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ABSTRACT

In this paper we use neural network models to forecast earnings per share (EPS) of Chinese listed companies using fundamental accounting variables. The sample includes 723 Chinese companies in 22 industries over 10 years. The result shows that the neural network model with weights estimated with genetic algorithm (GA) outperforms the neural network with weights estimated with back propagation (BP). Results also show that the addition of fundamental accounting variables used in the neural network models further improves the forecasting accuracy.

Keywords

EPS Forecasting, Neural Networks, Genetic Algorithm, China.

INTRODUCTION

China's economy plays an increasingly important role in the world economy. The Chinese financial market has been growing at an unprecedented speed and integrating into the world financial market. China's two securities exchanges, Shanghai Securities Exchange and Shenzhen Securities Exchange were established in late1990, and by the end of 1991, only 14 companies listed their stocks in the two exchanges. By the end of 2008, 1604 Chinese companies were listing their stocks in the two securities exchanges with a total stock market capitalization of US$ 1.76 trillion[1].

Before 2003, the Chinese financial market was almost closed to foreign investors. However, the Chinese financial market began to integrate into the world market. Since 2003, the so-called QFII (qualified foreign institutional investor) can trade Chinese stock in China and later the QDII (qualified domestic institutional investor) are allowed to invest in foreign financial markets. In addition, Chinese companies began to list their stock in foreign financial markets, like the NY Exchange, London Exchange, Singapore Exchange, etc.

In the meantime, international investors sense the potential profitability of investing in the Chinese financial market rather than the traditional investment channel—foreign direct investment as China's capital account had not been convertible. However, the Chinese financial market and listed companies are new to international investors and they need informed investment decisions. Among all kinds of information, the performance and earning capability of Chinese companies are two of the most interesting factors to the investors. Forecast of earning per share (EPS), one of the measures of the performance and earning capability, has been used widely for making investment or portfolio management decisions, and the accuracy of the forecast is essential for the investors and the companies as well (Elgers, Lo, & Murray, 1995; Jarrett, 1990). Many studies have been conducted to forecast the EPS of companies in the US and other industrial countries (Abarbanell & Bushee, 1997; Callen, Kwan, Yip, & Yuan, 1996; Zhang, Cao, & Schniederjans, 2004), while the research on the EPS forecasting of Chinese companies is non-existent. Various models have been developed to forecast EPS and generally they can be categorized into two—linear models and nonlinear models. Zhang et al. (2004) found that the nonlinear neural network (NN) model has higher forecasting accuracy than linear models in forecasting the EPS of the US companies, and the incorporation of fundamental accounting variables into the NN model further improves the forecasting accuracy of the model.

The NN model can be estimated with various algorithms, for example, back propagation (BP) and genetic algorithm (GA). Several studies suggest that GAs can outperform alternative estimation algorithms (Dorsey & Mayer, 1995; Sexton, Dorsey, & Johnson, 1999; Sexton, Dorsey, & Sikander, 2004). This paper compares the forecasting accuracy of the NN models

[1] Data source: Shanghai Securities Exchange and Shenzhen Securities Exchange websites: http://www.sse.com.cn, http://www.szse.cn/.

estimated with BP and GA (Wu, Chen, & Chian, 2006) in forecasting EPS of Chinese listed companies using fundamental accounting variables. To achieve this, we compare four models, the BP estimation NN model without fundamental variables, the GA estimation NN model without fundamental variables, the BP estimation NN model with fundamental variables, and the GA estimation NN model with fundamental variables.

Our paper contributes to the neural network literature by providing evidence regarding the relative effectiveness of two different approaches to estimating neural network weights. Our findings are consistent with Monte Carlo studies indicating that a genetic algorithm can find a more parsimonious model structure by reducing the number of hidden nodes and setting some parameter weights to zero. Our paper also contributes to the EPS forecasting literature that incorporating fundamental accounting variables in the NN models improves the forecasting accuracy.

The remainder of our discussion is organized as follows. In the next section, we provide a brief review on the literature of Chinese financial market research, followed by the neural network methodology and research design. We then present the data source and demographics and empirical results. We close with a discussion of implications and directions for future research.

