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The three-factor model and artificial neural networks: predicting stock price movement in China

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Abstract Since the establishment of the Shanghai Stock Exchange (SHSE) in 1990 and the Shenzhen Stock Exchange (SZSE) in 1991, China's stock markets have expanded rapidly. Although this rapid growth has attracted considerable academic interest, few studies have examined the ability of conventional financial models to predict the share price movements of Chinese stock. This gap in the literature is significant, given the volatility of the Chinese stock markets and the added risk that arises from the Chinese legal and regulatory environment. In this paper we address this research gap by examining the predictive ability of several well-established forecasting models, including dynamic versions of a single-factor CAPM-based model and Fama and French's three-factor model. In addition, we compare the forecasting ability of each of these models with that of an artificial neural network (ANN) model that contains the same predictor variables but relaxes the assumption of model linearity. Surprisingly, we find no statistical differences in the forecasting accuracy of the CAPM and three-factor model, a result that may reflect the emerging nature of the Chinese stock markets. We also find that each ANN model outperforms the corresponding linear model, indicating that neural networks may be a useful tool for stock price prediction in emerging markets.

Keywords Artificial neural networks · Three-factor model · Stock price prediction

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1 Introduction

Since the establishment of the Shanghai Stock Exchange (SHSE) in 1990 and the Shenzhen Stock Exchange (SZSE) in 1991, China's stock markets have expanded rapidly. By the end of 2002, more than 104 million investors owned shares in one or more of the 1,604 companies listed on the country's regional stock markets (Shanghai and Shenzhen Securities Exchanges, 2009). This rapid growth, which reflects China's high personal savings rate and the absence of alternative investment opportunities (Young and McGuiness 2001; Kang et al. 2002), has occurred despite market characteristics that raise important risk management questions for domestic investors.

Relative to stocks traded in more mature markets, the risk-adjusted mean returns of Chinese stocks are low and stock return volatility is high (Su and Fleisher 1998). This volatility reflects a variety of factors. One recent study of the Shanghai and Shenzhen Stock Exchanges noted that "the 'quality' of listed companies is not good," in the sense that the average listed company has a "comparability low dividend yield, low earning per share, and low book-to-market value" (Wang and Di Iorio 2007). The importance of individual investors in Chinese stock markets also affects stock return volatility. In sharp contrast with more developed equity markets, 99.5 percent of the almost 69 million domestic investor accounts in 2002 were held by individuals (Ng and Wu 2007). According to Ng and Wu (2007, p. 2697), the short history of the Chinese markets means the average Chinese investor has less trading experience and is relatively less sophisticated than investors in more established markets (Ng and Wu 2007, p. 2697).

This observation is consistent with several recent studies. From an analysis of price reactions to earnings changes, Su (2003) found that, relative to international investors, domestic investors, on average, did not accurately predict changes in earnings, nor did they respond quickly to new earnings information. He concluded that, in China, domestic investors "do not seem to completely understand the true nature of the equity market" (Su 2003, p. 285). A survey of 1,547 individual investors led Wang et al. (2006, p. 773) to conclude that most Chinese investors "lacked investment knowledge and skills" and underestimated investment risks. This lack of sophistication contributed to an environment in which "the stock market is mainly driven by market rumors and individual investors' sentiment" (Kang et al. 2002, p. 247).

The risk management problems facing Chinese investors are compounded by characteristics of the legal and regulatory environment in China. According to Zhang and Zhao (2004, p. 46), "The Chinese stock market poses a higher risk than seasoned markets in developed countries because of its only partially-reformed institutions, lack of clearly defined property rights, and inadequate legal protection under a transition economy." This risk is compounded by information problems. Shares sold to domestic investors (A-shares) are governed by Chinese Generally Accepted Accounting Principles (GAAP), rather than by International Accounting Standards (IAS). One study suggested that, relative to IAS standards, reported earnings are 20–30 percent higher under the Chinese GAAP (Chen et al. 1999). In addition, the interpretation of revenue figures is complicated by the fact that "related party sales between listed and holding companies may not be reported under [Chinese] GAAP" (Su 2003, p. 274).

Risk management in the Chinese stock market is further complicated by the Chinese government's attempt to gain the effects of privatization while retaining control of the country's largest enterprises. To accomplish this end, the government "imposes strict segmentation on the stock market to prevent private and foreign investors from acquiring controlling interest in Chinese listed companies" (Zhang and Zhao 2004, p. 58). In particular, company shares are divided between tradable shares, which can be bought and sold on one of the Chinese stock exchanges, and non-tradable shares, which cannot. According to Deng and Wang (2006), non-tradable shares accounted for almost 61 percent of outstanding shares at the end of 2001. Moreover, in over 80 percent of the listed companies, non-tradable shares accounted for at least half of the outstanding shares.

The existence of non-tradable shares has several important implications for domestic investors. First, listed companies do not face the discipline that arises from takeover threats. In addition, the concentration of state holdings and the large number of non-tradable shares "greatly restricts market-determined share price movements," which limits "the role of share prices in disciplining the management and behavior of firms" (Lin 2001, p. 25). Weak links between performance and managerial compensation add additional risk for investors (Lin 2001). Recent research indicates that the magnitude of state ownership has a negative effect on firm value (McGuinness and Ferguson 2005; Wei and Varela 2003). At the same time, state ownership reduces the probability of financial distress (Deng and Wang 2006), a result that may reflect the a lower probability of debt financing in state-owned firms (Chen and Strange 2005).

Given the unique characteristics of the Chinese stock market, several recent studies have examined the usefulness of established financial models for understanding Chinese share prices (Wang and Di Iorio 2007; Wong et al. 2006; Chen et al. 2007). Consistent with the work of Fama and French (1992, 1993), these studies suggest that both size and book-to-market ratio are significantly correlated with cross-sectional variations in Chinese stock prices. From a risk management perspective, however, it is important to understand whether these same variables are useful for predicting future stock price movements. It is also important to determine whether the linear functional form used in previous research is most appropriate or whether a non-linear functional form can provide better predictions of stock price movements in the Chinese stock markets.

