1a	ANF1a	ANF1a	ANF1a	ANF1a
	AN0223	AN0223	AN0223	AN0223	AN0223
	AN0223	AN0223	AN0223	AN0223	AN0223
59	ANFPa	ANFPa	ANFPa	ANFPa	AN0213
	ANF0b	ANF0b	ANF0b	ANF0b	ANF0b
	NOCHANGE	NOCHANGE	NOCHANGE	NOCHANGE	NOCHANGE
60	ANF0a	ANF0a	AN0203	AN0213	ANFPa
	ANF0a	ANF0a	ANF0a	EX1	EX1
	EX1	EX1	EX1	EX1	EX1
61	AN0213	AN0213	AN0213	AN0203	EX1
	EX1	EX1	EX1	NOCHANGE	NOCHANGE
	ANF0b	ANF0b	ANF0b	ANF0b	ANF0b
62	EX1	EX1	EX1	EX1	NOCHANGE
	AN0213	NOCHANGE	NOCHANGE	ANF0a	ANF0a
	ANF0a	ANF0a	ANF0a	ANF0a	ANF0a
63	NOCHANGE	NOCHANGE	NOCHANGE	NOCHANGE	AN0203
	NOCHANGE	AN0213	AN0213	AN0213	AN0213
	AN0213	AN0213	AN0213	AN0213	AN0213

Table 5

Rankings of various methods, combined over all series, for different cost functions: Untrimmed forecasts

Cost function = $E|e_t|^{\rho}$, e_t=forecast error

For each forecast, the first row corresponds to one-step ahead forecasts; the second row, to 6-step ahead forecasts; the third row, to 12-step ahead forecasts.

Rank	ρ = 1.00	1.50	2.00	2.50	3.00
1	M1	M1	M1	M1	M1
	M1	M1	M1	M1	M1
	C2000999	C2000999	C2000999	M1	M1
2	M3	M3	C2000999	C2000999	C2000999
	C2000999	C2000999	C2000999	C2000999	C2000999
	M1	M1	M1	C2000999	C2000999
3	C2000999	C2000999	C2001999	C2001999	C2001999
	C2001999	C2001999	M3	M3	M3
	C2001999	C2001999	C2001999	C2001999	C2001999
4	C2001999	C2001999	M3	M3	M3
	M3	M3	C2001999	C2001999	C2001999
	M3	M3	M3	M2	M2
5	M2	M2	M2	M2	M2
	M2	M2	M2	M2	M2
	M2	M2	M2	M3	M3
6	ARFCP4	ARFCP4	ARFCP4	ARFCP4	ARFCP4
	ARFCPb	ARFCPb	ARFCPb	ARFCPb	ARFCPb
	ARFCPa	ARFCPa	ARFCPa	ARFCPa	ARFC1a
7	ARFC14	ARFTP4	ARFTP4	ARFTP4	ARFTP4
	ARFCPa	ARFTPb	ARFTPb	ARFTPb	ARFTPb
	ARFC1a	ARFC1a	ARFC1a	ARFC1a	ARFCPa
8	ARFTP4	ARFC14	ARFC14	ARFC14	ARFC04
	ARFTPb	ARFC1b	ARFC1b	ARFC1b	ARFC1b
	ARFTPa	ARFTPa	ARFTPa	ARFTPa	ARFTPa
9	P2999	ARFC04	ARFC04	ARFC04	ARFC14
	ARFC1a	ARFCPa	ARFCPa	ARFCPa	ARFCPa
	ARFCPb	ARFCPb	ARFCPb	ARFCPb	ARFCPb
10	ARFCPb	P2999	P2999	P2999	P2999
	ARFC1b	ARFC1a	ARFC1a	ARFC1a	ARFC1a
	ARFTPb	ARFC1b	ARFC1b	ARFC1b	ARFC1b