CHINESE FINANCIAL MARKET RESEARCH

Chinese economy and financial market becomes increasingly interwoven with the world economy and financial markets over recent years. However, the research on the Chinese financial market was not proportionate to the growing importance of it on the world stage. The existing literature on the Chinese financial market is much less than those on other economies. Only over recent years, more research efforts have been paid on the Chinese financial market. Though the existing literature on the Chinese financial market covers many aspects of the market, still more concentrated and continuous studies are needed in some specific areas of research. The present literature just sparsely scatters in various research areas and follow-up studies are not enough.

Stock price movement and stock returns in Chinese stock market has become more popular among research interests. Researchers tried to predict the price movement and investigate the relations between stock returns and various factors. Cao et al. (2005) compared several models to predict stock price movement for companies traded on the Shanghai stock exchange and found that the artificial neural networks model has more predictive power.

As the earning capability of companies are essential in financial decisions, many researchers related company earnings to the stock returns in Chinese stock market and found earnings or earning changes affect the stock returns. Chen et al. (2007) found that unexpected earnings are positively related to abnormal returns. Su et al. (2003) examined the stock price reactions to changes in EPS in the Chinese stock markets and found that domestic A-share investors do not correctly anticipate the changes in earnings and fail to adjust new earnings information quickly, unlike the international B-share investors who are better able to predict earning changes

In addition, some found the audit quality has a positive effect on the market reaction to the increase in earnings (Gul, Sun, and Tsui 2003) and accounting standards change have some effects on stock returns (Jun Lin and Chen 2005).

The other field of Chinese financial market that receives research interest is the corporate governance of Chinese listed companies and their performance. Ding et al. (2007) found that the relationship between earnings management measures and ownership concentration exhibits a statistically significant “entrenchment versus alignment” effect. Chen (2009) found that types of controlling shareholder affect the operating efficiency of Chinese listed companies. Chen (2008) investigated performance effects for China's listed companies when there is a change in the controlling shareholder and found positive performance effects when control is passed to a private entity. Liu (2007) found that the conflicts between controlling shareholders and minority investors account for a significant part of earning management in China.

The previous literature also documented that earnings and earnings forecasts provide strong signals about future performance of a firm. Chen et al. (2004) investigated the earnings management and capital resource allocation and found that the Chinese regulators' objective of guiding capital resources toward the well-performing sectors is partially compromised by earnings management.

Other studies include using financial ratios to predict business failure in China. Chen et al. (2006) uses four alternative prediction models to examine the relation and found Earnings Before Interest and Tax to Total Assets, Earning Per Share Total Debt to Total, Price to Book and the Current Ratio, to be significant predictors. Logit and Neural Network models are shown to be the optimal prediction models.

Although prior studies have tackled research topic such as Chinese Companies Earnings (EPS), fundamental accounting information or even the effects of earning forecasts on some other variables, to the best of our knowledge, no single paper studies the forecasting process of earnings or EPS. The forecasts of EPS seem to come from a "black box". This paper is to address this forecasting issue of the EPS of the Chinese companies.

In addition, some scholars found that the use of fundamental accounting variables will improve accuracy of forecasting EPS (Abarbanell & Bushee, 1997; Zhang, et al., 2004). We are interested whether the use of fundamental accounting variables of Chinese companies can improve the accuracy of forecasting their EPS even though there are great differences between Chinese economy and US economy. For example, the two countries have different accounting practices. Inventory, one of the fundamental accounting variables may be calculated differently in China and US. Moreover, the regulations on Chinese listed companies are different from US' regulations. There are also some non-economic factors such as culture, social responsibilities that might influence the companies' earnings. Therefore, some methodologies that are useful to forecast US companies' EPS might not be useful for Chinese ones. This is the second issue this paper tries to address, that is, whether some methodologies used to forecast US companies' EPS are still useful to forecast Chinese companies' EPS.

NEURAL NETWORK METHODOLOGIES

Neural Network Models

Neural network models are inspired by studies of the information-processing abilities of the human brain. Key attributes of the brain's information network include a nonlinear, parallel structure and dense connections between information nodes (Haykin, 1998). Neural network models have been successfully applied in a variety of business fields including accounting (Kuldeep & Sukanto, 2006; Landajo, de Andres, & Lorca, 2007; Lenard, Alam, & Madey, 1995), management information systems (Huang, Chiu, & Chen, 2008; Kuflik, Boger, & Shoval, 2006; Zhu & Premkumar, 2001), marketing (Cui, Wong, & Lui, 2006; Kim, Street, Russell, & Menczer, 2005; Thieme, Song, & Calantone, 2000), and production management (Kaparthi & Suresh, 1994; Wang, Chen, & Lin, 2005; Wu, et al., 2006).