To explore these issues, we examine the predictive performance of several artificial neural network (ANN) models using data from the Shanghai stock market. The structure of ANN 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 information processing structure and multiple connections between information nodes (Haykin 1998). By permitting a more complicated functional relationship between stock prices and predictor variables, ANN models may capture previously undetected regularities in asset price movements (White 1989).

While previous studies have applied neural network models to stock returns in the United States (e.g., Callen et al. 1996; Zhang et al. 2004), there is little research on the value of ANN models for predicting stock price movement in emerging markets. In fact, while several recent studies have used a neural network approach to examine the financial condition of Chinese companies (e.g., Wu et al. 2008; Liang and Wu 2005), we have not found any published studies that evaluate the effectiveness of neural network models in predicting pricing movements on the Chinese stock markets. However, recent research has identified important differences between established and emerging markets. For example, Harvey (1995) found emerging market returns are more likely to be influenced by local information than developed markets; in fact, emerging market returns are generally more predictable than developed market returns. Bhattacharya et al. (2000) concluded the Mexican stock markets behave differently than the U.S. markets, because the prevalence of insider trading results in no announcement effect with public news releases. Consistent with these results, recent studies of Chinese stock markets have indicated that various aspects of stock price movement and investor behavior are inconsistent with the behavior of more mature markets (e.g., Mookerjee and Yu 1999; Kang et al. 2002; Su 2003;

Wang et al. 2006). These findings raise the following questions: do linear financial models adequately capture the idiosyncratic factors that influence stock prices present in emerging markets? Relative to conventional financial models, can neural network forecasting models enable investors to better manage risk and earn excess returns in emerging markets?

In this study we address these questions by comparing the forecast accuracy of several artificial neural network models with three linear models: a univariate time series model, a dynamic version of the capital-asset pricing model (CAPM), and a dynamic version of Fama and French's three-factor model. In particular, we compare the forecasting ability of each linear model with an artificial neural network (ANN) model that contains the same predictor variables but relaxes the assumption of model linearity. Our analysis is based on data from 1,179 corporations traded on the Shanghai Stock Exchange (SHSE) between January 1999 and December 2008. We find no statistical difference between the forecasting accuracy of CAPM and the three-factor model, but both multivariate models dominate the univariate forecasting model. In addition, we find the neural network models outperform the linear models. This result, which is statistically significant across our sample firms, indicates the usefulness of neural network models for stock price prediction in emerging markets.

The remainder of our discussion is organized as follows. In the next section we briefly review existing studies of stock price movements in China and the application of neural network models to financial forecasting. After describing our data and our research methodology in Sect. 3, we present the results of our analysis in Sect. 4. We close with a discussion of implications and directions for future research.

2 Review of literature

2.1 The CAPM and three-factor models

The traditional linear model used to explain the cross section of stock returns is the Capital Asset Pricing Model (CAPM), which was proposed in separate studies by Sharpe (1964) and Lintner (1965). CAPM assumes that an asset's return is a linear function of the risk of the asset relative to that of the market. A key implication is that market betas suffice to describe the cross-section of expected returns. An alternative model, proposed by Fama and French (1992, 1993), links cross-sectional variations in average stock returns to variations in three factors: market risk, firm size, and book-to-market ratio. Subsequent research has examined the applicability of the three-factor model to non-U.S. markets. Studies by Fama and French (1998), Drew and Veeraraghavan (2001), and Barry et al. (2002) provide evidence that, in emerging markets, average stock returns are an increasing function of the B/M ratio and a decreasing function of firm size.

One early study of the Shanghai and Shenzhen stock exchanges found support in both markets for the random walk hypothesis (Liu et al. 1997), while a second study found linkages to lagged interest rates and returns in other foreign markets (Su and Fleisher 1998). Most recent studies of the Chinese A-share market find at least partial support for variations of the Fama-French model. While Drew et al. (2003) concluded that both firm size and book-to-market ratio (B/M) have a negative influence on cross-sectional variations in stock price, more recent studies have found a positive relationship between B/M and price.

For example, Wang and Di Iorio (2007) examined data from 1994 to 2002 and found that, while beta did not have significant explanatory power, both firm size and book-to-market ratio (B/M) were significantly related to cross-sectional variations in stock price. Wong et al. (2006) reported similar results, which also held when the Fama-French model was expanded to include added two additional variables (floating equity and average return in the preceding six months). Chen et al. (2007) examined data from 1998–2001 and found some evidence, among smaller firms, of an inverted u-shaped relationship between B/M and returns. This result suggests that a non-linear model might provide increased forecasting accuracy relative to a linear model. Unfortunately, the authors did not report any tests of this implication.

2.2 Artificial neural network models

Both CAPM and the three-factor model assume that stock prices are a linear function each model's independent variables. One potential way to enhance forecasting accuracy is to relax this assumption through the use of artificial neural network (ANN) models, which are designed to mimic the knowledge-acquisition and organizational skills of the human brain (Bergerson and Wunsch 1991; Sharda and Patil 1992). In particular, ANN models attempt to capture the nonlinear, parallel structure of the brain's information network and the multiple linkages between individual information nodes (Haykin 1998). Coefficient weights are estimated in an iterative process by presenting sample data as inputs, predicting output states, and adjusting the coefficient weights to improve the fit between the estimated and actual output states. The training process enables ANN models to experientially accumulate, store, and recognize patterns of knowledge and adjust those patterns as the environment evolves.

ANN models have been successfully applied in a variety of business fields including accounting (Lenard et al. 1995), economics (Hu et al. 1999), finance (Etheridge et al. 2000; Bruce and Michael 1998), management information systems (Zhu et al. 2001), marketing (Papatla et al. 2002; Thieme et al. 2000), and production management (Kaparthi and Suresh 1994). Popular applications include a wide range of forecasting tasks, and the literature in this area is growing (see Zhang et al. 1998). In one comparative analysis study after another (e.g., Desai and Bharati 1998; Bhattacharyya and Pendharkar 1998; Jiang et al. 2000), ANN models have consistently outperformed other, more traditional quantitative forecasting methods.