11	ARFC04	ARFCPb	ARFCPb	ARFCPb	ARFCPb
	ARFTPa	ARFTPa	ARFTPa	ARFTPa	ARFTPa
	ARFC1b	ARFTPb	ARFTPb	ARFTPb	ARFTPb
12	ARFC1b	ARFTPb	ARFTPb	ARFC0b	ARFC0b
	ARFCP4	ARFCP4	ARFCP4	ARFCP4	ARFCP4
	ARFCP4	ARFCP4	ARFCP4	ARFCP4	ARFCP4
13	ARFTPb	ARFC1b	ARFC1b	ARFTPb	ARFTPb
	ARFC14	ARFC14	ARFC14	ARFTP4	ARFTP4
	ARFC14	ARFC14	ARFC14	ARFC14	ARFC14
14	ARFC0b	ARFC0b	ARFC0b	ARFC1b	ARFT04
	ARFTP4	ARFTP4	ARFTP4	ARFC14	ARFC14
	ARFTP4	ARFTP4	ARFTP4	ARFTP4	ARFTP4
15	ARFCPa	ARFT14	ARFT14	ARFT14	ARFC1b
	P2999	P2999	ARFC0b	ARFC04	ARFC04
	ARFC0a	ARFC0a	ARFC0a	ARFC0a	ARFC0a
16	ARFC1a	ARFCPa	ARFCPa	ARFT04	ARFT14
	ARFC0b	ARFC0b	P2999	P2999	P2999
	ARFC0b	ARFC0b	ARFC0b	ARFC0b	ARFC0b
17	ARFTPa	ARFC1a	ARFT04	ARFCPa	ARFC0a
	ARFC0a	ARFC0a	ARFC0a	ARFC0b	ARFC0b
	P2999	P2999	P2999	P2999	P2999
18	ARFT14	ARFTPa	ARFC1a	ARFC0a	ARFT0b
	ARFC04	ARFC04	ARFC04	ARFC0a	ARFC0a
	ARFC04	ARFC04	ARFC04	ARFC04	ARFC04
19	ARFC0a	ARFC0a	ARFC0a	ARFC1a	ARFT1b
	ARFT1b	ARFT1b	ARFT1b	ARFT1b	ARFT14
	P1999	ARFT1a	ARFT1a	ARFT1a	ARFT1a
20	ARFT1b	ARFT04	ARFTPa	ARFT1b	ARFCPa
	ARFT1a	ARFT1a	ARFT14	ARFT14	ARFT1b
	P0999	ARFT1b	ARFT1b	ARFT1b	ARFT1b
21	ARFT04	ARFT1b	ARFT1b	ARFTPa	ARFC1a
	PA999	ARFT14	ARFT1a	ARFT1a	ARFT1a
	ANFPb	P0999	ARFT14	ARFT14	ARFT14
22	P1999	ARFT0b	ARFT0b	ARFT0b	ARFTPa
	ARFT14	PA999	ARFT04	ARFT04	ARFT04
	ANP203	ARFT14	P0999	EXP	EXP
23	ARFT1a	ARFT1a	ARFT1a	ARFT1a	ARFT0a
	P1999	EXP	ARFT0b	ARFT0b	ARFT0b
	AN1203	EXP	EXP	EX2	EX2
24	ARFT0b	ARFT0a	ARFT0a	ARFT0a	ARFT1a
	EXP	ARFT04	EXP	ARFT0a	ARFT0a

	ARFT1a	EX2	EX2	ARFT0b	ARFT0b
25	ARFT0a	EXP	EXP	EXP	EXP
	EX2	EX2	PA999	EXP	EXP
	ARFT1b	P1999	ARFT0b	ARFT0a	ARFT0a
26	EXP	EX2	EX2	EX2	EX2
	P0999	ARFT0b	ARFT0a	EX2	EX2
	ARFT14	ARFT0b	ARFT0a	ARFT04	ARFT04
27	EX2	P1999	P1999	EX1	EX1
	LS0063	ARFT0a	EX2	PA999	PA999
	ANF1b	ARFT0a	ARFT04	P0999	P0999
28	P0999	P0999	EX1	NOCHANGE	NOCHANGE
	ARFT04	LS0063	LS0063	EX1	EX1
	EXP	ARFT04	NOCHANGE	NOCHANGE	NOCHANGE
29	LSP063	AN0223	NOCHANGE	P1999	P1999
	ARFT0b	LS0103	EX1	NOCHANGE	NOCHANGE
	EX2	ANP203	EX1	EX1	EX1
30	ANF0b	ANF0b	P0999	P0999	P0999
	ARFT0a	EX1	NOCHANGE	LS0063	LS0063
	LS0063	AN1203	LS0103	LS0103	LS0103
31	AN0223	EX1	ANF0b	ANF0b	ANFPb
	ANP203	NOCHANGE	LS0103	LS0103	LSF0b
	LSP063	ANFPb	P1999	P1999	ANF0a
32	ANFPb	NOCHANGE	AN0223	ANFPb	ANF1b
	AN1203	P1999	AN0223	LSF0b	LS0103
	ARFT0b	LS0103	ANP203	ANP203	ANF0b
33	ANF1b	ANFPb	ANFPb	AN0223	ANF0b
	ANF1b	ANP223	LSF0b	AN0223	AN0223
	ARFT0a	ANF1b	AN1203	AN1203	P1999
34	ANF0a	ANF1b	ANF1b	ANF1b	AN0223
	ANFPb	P0999	ANP223	LSF0a	LSF0a
	ARFT04	NOCHANGE	ANFPb	ANF0a	ANP203
35	AN1223	ANF0a	ANF0a	ANF0a	ANF0a
	P3999	AN1223	LSF0a	ANP223	ANP223
	LSF1a	EX1	ANFPa	ANF0b	AN1203
36	EX1	LSP063	AN0213	AN0213	AN0213
	ANP223	LSF0b	AN1223	AN1223	ANF0a
	LSFPb	ANFPa	ANF1b	ANFPa	ANFPa
37	ANP223	ANFPa	LSP063	LSP063	ANFPa
	AN1223	AN0223	ANF1a	ANF0a	AN1223
	LSF1b	LS0063	ANF1a	ANFPb	ANF1a