Neural network (NN) models represent the information-processing characteristics of the brain by linking layers of input and output variables through processing units called hidden nodes. Following Callen *et al.* (1996) and ZCS, we use a three-layer neural network model consisting of an input layer, a hidden layer, and an output layer. Each independent variable (i.e., each input layer node) has a weighted connection to each hidden node in the input layer. Similarly, each hidden layer node has a weighted connection to each dependent variable (i.e., each output layer node). In this paper we will consider a model with a single output variable.

The NN models are commonly estimated using a backward propagation (BP) algorithm that specifies an initial set of neural network weights and then adjusts these weights to reduce an overall measure of model fit or forecast accuracy. BP algorithms are easy to implement and provide "effective solutions to large and difficult problems" (Haykin, 1998). However, like other gradient search techniques, BP algorithms evaluate a fit function at a single point (i.e., a single vector of parameter estimates) and use information about the curvature and steepness of the fit function around that point to generate a new point for evaluation. This process is repeated until the improvement in fit observed in successive iterations falls below a user-specified threshold level. The resulting solution is typically the local optimum nearest the algorithm's starting point (Dorsey & Mayer, 1995). As a result, parameter estimates produced by these algorithms may not be optimal over the entire parameter space. In fact, a literature review led by Sexton, Dorsey and Johnson (Sexton, et al., 1999) concluded that back propagation is "plagued with inconsistent and unpredictable performances."

Genetic Algorithms

Genetic algorithms are a family of search techniques inspired by studies of evolution and natural selection. Unlike BP, genetic algorithms (GAs) do not depend on the iterative modification of a single vector of neural network weight estimates. Instead, GAs work with sets (a population) of NN weight vectors. A randomly-generated initial population of vectors evolves through a series of operations that typically includes reproduction, crossover, and mutation. The result is a "randomized but structured" search that "sweeps through the parameter space in many directions simultaneously and thereby reduces the probability of convergence to false optima" (Dorsey & Mayer, 1995).

Several studies suggest that GAs can outperform alternative estimation algorithms. In this paper we use the GA based on the work of Dorsey and Mayer (1995) and Sexton et al. (2004). This algorithm begins by assuming a single hidden node, evolving 1000 generations, adding a second node, and evolving another N generations. This process continues until the addition of three consecutive nodes fails to produce a new set of parameter estimates with better fit characteristics than all preceding solutions.

Given a specific assumption about the number of hidden nodes, the GA we use generates 20 random NN weight vectors that constitute the first generation of solutions. To create the next generation of weight vectors, a reproduction operator assigns each vector a probability that reflects the fitness of that vector relative to the remaining 19 vectors. Then a mating pool is created by choosing vectors with replacement from the existing generation.

The vectors within the mating pool are adjusted in three steps. First, a crossover operator randomly pairs the vectors in the mating pool, identifies any weights that exceed a randomly-drawn number, and switches those weights between the paired vectors. Second, a mutation operator replaces a small, random number of the individual neural network weights in the mating pool with random numbers drawn from the range of possible values for that weight. This step is designed to increase the probability that the algorithm finds a global solution. Third, a second mutation number replaces a small, random number of weights with a hard zero (Sexton, et al., 2004). The resulting vectors define the second generation. This process is repeated until 1000 generations have occurred.

Hypotheses

To evaluate the usefulness of the genetic algorithm described in Table 1, we use the financial data set of Chinese listed companies and statistically evaluate the relative forecasting accuracy of NN models estimated with BP and comparably-specified models estimated with the GA algorithm described in Table 1. We test the following null hypothesis:

> H1: There will be no forecasting accuracy difference between NN models estimated with BP and NN models estimated with GA.

For purposes of statistical testing we break this hypothesis into two parts in order to distinguish between univariate and multivariate models:

> H1a: There will be no forecasting accuracy difference between univariate NN models estimated with BP and univariate NN models estimated with GA.
>
> H1b: There will be no forecasting accuracy difference between multivariate NN models estimated with BP and multivariate NN models estimated with GA, where the predictor variables include both lagged dependent variables and fundamental accounting variables.