In financial data forecasting, examples of the application of the neural network approach include (but are not limited to) studies by Kryzanowski et al. (1993), Hutchinson et al. (1994), Callen et al. (1996), Church and Curram (1996), Curry and Peel (1998), Tkacz (2001), Qi (2001), and McGrath (2002). In most of these applications, neural networks outperformed traditional statistical models, such as discriminant and regression analysis (Fadlalla and Lin 2001). However, few studies have applied ANN methodologies to emerging markets, and we have been unable to find any published studies applying neural network models to the Chinese stock markets.

To address this gap in the literature we compare the relative forecasting accuracy of several traditional neural-network models with a univariate time series model and two multivariate models: CAPM and the Fama-French three-factor model. Based on the work of Ferson and Harvey (1999) and Brennan et al. (1998), we expand both multivariate models to include lagged returns. We expect these models will have less predictive accuracy than neural network models that include the same independent variables but relax the assumption of linearity. We restate this expectation though a series of research hypothesis in the next section, which describes our data and research methodology.

3 Data and methodology

3.1 Data

Our study focuses on the price movements of the A-share stocks traded on the Shanghai Stock Exchange (SHSE) and covers the time period of January 1, 1999 through December 31, 2008. To simplify comparisons with earlier studies (e.g., Drew et al. 2003; Wang and Di Iorio 2007; Wong et al. 2006; Chen et al. 2007), we first analyze the A-share stocks issued by 367 public corporations and traded during the time period of January 1, 1999 through December 31, 2002. If this first data set included data from a later time period, it would be unclear whether any changes we found reflected the use of a different estimation technique or the evolution of the Shanghai stock market. To determine whether the results from this analysis generalize to more recent years, we then analyze the A-stocks issued by 1,179 companies (including the 367 companies from the earlier period) and traded from January 1, 2003 to December 31, 2008.

Our data consist of daily closing prices and quarterly book value and common shares outstanding, because research shows that the combination of daily data with monthly or quarterly data increases forecasting accuracy (Shen 1996). The source for the closing price data is SinoFin, the Chinese equivalent of CRSP. The book value and shares outstanding data were hand-collected from the annual reports of each firm. Daily betas were calculated by regressing the daily return for each stock on the daily return of the SHSE. One year's worth of return data is used, with the betas updated and recalculated daily.

3.2 Methodology

To test our research hypotheses, we compared the performance of three linear models and three neural network models. The linear models consist of a univariate time series model and dynamic versions of the CAPM and Fama-French models. For each of these models we also estimated an artificial neural network (ANN) model that contains the same predictor variables. As a result, our research design, which is summarized in Table 1, consists of six models.

3.2.1 Linear models

Studies of the time series process underlying quarterly earnings indicate that "there are two components to the quarterly earnings process: (1) a four-period seasonal component and (2) an adjacent quarter component which describes the seasonally adjusted series" (Griffin 1977, p. 71). Several different models have been proposed to represent these two components. Using U.S. data from 1947 to 1974, Foster (1977) examined the predictive accuracy of six univariate forecasting models. He concluded that a model with a single autoregressive parameter generated the most accurate one-step-ahead forecast of sales and earnings. However, Brown and Rozeff (1979) concluded that the forecasting accuracy of the simple autoregressive model could be improved with the addition of a moving average parameter (Griffin 1977; Watts and Leftwich 1977). Based on this conclusion we examine the forecasting performance of the following ARIMA(1, 1, 1) model:

$$\textbf{Model 1:}\quad y_t = \alpha + \varphi y_{t-1} + \varepsilon_t + \delta\varepsilon_{t-1}, \tag{1}$$

where α is the constant term of the ARIMA model, ε_t as the disturbance term at period t, φ as the autoregressive parameter, and δ as the moving-average parameter. We assume the

Table 1 A three-by-two research design. The research design includes six models: three linear models and three neural network models. The univariate models (UVL and UANN) are time series model. The multivariate models include both the Capital Asset Pricing model (MVL(CAPM) and MANN(CAPM)) which regresses the stock returns on market returns (beta), and the Fama-French three-factor model (MVL(3 factor) and MANN(3 factor)). In addition to regressing the stock returns on the market return, the two additional dependent variables are the firm's market capitalization (CAP) and the firm's ratio of book value of equity to market value of equity (B/M)

Variables	Linear models	ANN models
y_{t-1}	UVL (ARIMA)[1] Category 1	UANN[2] Category 4
y_{t-1} and Beta	MVL (CAPM)[3] Category 2	MANN (CAPM)[4] Category 5
y_{t-1}, Beta, Cap, and B/M	MVL (3 factor)[5] Category 3	MANN (3 factor)[6] Category 6

[1]UVL (ARIMA)—Univariate Linear (y_{t-1})

[2]UANN (ARIMA)—Univariate Neural Networks (y_{t-1})

[3]MVL (CAPM)—Multivariate Linear (β and y_{t-1})

[4]MANN (CAPM)—Multivariate Neural Networks (β and y_{t-1})

[5]MVL (3 factor)—Multivariate Linear (y_{t-1}, β, cap, and B/M)

[6]MANN (3 factor)—Multivariate Neural Networks (y_{t-1}, β, cap, and B/M)

disturbance term ε_t is a random variable with mean zero. The coefficients α and φ are selected to minimize the sum of the squared residuals. In our study, the independent variable (y_{t-1}) is the lagged market return at time $t-1$ and the dependent variable (y_t) denotes stock returns predicted at time t.