38	NOCHANGE	ANF1a	ANFPa	ANFPa	ANF1a
	LS0103	ANP203	ANFPa	ANF1a	ANF1a
	P3999	ANF1a	ANF0b	ANF1a	ANFPb
39	ANFPa	AN0213	ANF1a	ANF1a	LSP063
	AN1213	AN1203	ANF0a	ANFPa	ANFPa
	AN1223	AN1223	ANF0a	ANF1b	ANF1b
40	ANP213	AN1223	AN1223	AN1223	AN1223
	ANF1a	ANF1b	ANF1b	ANF1b	ANF1b
	ANFPa	LSF0b	LSF0b	LSF0b	LSF0b
41	ANF1a	ANP223	ANP223	ANP223	ANP223
	ANFPa	ANFPb	ANFPb	ANFPb	ANFPb
	LS1063	ANF0b	LS0063	AN1223	AN1223
42	AN1213	ANP213	ANP213	ANP213	ANP213
	ANP213	ANF1a	P1999	P1999	P1999
	ANF1a	ANF0a	AN1223	LS0063	LS0063
43	C1001999	AN1213	AN1213	AN1213	AN1213
	C1001999	ANFPa	P0999	P0999	P0999
	LSFPa	LSP063	AN0213	AN0213	AN0213
44	AN0213	C1001999	C1001999	AN0203	AN0203
	LSP103	LSF0a	ANP203	ANP203	ANF0b
	PA999	P3999	LSP063	LSP063	LSP103
45	ANP203	AN0203	AN0203	C1001999	C1001999
	LS1103	P3999	AN1203	AN1203	ANP203
	LS0103	LSF1a	P3999	P3999	LS1103
46	AN1203	LS1063	LS1063	LS1063	LS1063
	LSF0b	ANF0a	ANF0b	ANF0b	AN1203
	LSP103	LSFPb	LSF1a	LSF1a	LSP063
47	LS1063	ANP203	ANP203	ANP203	C1000999
	LSF0a	AN1213	AN1213	AN1213	AN1213
	LS1103	LSF1b	LSF1b	LSF1b	P3999
48	AN0203	AN1203	AN1203	AN1203	ANP203
	AN0223	ANF0b	P3999	P3999	ANP213
	ANP223	LSF0a	LSFPb	LSFPb	LSF1a
49	LSP103	C1000999	C1000999	C1000999	AN1203
	EX1	ANP213	ANP213	ANP213	P3999
	NOCHANGE	AN0203	LSF0a	LSP103	LSF1b
50	LS1103	LSP103	LSP103	LSP103	LSP103
	NOCHANGE	AN0203	AN0203	AN0203	AN0203
	EX1	AN0213	AN0203	LS1103	LSFPb
51	C1000999	LS1103	LS1103	LS1103	LS1103
	ANF0b	LSP103	LSP103	LSP103	LSP103