Based on prior research, we expect that the use of a genetic algorithm for estimation purposes will improve forecasting accuracy, leading to a rejection of these null hypotheses.

RESEARCH DESIGN

NN Models and Variables

To test the hypotheses, we compare the performance of the four NN models of forecasting quarterly EPS. We divide the four models into four categories as shown in table 1. We compare the NN model estimated with BP and GA in both situations of including fundamental accounting variables and not including them.

Category	Models
1. Univariate Neural Network Model estimated with BP (UBP)	UBP: $E(Y_t) = \sum_{j=1}^{n} \alpha_j \log \mathrm{sig}\left(\beta_{0j} + \sum_{i=1}^{4} \beta_{ij} Y_{t-i}\right)$
2. Multivariate Neural Network Model estimated with BP (MBP)	MBP: $E(Y_t) = \sum_{j=1}^{n} \alpha_j \log \mathrm{sig}\left(\beta_{0j} + \sum_{i=1}^{4} \left\{ \begin{array}{l} \beta_{1i} Y_{t-i} + \beta_{2i} INV_{t-i}\delta + \beta_{3i} AR_{t-i} \\ +\beta_{4i} CAPX_{t-i} + \beta_{5i} GM_{t-i} + \beta_{6} SA_{t-i} \\ +\beta_{7i} ETR_{t-i} + \beta_{8i} LFP_{t-i} \end{array} \right\} \right)$
3. Univariate Neural Network Model estimated with GA (UGA)	UGA: $E(Y_t) = \sum_{j=1}^{n} \alpha_j \log \mathrm{sig}\left(\beta_{0j} + \sum_{i=1}^{4} \beta_{ij} Y_{t-i}\right)$
4. Multivariate Neural Network Model estimated with GA (MGA)	MGA: $E(Y_t) = \sum_{j=1}^{n} \alpha_j \log \mathrm{sig}\left(\beta_{0j} + \sum_{i=1}^{4} \left\{ \begin{array}{l} \beta_{1i} Y_{t-i} + \beta_{2i} INV_{t-i}\delta + \beta_{3i} AR_{t-i} \\ +\beta_{4i} CAPX_{t-i} + \beta_{5i} GM_{t-i} + \beta_{6} SA_{t-i} \\ +\beta_{7i} ETR_{t-i} + \beta_{8i} LFP_{t-i} \end{array} \right\} \right)$

Table 1: Research Design

Our dependent variable is earnings per share. Our predictor variables are based on the work of Lev and Thiagarajan (1993), who studied the written statements of financial analysts in order to identify accounting variables used in security valuation and earnings prediction, and the subsequent analysis of Abarbanell and Bushee (1997). Later studies (Abarbanell & Bushee, 1998; Beneish, Lee, & Tarpley, 2001) have confirmed the usefulness of these variables in predicting EPS. The formal definitions of our predictor variables are as follows:

INV = Dollar value of inventory;

AR = Accounts receivables;

CAPX = Capital Expenditure;

GM = Gross margin, defined as sales less cost of goods sold;

SA = Selling and administrative expenses;

ETR = Effective tax rates, defined as income taxes divided by pretax income; and

LFP = Log of labor force productivity, defined as the log of the ratio of sales to the number of employees.

Note: we take the log of the labor force productivity ratio in order to make the range of this variable (which extends into the millions) more comparable with the remaining variables.

Data Source and Demographics

Following ZCS, we collected the quarterly EPS and fundamental accounting data of Chinese listed companies from CSMAR® (China Stock Market Trading Database). CSMAR® is similar to Compustat in US. Before 1999, the Chinese listed companies normally did not report quarterly EPS and some of the fundamental accounting information. Therefore, we collect the data from the first quarter of 1999 to the third quarter of 2008. We only include the companies that were listed before 1999 and stay till the present, as a result, our analysis applies to successful firms with a history of 10 or more years (Lorek & Willinger, 1996). Finally, we obtain a sample of 723 companies, each having 39-quarter observations from the first quarter of 1999 to the third quarter of 2008. The 723 firms in our sample represent 22 industries (classified by China Securities Regulatory Commission (CSRC)), which are listed in Table 2. Among them, the industry of Machinery, Equipment and Instrument accounts for the largest portion of the sample (15.49%). The industry of Crude oil, Chemistry, Plastics ranks the second (11.07%). The industry of Wholesale, Retail ranks the third. The first five industries account for 53.39% in the sample.