The remaining linear models include one or more predictor variables other than lagged stock returns. The first model is a dynamic version of the CAPM-based model that includes lagged market return. In essence, this model is formed by merging CAPM with the ARIMA model. The second multivariate model includes lagged market returns along with the three factors of the Fama-French model: market risk, firm size (measured as market capitalization), and the B/M ratio. Note that this dynamic version of the Fama-French model contains the dynamic CAPM model as a special case. In both models, the dependent variable is assumed to be a linear function of one or more independent variables plus an error introduced to account for all other factors.

More formally, the two multivariate linear models are described by the following equations:

$$\textbf{Model 2:} \quad y_t = \alpha + \varphi y_{t-1} + b_1 X_{i1} + \varepsilon_t + \delta\varepsilon_{t-1}, \tag{2}$$

$$\textbf{Model 3:} \quad y_t = \alpha + \varphi y_{t-1} + b_1 X_{i1} + b_2 X_{i2} + b_3 X_{i3} + \varepsilon_t + \delta\varepsilon_{t-1}, \tag{3}$$

where: y_t = Stock returns, α = Constant term, $X_{i1} = \beta$, X_{i2} = Market capitalization, X_{i3} = Book to market value (B/M), ε_t = Disturbance or error term, δ = Moving-average parameter.

3.2.2 Neural network models

Based on models of the information-processing in the human brain, artificial neural network (ANN) models use processing units called hidden nodes to link layers of input and output variables. Previous research indicates that a three-layer feed-forward network with an identify transfer function in the output unit and logistic functions in the middle-layer units can approximate any continuous functions arbitrarily well, given sufficiently many middle-layer units (Qi 1999). Thus we follow Callen et al. (1996) and Zhang et al. (2004) and assume that a single layer of hidden nodes links the two layers of input and output variables. Each input layer node (i.e., each independent variable) has a weighted connection to each hidden node in the middle layer. Similarly, each hidden layer node has a weighted connection to the output layer node, which in this case consists of a single output variable.

Formally, let Y_t denote the output of the neural network and let x_i and z_j denote, respectively, the ith input variable ($i = 1, \ldots, k$) and the jth middle layer variable. Under the assumptions that (1) logistic functions link the input variables to the middle layer (hidden) variables and (2) an identify transfer function connects the middle layer variables to the output variable, we can write the generic three-layer network model as:

$$y_t = f[(X, a, b] = \sum_{j=1}^{n} a_j \log \text{sig}\left(\sum_{i-1}^{k} b_{ij} x_i + b_{0j}\right) \tag{4}$$

where: y_t = the network's output, X = the vector of input variables, x_i = the ith input, n = the number of units in the middle layer, k = the number of inputs, a = a vector of coefficients (weights) from the middle to output layer units, b = a matrix of the coefficients from the input to middle-layer units, a_j = the weight of the output layer that connects the jth hidden layer unit to the output variable, b_j = the weight vector of the jth unit of the middle layer $\{b_{ij}, i = 1, 2, \ldots, k\}$, b_{0j} = the bias weight of the jth unit of middle layer unit, $\log\text{sig}$ = the logistic transfer function $\log\text{sig}(a) = 1/[(1 + \exp(-a)]$.

Based on (4), we define the following three ANN models that correspond to the three linear models defined in the previous sub-section.

Model 4: $$y_t = f[y_{t-1}, a, b] = \sum_{j=1}^{n} a_j \log\text{sig}(b_{ij} y_{t-1} + b_{0j}), \tag{5}$$

Model 5: $$y_t = f[(y_{t-1}, \beta), a, b] = \sum_{j=1}^{n} a_j \log\text{sig}(b_{i1} y_{t-1} + b_{i2}\beta + b_{0j}), \tag{6}$$

Model 6: $$y_t = f[(y_{t-1}, \beta, \text{cap}, B/M), a, b] = \sum_{j=1}^{n} a_j \log\text{sig}\left(\sum_{i-1}^{4} b_{ij} x_i + b_{0j}\right). \tag{7}$$

Equation (5) is the ANN version of the ARIMA model in (1), while (6) and (7) are the ANN version of the dynamic CAPM and three-factor models in (2) and (3). To simply our discussion, we will refer to the model in (5) as the univariate ANN model, the model in (6) as the CAPM ANN model, and the model in (7) as the three-factor ANN model.

3.3 Forecasting accuracy procedure

As described above, our analysis is based on two sets of data. The first data set is based on 367 firms and covers the time period from January 1999 through December 2002. Because we lose one data point due to differencing, our analysis sample consists of 15 observations for each firm ranging from the second quarter of 1999 to the fourth quarter of 2002. While a total of 15 observations are used in forecasting for each company, we use a rolling estimation forecasting procedure to generate three forecasts per company, with each forecast based on 12 observations. In particular, we use the models identified by the data from the 1st to 12th quarters to forecast for the 13th quarter, and use the models identified by the data from the 2nd to 13th quarters to forecast for the 14th quarter, and so on.

Our second data set is based on 1,179 firms and covers the time period from January 2003 through December 2008. In this case, because we lose one data point due to differencing, our analysis sample consists of 23 observations for each firm. We again use a rolling estimation forecasting procedure to generate three forecasts per company, meaning that each forecast in the later data set is based on 20 observations.

To assess forecast accuracy, we use the following measures of fit (Callen et al. 1996; Zhang et al. 2004):

$$\text{Mean Absolute Deviation (MAD)} = \frac{1}{N-n}\sum_{t=n+1}^{N} |y_t - \hat{y}_t|, \tag{8}$$

$$\text{Mean Absolute Percentage Error (MAPE)} = \frac{1}{N-n}\sum_{t=n+1}^{N} \left|\frac{y_t - \hat{y}_t}{y_t}\right|, \tag{9}$$

$$\text{Mean Squared Error (MSE)} = \frac{1}{N-n}\sum_{t=n+1}^{N} \left(\frac{y_t - \hat{y}_t}{y_t}\right)^2, \tag{10}$$

where n is the number of observations used for estimation, N is the total number of observations, and $\hat{y}_t$ is the forecasted value of stock returns for period t. Observations with a zero-stock return are eliminated. The MAD metric is a measure of total deviation between predicted and actual values, while MAPE and MSE assign greater weight to deviations that are a large percent of the value of the dependent variable.