	LSF0b	LS1063	LSP103	AN0203	AN0203
52	C3001999	C3001999	C3001999	C3001999	C3001999
	ANF0a	LS1103	LS1103	LS1103	LS1103
	LSF0a	LSFPa	LS1103	LSF0a	LSF0a
53	C3000999	C3000999	C3000999	C3000999	C3000999
	AN0203	C1001999	C1001999	C1001999	C1001999
	AN0203	LSP103	LS1063	LS1063	LS1063
54	LSFPb	LSFPb	LSFPb	LSFPb	LSFPb
	C3001999	C3001999	C1000999	C1000999	C1000999
	AN0223	LS1103	LSFPa	LSFPa	LSFPa
55	LSF1b	LSF1b	LSF1b	LSF1b	LSF1b
	LSFPb	C1000999	C3001999	C3001999	C3001999
	ANF0b	PA999	PA999	PA999	PA999
56	LS0063	LS0063	LS0063	LS0063	LS0063
	LSF1b	LSFPb	LSFPb	LSFPb	LSFPb
	ANF0a	ANP223	AN0223	AN0223	AN0223
57	PA999	PA999	PA999	PA999	PA999
	LSFPa	LSFPa	LSFPa	LSFPa	LSFPa
	AN0213	AN0223	ANP223	ANP223	ANP223
58	LS0103	LS0103	P3999	P3999	P3999
	C1000999	LSF1b	LSF1b	LSF1b	LSF1b
	C1000999	C1000999	C1000999	C1000999	C1000999
59	P3999	P3999	LS0103	LS0103	LS0103
	LSF1a	LSF1a	LSF1a	LSF1a	LSF1a
	C1001999	C1001999	C1001999	C1001999	C1001999
60	LSF0b	LSF0b	LSF0b	LSF0b	LSF0b
	C3000999	C3000999	C3000999	C3000999	C3000999
	C3000999	C3000999	C3000999	C3000999	C3000999
61	LSF0a	LSF0a	LSF0a	LSF0a	LSF0a
	AN0213	AN0213	LSP063	LSP063	LSP063
	C3001999	C3001999	C3001999	C3001999	C3001999
62	LSFPa	LSFPa	LSFPa	LSFPa	LSFPa
	LSP063	LSP063	AN0213	LS1063	LS1063
	ANP213	ANP213	ANP213	AN1213	ANP213
63	LSF1a	LSF1a	LSF1a	LSF1a	LSF1a
	LS1063	LS1063	LS1063	AN0213	AN0213
	AN1213	AN1213	AN1213	ANP213	AN1213

Table 6

Forecasting performance broken down by category of series

Numbers in parentheses are the number of time series in each category

For each forecast, the first row corresponds to one-step ahead forecasts; the second row, to 6-step ahead forecasts; the third row, to 12-step ahead forecasts.

Category	--- Fraction Best of ---			-- Fraction Best of --	
	AR	ANN	LSTAR	Lin-Comb	NonLin-Comb
Production	0.50	0.00	0.50	0.63	0.38
(24)	0.58	0.00	0.42	0.63	0.38
	0.58	0.00	0.42	0.54	0.46
Employment	0.48	0.10	0.41	0.45	0.55
(29)	0.62	0.24	0.14	0.52	0.48
	0.38	0.17	0.45	0.31	0.69
Wages	0.86	0.00	0.14	0.43	0.57
(7)	0.71	0.00	0.29	0.14	0.86
	0.29	0.14	0.57	0.14	0.86
Construction	0.43	0.14	0.43	0.48	0.52
(21)	0.48	0.14	0.38	0.38	0.62
	0.48	0.24	0.29	0.38	0.62
Trade	0.60	0.00	0.40	0.50	0.50
(10)	0.70	0.00	0.30	0.70	0.30
	0.60	0.00	0.40	0.90	0.10
Inventories	0.80	0.00	0.20	0.70	0.30
(10)	0.90	0.00	0.10	0.60	0.40
	0.80	0.00	0.20	0.80	0.20
Orders	0.79	0.00	0.21	0.57	0.43
(14)	0.79	0.00	0.21	0.86	0.14
	0.86	0.00	0.14	0.36	0.64
Money & Credit	0.43	0.22	0.35	0.74	0.26
(21)	0.65	0.17	0.17	0.70	0.30
	0.39	0.30	0.30	0.61	0.39
Stock Prices	0.64	0.09	0.27	0.64	0.36
(11)	0.64	0.18	0.18	0.91	0.09
	1.00	0.00	0.00	1.00	0.00
Interest Rates	0.91	0.00	0.09	0.73	0.27
(11)	0.73	0.09	0.18	0.36	0.64
	0.45	0.18	0.36	0.64	0.36

Exchange Rates	0.83	0.00	0.17	0.67	0.33
(6)	0.83	0.00	0.17	0.33	0.67
	0.67	0.17	0.17	0.33	0.67
Producer Prices	0.38	0.19	0.44	0.38	0.63
(16)	0.69	0.06	0.25	0.75	0.25
	0.63	0.13	0.25	0.38	0.63
Consumer Prices	0.50	0.13	0.38	0.63	0.38
(16)	0.50	0.00	0.50	0.69	0.31
	0.44	0.06	0.50	0.75	0.25
Consumption	0.40	0.20	0.40	0.40	0.60
(5)	0.60	0.00	0.40	0.80	0.20
	0.80	0.00	0.20	1.00	0.00
Miscellaneous	0.50	0.07	0.43	0.57	0.43
(14)	0.79	0.00	0.21	0.64	0.36
	0.79	0.14	0.07	0.71	0.29

Notes: The forecasts being compared are, in the first numerical column, the recursive PLS-selected AR forecast; in the second column, the recursive PLS-selected ANN forecast; in the third column, the recursive PLS-selected LSTAR forecast; in the fourth column, the C2001999 forecast; and in the fifth column, the C3001999 forecast.