CSRC Industry Classification	CSRC coding	Number of companies	Percentage (%)
Agriculture, Forestry, Livestock Raising, Fishing	A	11	1.52
Mining	B	6	0.83
Food and beverage	C0	34	4.70
Textile, Apparel, Fur	C1	28	3.87
Furniture, Timber	C2	1	0.14
Papermaking, Printing	C3	14	1.94
Crude oil, Chemistry, Plastics	C4	80	11.07
Electronics	C5	21	2.90
Metal, non-Metal	C6	60	8.30
Machinery, Equipment, Instrument	C7	112	15.49
Pharmaceutical, Biotech	C8	42	5.81
Other manufacture	C99	4	0.55
Utilities	D	33	4.56
Construction	E	10	1.38
Transportation, Storage	F	22	3.04
Information Technology	G	43	5.95
Wholesale, Retail	H	70	9.68
Financial, insurance	I	2	0.28
Real Estate	J	35	4.84
Social Service	K	23	3.18
Mass Communication and Culture	L	8	1.11
Comprehensive	M	64	8.85
Total		723	100

Table 2: A breakdown of the sample by industries used in the study

Note that, in the variables description of previous section, the meaning of the “number of employees” variable is not constant across companies in the CSMAR® database. Some companies report the number of employees at the end of the year, while others report the average number of employees during the year.

Because CSMAR® reports the annual number of employees, we assume that number of employees in each quarter was constant through the year. ZCS argued that any bias introduced by these assumptions would “very likely” be independent of the functional forms of the models incorporating these two variables. They also examined the sensitivity of their results to (1) dropping the labor force productivity variable and (2) replacing the capital expenditures variable with an alternative measure available from quarterly cash flow statements. These changes had no impact on the relative accuracy of the different multivariate models examined by the authors. For these reasons we follow ZCS and assume the number of employees is relatively constant over the course of the year.

Following ZCS, our analysis omits two variables considered by Abarbanell and Bushee (1997): a dummy variable for inventory policy and an auditor opinion variable. We do not have this information from the database.

Forecasting Accuracy Procedure

As described above, our analysis is based on CSMAR® data for 723 firms over 39 quarters. For each firm we lose 3 data points due to differencing. Thus, our analysis sample consists of 36 observations for each firm ranging from the first quarter of 1999 to the second quarter of 2007. We group these observations to form rolling samples of 28 quarters. Within each rolling sample we use the first 27 observations to estimate the neural network weights of each forecasting model and use the last observations in the estimation set to make a one-step ahead forecast. Thus, for each model, we make 9 forecasts based on data from the preceding 27 quarters. To assess forecast accuracy, we use the following measures of fit (Callen, et al., 1996; Zhang, et al., 2004):

$$\text{Mean Absolute Percentage Error (MAPE)} = \frac{1}{9}\sum_{t=28}^{36}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right|, \text{ and} \tag{1}$$

$$\text{Mean Squared Error (MSE)} = \frac{1}{9}\sum_{t=28}^{36}\left(\frac{Y_t - \hat{Y}_t}{Y_t}\right)^2, \tag{2}$$

where $\hat{Y}_t$ is the forecasted value of EPS_t. We omit observations for which $EPS_t = 0$. Consistent with prior work by ZCS (2004), Brown and Rozeff (1979), and Lorek and Willinger (1996), we impose an upper bound of one on individual errors and report the percentage of errors affected by this constraint.

EMPIRICAL RESULTS

Results on H1 Hypothesis

Table 3 reports the forecast accuracy of one-step-ahead quarterly EPS forecasts for four forecast models. For the univariate neural network models (category 1 and category 3), the MAPEs of the univariate NN model estimated with BP (between 0.56 and 0.62) are all higher than the corresponding MAPEs of the univariate NN model estimated with GA (between 0.47 and 0.51), for each quarter and for all the quarters combined. This supports the better performance of the univariate NN model estimated with GA than that of the univariate NN model estimated with BP, which is related to H1a. For the multivariate NN models (category 2 and category 4), the multivariate NN model estimated with GA outperforms the multivariate NN model estimated with BP, which is related to H1b. The MAPEs of the multivariate NN model estimated with BP (between 0.40 and 0.43) are much higher than the multivariate NN model estimated with GA (between 0.20 and 0.25). Furthermore, both the MSE measure and the percentage of large errors (defined as forecast errors above 100%) exhibit the same patterns.