3.4 Hypotheses

To evaluate the incremental value of using Beta, CAP, and B/M as predictor variables, we test the following null hypothesis:

H1: There is no forecasting accuracy difference in linear models and nonlinear ANN models when Beta, CAP, and B/M are present.

For purposes of statistical testing we break this hypothesis into six parts:

H1a: There will be no forecasting accuracy difference between the univariate time series and the linear CAPM-based models.
H1b: There will be no forecasting accuracy difference between the univariate time series and the linear three-factor models.
H1c: There will be no forecasting accuracy difference between the linear CAPM-based model and three-factor models.
H1d: There will be no forecasting accuracy difference between the univariate and CAPM-based ANN models.
H1e: There will be no forecasting accuracy difference between the univariate and three-factor ANN models.
H1f: There will be no forecasting accuracy difference between the CAPM-based and three-factor ANN models.

We expect, based on prior research, that the movement from a univariate to a multivariate model, as well as the shift from a CAPM-type model to the three-factor model, will increase forecasting accuracy, resulting in a rejection of the null H1.

Our second hypothesis addresses the effectiveness of the ANN models relative to their linear alternatives.

H2: There is no forecasting accuracy difference between linear models and nonlinear ANN models.

For purposes of statistical testing, we divide this hypothesis into three parts:

H2a: There will be no forecasting accuracy difference between the univariate linear and ANN models.
H2b: There will be no forecasting accuracy difference between the linear CAPM-based and ANN CAPM-based models.
H2c: There will be no forecasting accuracy difference between the linear and ANN three-factor models.

We expect, based on prior research, that ANN models will outperform linear models in forecasting accuracy.

To evaluate hypothesis H1, we assessed the statistical significance of differences in the forecast accuracy statistics computed for each model. For example, to evaluate H1a (which addressed the relative predictive accuracy of the univariate time series and linear CAPM models), we computed the forecast accuracy statistics for Models 1 and 2. To evaluate H1d (which addressed the relative predictive accuracy of the univariate and CAPM ANN models), we compared Models 4 and 5. To determine the significance of differences in the forecast accuracy statistics computed for each sub-hypothesis, we used the paired sample t-test (Conover 1980). A similar testing procedure was also used for testing H2.

4 Results

4.1 Hypothesis H1

Table 2 reports the averages of the three forecast accuracy measures for all six forecasting models. The first three numerical columns of Table 2 contain the analysis results from the 1999–2002 time period, while the last three columns contain the results from the 2002–2008 time period. With regard to H1a, we find that, in both periods, all three forecast accuracy measures for the linear three-factor model are consistently lower than the corresponding statistics for the univariate time series model. For example, in the 1999–2002 period, the CAPM multivariate linear model (Model 2) has higher MAD, MAPE, and MSE statistics (0.0151, 0.5284, and 0.49638, respectively) than those of the univariate time series model (0.0235, 0.6212, and 0.5872). Similarly, in both periods, the forecast accuracy statistics for the linear three-factor model (Model 3) are significantly lower than the corresponding statistics for the univariate time series and linear CAPM-based models (Models 1 and 2). These comparisons do not support the null hypotheses H1a–H1c.

When we consider the ANN forecasting models, we find again that, in both time periods, adding variables to the models improves their predictive power. For example, the CAPM ANN model (Model 5) has higher MAD, MAPE, and MSE statistics (0.0123, 0.3364, and 0.2882, respectively) than those of the univariate ANN model (0.0208, 0.5732, and 0.5409). Similarly, in both periods, the three-factor ANN model (Model 6) outperforms both the

Table 2 Comparisons of forecast accuracy measures. A comparison of the mean absolute deviation (MAD), mean absolute percentage error (MAPE), and mean square error (MSE) for the six categories of models: UVL = the univariate linear model; MVL(CAPM) = the multivariate linear CAPM-based model; MVL(3 factor) = the multivariate linear 3 factor-based model; UANN = the univariate ANN model; MANN(CAPM) = the multivariate ANN CAPM-based model; and MANN(3 factor) = the multivariate ANN 3 factor-based model. There are 367 firms in the study

Model	Forecast accuracy measures 1999–2002			Forecast accuracy measures 2003–2008		
	MAD	MAPE	MSE	MAD	MAPE	MSE
1. UVL	0.0235	0.6212	0.5872	0.0236	0.6206	0.5924
2. MVL(CAPM)	0.0151	0.5284	0.4963	0.0157	0.5291	0.5252
3. MVL(3 factor)	0.0141	0.4776	0.4548	0.0145	0.4760	0.4478
4. UANN	0.0208	0.5732	0.5409	0.0215	0.5828	0.5314
5. MANN(CAPM)	0.0123	0.3364	0.2882	0.0126	0.3357	0.2922
6. MANN(3 factor)	0.0107	0.3125	0.2743	0.0113	0.3118	0.2807

Table 3 Hypotheses testing for the 1999–2002 period. A comparison of the predictive power of the six models: UVL = the univariate linear model; MVL(CAPM) = the multivariate linear CAPM-based model; MVL(3 factor) = the multivariate linear 3 factor-based model; UANN = the univariate ANN model; MANN(CAPM) = the multivariate ANN CAPM-based model; and MANN(3 factor) = the multivariate ANN 3 factor-based model

	MAD		MAPE		MSE	
	t-score	Sig. (2-tailed)	t-score	Sig. (2-tailed)	t-score	Sig. (2-tailed)
Panel A: Hypothesis 1						
UVL vs. MVL(CAPM)	3.332	0.0018**	2.5452	0.0427*	3.0967	0.0102*
UVL vs. MVL(3 factor)	3.578	0.0000**	2.7039	0.0214*	3.2198	0.0023**
MVL(CAPM) vs. MVL(3 factor)	1.872	0.0612	1.7378	0.0751	1.934	0.0509
UANN vs. MANN(CAPM)	3.574	0.0000**	2.7267	0.0095**	3.195	0.0037**
UANN vs. MANN(3 factor)	3.619	0.0000**	2.9324	0.0086**	3.250	0.0046**
MANN(CAPM) vs. MANN(3 factor)	1.905	0.0587	1.9345	0.0549	1.934	0.0525
Panel B: Hypothesis 2						
UVL vs. UANN	4.317	0.0000**	4.136	0.0027**	3.904	0.0000**
MVL(CAPM) vs. MANN(CAPM)	3.682	0.0022**	3.451	0.0034**	3.531	0.0040**
MVL(3 factor) vs. MANN(3 Factor)	5.095	0.0000**	4.7293	0.0000**	4.653	0.0000**

*Indicates significance at the 95% level

**Indicates significance at the 99% level

univariate and CAPM ANN models (Models 4 and 5). These comparisons do not support the null hypotheses H1a–H1c.

To provide a more formal test of the H1 sub-hypotheses, we computed paired sample t-statistics to gauge the statistical significance of the differences between forecast accuracy statistics for different models. The results of these tests for the 1999–2002 time period, which are presented in Table 3, show a significant difference in forecast accuracy across the proposed models. Panel A contains the t-statistics used to evaluate H1. An examination of these statistics indicates that the multivariate linear models outperform the time series model ($p < 0.01$) and the multivariate ANN models outperform the univariate ANN model

($p < 0.01$). However, when we compare the predictive power of the two CAPM-based models with the two three-factor models, the differences are not statistically significant for either the linear models or the neural network models.

Table 4 reports the results of the same analysis for the 2003–2008 time period. The results in Panel A are consistent with those reported in Table 3. In particular, the multivariate linear models again outperform the time series model ($p < 0.01$) and the multivariate ANN models outperform the univariate ANN model ($p < 0.01$). Based on these results, we reject H1a, H1b, H1d, and H1e.

As in Table 3, when we compare the predictive power of the two CAPM-based models with the two three-factor models, the differences in general are not statistically significant for either the linear models or the neural network models. (The sole exception to this statement involves the t-statistic for the mean difference in MAD scores between the CAPM and multivariate linear models.) Given these results and those in Table 3, we fail to reject sub-hypotheses H1c and H1f. These results are surprising, given recent analyses of the Chinese stock market have found that the addition of firm size and the B/M ratio increase the explanatory power of the CAPM model (Wong et al. 2006; Wang and Di Iorio 2007).

4.2 Hypothesis H2

Hypothesis 2 addresses the relative performance of the linear and ANN models. With regard to H2a, in the 1999–2002 period all three forecast accuracy statistics (MAD, MAPE, and MSE) for the univariate ANN model (0.0208, 0.5732, and 0.5409) are lower than the corresponding statistics for the univariate time series model (0.0235, 0.6212, and 0.5872). The same relationship also holds in the 2003–2008 period. These results suggest the univariate ANN model outperform the univariate linear model in terms of forecasting accuracy.

A comparison of the two multivariate linear and ANN models yields similar results. For example, in the 1999–2002 period the CAPM-based ANN model has lower MAD, MAPE, and MSE statistics (0.0123, 0.3364, and 0.2882, respectively) relative to the linear CAPM-based model (0.0151, 0.5284, and 0.4963). A similar conclusion follows from a comparison of the forecast accuracy statistics for the two three-factor models, as well as from a review of the forecast accuracy statistics from the 2003–2008 period.

Panel B of Tables 3 and 4 presents the test statistics used to evaluate H2. Every t-statistic contained in this panel is greater than 3.0 and the associated probability levels are all less than 0.01, indicating that forecast accuracy varies significantly between the linear models and their ANN counterparts. The clear implication is that the use of ANN models improves the accuracy of stock price forecasts in the Shanghai Stock Exchange. Thus H2 in its null form is rejected in its entirety. These results are in line with the previous research (Fadlalla and Lin 2001; Zhang et al. 2004) on the superiority of the neural network approach in applications to financial forecasting.

4.3 Fama-French portfolios

To provide further insight into the relative forecasting accuracy of our six models, we ranked all firms based on size (closing price multiplied by number of shares outstanding) on the first trading day of January each year. After splitting this group in half, thereby creating a small (S) and big (B) group, we sub-divided each group into three sub-groupings based on the magnitude of the B/M ratio (low (L), medium (M), and high (H)). This process resulted in six Fama-French-style portfolios characterized by different average values of market capitalization and book-to-market value.

Table 4 Hypotheses testing for the 2003–2008 period. A comparison of the predictive power of the six models: UVL = the univariate linear model; MVL(CAPM) = the multivariate linear CAPM-based model; MVL(3 factor) = the multivariate linear 3 factor-based model; UANN = the univariate ANN model; MANN(CAPM) = the multivariate ANN CAPM-based model; and MANN(3 factor) = the multivariate ANN 3 factor-based model

	MAD		MAPE		MSE	
	t-score	Sig. (2-tailed)	t-score	Sig. (2-tailed)	t-score	Sig. (2-tailed)
Panel A: Hypothesis 1						
UVL vs. MVL(CAPM)	2.4853	0.0257*	2.6394	0.0139*	2.8389	0.0167*
UVL vs. MVL(3 factor)	3.7969	0.0000**	2.4300	0.0283*	3.0851	0.0009**
MVL(CAPM) vs. MVL(3 factor)	2.1719	0.0323*	1.5179	0.1326	2.2116	0.0218*
UANN vs. MANN(CAPM)	2.6803	0.0172*	2.7044	0.0104*	2.8732	0.0140*
UANN vs. MANN(3 factor)	3.9055	0.0000**	3.4548	0.0000**	3.8315	0.0000**
MANN(CAPM) vs. MANN(3 factor)	1.7005	0.1021	1.9848	0.0503	1.5173	0.0856
Panel B: Hypothesis 2						
UVL vs. UANN	4.2380	0.0000**	2.9201	0.0052**	3.5990	0.0000**
MVL(CAPM) vs. MANN(CAPM)	3.0751	0.0010**	3.3845	0.0000**	3.2954	0.0000**
MVL(3 factor) vs. MANN(3 Factor)	5.2026	0.0000**	3.9353	0.0000**	5.5501	0.0000**

*Indicates significance at the 95% level

**Indicates significance at the 99% level

The majority of the firms in our sample (199 of 261 firms studied in the first data set and 732 of 987 firms studied in the second data set) remained in the same portfolio grouping throughout the study. However, some firms did move between portfolios, most commonly due to a change in the firm's relative book-to-market value ranking. Tables 4 and 5 report the mean absolute deviation (MAD) for each of the six portfolios and for the sub-classifications with a sample size greater than ten.