In addition, by comparing categories 1, 2, 3 and 4 we find that the addition of fundamental variables in either case (estimated with BP or GA) result in more accurate forecasting of the future EPS. This is consistent with the findings of ZCS, that the addition of fundamental variables in NN models will result in more predicting accuracy.

With the results from Table 3, we are confident the NN model estimated with GA based on statistical significance, is more accurate in forecasting future EPS than the NN model estimated with BP. When fundamental accounting variables are added to the forecasting models, the forecasting accuracy of the models is improved.

CONCLUSIONS

This paper compares the forecasting accuracy of the Neural Network model estimated with back propagation and genetic algorithm. We apply the models to predict EPS of Chinese listed companies in two situations (with and without fundamental accounting data). Our results show that, without using fundamental variables, the forecasting accuracy of the NN model estimated with GA is higher than that of the NN model estimated with BP. When using the fundamental variables, the forecasting accuracy of the NN model estimated with GA is improved and is the highest among all the models compared. In previous study, ZCS found that the NN model outperforms linear models in predicting EPS of US companies. We further contribute to the literature that the NN model estimated with GA has higher forecasting accuracy than the NN model estimated with BP. In addition, our research confirms the ZCS's empirical result that the addition of fundamental accounting variables in the NN model would improve forecasting accuracy of predicting EPS.

On the other hand, our research is only on the Chinese listed companies. Previous research, ZCS for instance, found the addition of fundamental accounting variables in the NN model would improve forecasting accuracy of predicting EPS of US companies. Even though the Chinese financial market differs from other financial markets of the world in many aspects, such as market structure, regulation, accounting principles, etc., our empirical results still show that the NN model estimated with GA has a higher accuracy in predicting future EPS using fundamental accounting variables. As the Chinese financial market is becoming more visible and accessible to foreign investors, our research contributes to the practitioners who use EPS forecasts to help make better investment decisions on Chinese listed companies.

We should note that, due to the emerging feature of Chinese financial market and the availability of the Chinese companies' quarterly EPS and fundamental accounting data, we have shorter periods and fewer rounds of predictions than ZCS's study. This might lead to higher forecasting accuracy. While we have more companies, the total number of observations is more than that of ZCS. This might mitigate the issue. This issue will be left for future research when there is more available data. In addition, a comparative study on the EPS forecasting between Chinese listed companies and US companies will also be a future research direction.

	1st Quarter			2nd Quarter			3rd Quarter			4th Quarter			Overall		
	MAPE[1]	MSE[2]	Large Forecast Error[3]	MAPE	MSE	Large Forecast Error	MAPE	MSE	Large Forecast Error	MAPE	MSE	Large Forecast Error	MAPE	MSE	Large Forecast Error
Category 1 UBP.1	0.612	0.519	37.3%	0.569	0.491	37.6%	0.608	0.502	35.9%	0.596	0.472	35.5%	0.576	0.491	35.7%
Category 2 MBP.1	0.423	0.324	20.8%	0.428	0.331	23.2%	0.415	0.298	20.1%	0.421	0.307	20.5%	0.409	0.315	19.8%
Category 3 UGA.1	0.473	0.417	23.9%	0.501	0.406	25.7%	0.507	0.420	24.3%	0.487	0.433	24.5%	0.472	0.429	24.3%
Category 4 MGA.1	0.233	0.201	12.4%	0.249	0.195	13.1%	0.229	0.192	12.5%	0.243	0.201	11.8%	0.250	0.207	12.9%

[1]Mean Absolute Percentage Error (MAPE)
[2]Mean Squared Error (MSE)
[3]We set the forecast error $\left(\left|\left(Q_t - \hat{Q}_t\right)/Q_t\right|\right)$ = 100% when this expression exceeded 100% (large forecast error).

Table 3: Comparing forecast accuracy of one-step-ahead quarterly EPS forecasts for four forecast models

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