The first three numerical columns in Table 5 report the test statistics resulting from within-portfolio comparisons among the three linear models using the 1999–2002 data. A review of these columns reveals that, for three of the six portfolios, the linear CAPM model provided greater forecasting accuracy than the univariate model. Moreover, in all six portfolios, the linear three-factor model outperformed the univariate time series model. However, in no case did the three-factor model outperform the CAPM model. An examination of the adjacent three columns in Table 5 yields identical conclusions regarding the relative accuracy of the three ANN models.

Table 6 repeats the preceding analysis using the 2003–2008 data. Two differences from the results in Table 5 should be noted. First, in the 2003–2008 data set the linear three-factor model outperformed the univariate time series model in five of the portfolios (as opposed to six in the 1999–2002 data set). Second, the CAPM-based ANN model outperformed the univariate ANN model in two (as opposed to three) of the portfolios. Despite these differences, the results in the first six numerical columns Table 6 are consistent with those in Table 5.

The last three columns of Tables 5 and 6 report the test statistics resulting from comparisons of the three linear models with their ANN counterparts. In five of six portfolios,

Table 5 Hypotheses testing for the Fama French portfolios in the 1999–2002 period. Table entries report the mean absolute deviation for the six Fama and French-based portfolios (S = small market capitalization; B = large market capitalization; H = high book to market value; M = medium book to market value; L = low book to market value). We use the following abbreviations to denote the various models: UVL = the univariate linear model; MVLC= the multivariate linear CAPM-based model; MVLF = the multivariate linear 3 factor; UANN = the univariate ANN model; MANNC = the multivariate CAPM-based ANN model; and MANNF = the multivariate 3 factor ANN model

Portfolio	Linear model comparisons			ANN model comparisons			Linear versus ANN model comparisons		
	UVL vs. MVLC	UVL vs. MVLF	MVLC vs. MVLF	UANN vs. MANNC	UANN vs. MANNF	MANNC vs. MANNF	UVL vs. UANN	MVLC vs. MANNC	MVLF vs. MANNF
SH	1.50	2.62*	0.97	1.40	2.47*	1.53	2.01*	2.45*	2.18*
SM	1.88	3.11**	1.26	1.76	2.93**	1.37	3.45**	3.42**	3.52**
SL	2.67*	2.45*	1.01	2.51*	2.31*	0.85	4.62**	4.99**	5.63**
BH	2.20*	3.29**	1.44	2.06*	3.10**	1.21	2.89**	3.01**	2.45*
BM	3.14**	2.95*	0.92	2.96**	2.81*	1.16	1.75	1.37	1.15
BL	1.84	3.21*	0.82	1.73	3.03**	0.99	3.39**	3.10**	3.51**

*Indicates significance at the 95% level

**Indicates significance at the 99% level

Table 6 Hypotheses testing for the Fama French portfolios in the 2003–2008 period. Table entries report the mean absolute deviation for the six Fama and French-based portfolios (S = small market capitalization; B = large market capitalization; H = high book to market value; M = medium book to market value; L = low book to market value). We use the following abbreviations to denote the various models: UVL = the univariate linear model; MVLC = the multivariate linear CAPM-based model; MVLF = the multivariate linear 3 factor; UANN = the univariate ANN model; MANNC = the multivariate CAPM-based ANN model; and MANNF = the multivariate 3 factor ANN model

	Linear model comparisons			ANN model comparisons			Linear versus ANN model comparisons		
SH	1.37	2.72*	0.98	1.36	2.43*	1.49	2.20*	2.36*	2.02*
SM	1.70	2.90**	1.20	1.65	2.67*	1.47	3.11**	3.75**	3.24**
SL	2.79*	2.21*	0.92	2.55*	2.42*	0.85	4.16**	4.52**	5.42**
BH	2.01*	3.33**	1.46	1.93	3.11**	1.20	3.09**	2.92**	2.43*
BM	3.14*	2.67*	0.97	2.87*	2.53*	1.26	1.72	1.38	1.26
BL	1.75	3.14	0.81	1.89	3.05**	1.01	3.40**	3.15**	3.17**

*Indicates significance at the 95% level

**Indicates significance at the 99% level

the ANN models are statistically more accurate. The sole exception in both time periods involves the portfolio created from large size firms with medium B/M ratios.

4.4 Diebold and Mariano test

Given the relatively small sample sizes used to generate individual stock price forecasts in this study, our forecasts may reflect the possible presence of autocorrelation. As a result, a conventional t-test may not be appropriate for testing mean differences in forecast accuracy (Corradi and Swanson 2002). To address this problem, Diebold and Mariano (1995) developed an asymptotic test of the difference in mean squared errors to measure the significance in forecast improvements. Table 7 reports the Diebold and Marino test statistics calculated from our data. The results, which are consistent across time periods, reinforce our earlier conclusions. In separate comparisons of the linear and ANN models, the two multivariate models outperformed the univariate model and, as before, the differences between the two multivariate models were not statistically significant. Moreover, the ANN models consistently outperformed the linear models in forecasting stock returns. Thus the use of the Diebold and Mariano test generated the same conclusions as the use of a conventional t-test.

Based on the results reported in Tables 2 through 7, we conclude that (1) moving from the univariate to the multivariate models significantly improves forecasting accuracy, and (2) relaxing the assumption of model linearity through the use of ANN models significantly improves forecasting accuracy. Simply stated, we reject most aspects of H1 and conclude that multivariate models are more accurate at predicting stock market returns. Importantly, however, we find no evidence that the three-factor model provides greater forecasting accuracy than CAPM. We also reject H2 and conclude that ANN forecast models are superior, relative to linear models, in predicting Chinese stock returns.

5 Discussion

Existing research has not examined the relative ability of CAPM and the three-factor model to forecast stock returns in China. This gap in the literature is significant, given the volatility

Table 7 Hypotheses testing—Diebold and Mariano test.[a] Table entries report the Diebold-Mariano test statistics and associated significance levels for pairwise comparisons of the three linear and three ANN models (UVL = the univariate linear model; MVL(CAPM) = the multivariate linear CAPM-based model; MVL(3 factor) = the multivariate linear 3 factor-based model; UANN = the univariate ANN model; MANN(CAPM) = the multivariate ANN CAPM-based model; and MANN(3 factor) = the multivariate ANN 3 factor-based model)

	1999–2002		2003–2008	
	Observation value	Asymptotic p-value	Observation value	Asymptotic p-value
Panel A: Hypothesis 1				
UVL vs. MVL(CAPM)	2.53	0.0032**	2.57	0.0032**
UVL vs. MVL(3 factor)	3.22	0.0007**	3.92	0.0000**
MVL(CAPM) vs. MVL(3 factor)	1.22	0.0812	1.36	0.1034
UANN vs. MANN(CAPM)	3.42	0.0004**	4.15	0.0000**
UANN vs. MANN(3 factor)	3.28	0.0010**	3.89	0.0007**
MANN(CAPM) vs. MANN(3 factor)	1.48	0.0787	1.55	0.0926
Panel B: Hypothesis 2				
UVL vs. UANN	4.23	0.0000**	4.77	0.0000**
MVL(CAPM) vs. MANN(CAPM)	3.54	0.0057**	4.06	0.0000**
MVL(3 factor) vs. MANN(3 Factor)	4.89	0.0000**	5.51	0.0000**

*Indicates significance at the 95% level

**Indicates significance at the 99% level

of the Chinese stock markets and the added risk that arises from the Chinese legal and regulatory environment. In this paper we have addressed this gap by comparing the predictive ability of three linear forecasting models: a simple ARIMA model, a dynamic version of a single-factor CAPM-based model, and a dynamic version of Fama and French's three-factor model. In addition, we compared these linear models with three comparably-specified neural network models that contained the same predictor variables but relaxed the assumption of model linearity. Our analysis was based on two data sets from the Shanghai stock exchange, one based on data from 1999 to 2002 and a second covering the years 2003 to 2008.

Our results indicate that the multivariate forecasting models (the CAPM-based and three-factor models) outperform the univariate model that only incorporates lagged values of a company's stock price. In addition, the use of ANN models significantly improves forecasting accuracy relative to linear models incorporating the same independent variables. However, regardless of the forecasting model used (linear or ANN), we found no significant difference in forecasting accuracy between the CAPM and three-factor model.

Our findings have several important theoretical and practical implications. First, previous research has indicated that, relative to linear models, neural network models generate superior forecasts of stock price movements (Fadlalla and Lin 2001; Zhang et al. 2004). Our results indicate that this finding applies not only to mature financial markets but also to emerging markets characterized by relatively higher levels of risk. The findings presented here are consistent with the argument that a non-linear functional form is necessary to adequately capture the idiosyncratic factors that influence stock prices in emerging markets (e.g., Mookerjee and Yu 1999; Kang et al. 2002; Su 2003; Wang et al. 2006).

Second, contrary to expectations, we found no significant difference in the forecasting accuracy of the CAPM and three-factor models. This finding, which emerged in our analysis of both the individual Fama-French portfolios and in the pooled analysis of our entire data set, is surprising, because several recent studies have found that cross-sectional variations in Chinese stock prices were significantly related to firm-size and book-to-market value (Drew et al. 2003; Wang and Di Iorio 2007; Wong et al. 2006). The difference between our results and those reported in earlier studies does not reflect our use of nonlinear ANN models, because we found the same results when we estimated linear forms of the CAPM and three-factor models.

One possible explanation for our results is that earlier studies have examined the contemporaneous relationship between stock price and both firm size and the B/M ratio (Drew et al. 2003; Wang and Di Iorio 2007; Wong et al. 2006). In contrast, we estimated dynamic versions of CAPM and the three-factor model in which current values of beta, firm size, and B/M influence stock returns in the subsequent period. The results presented here raise the possibility that earlier studies reflect the influence of correlated contemporaneous errors in the measurement of beta, firm size, and B/M. Alternatively, there may exist one of more unobserved variables that simultaneously influence contemporaneous measures of stock returns, firm size, and B/M. Assessing the validity of these explanations is one important topic for future research.

The results presented above suggest several additional directions for future research. First, future research should examine whether, as Chinese stock markets continue to mature, the impact of firm size and B/M on future stock returns will become significant. In addition, recent research indicates that the accuracy of forecasting models designed to predict U.S. stock returns can be further improved through the addition of fundamental accounting variables (e.g., Zhang et al. 2004). Perhaps similar variables can be used to improve forecasting performance in emerging markets as well. Moreover, forecasting accuracy in developing markets may also be enhanced by the addition of variables such as trading volume, stock prices, and leading economic indicators. Finally, our results demonstrate that an appropriately-specified ANN model dominates linear versions of three popular forecasting models. However, it is possible that forecasting performance can be further improved through the use of alternatively-specified nonlinear models. Each of these possibilities should be explored in future research.

From a practical perspective, investors continue to seek ways to create investment portfolios that outperform the market while reducing risk. The results from this study indicate that artificial neural network models can provide investors with opportunities to reduce forecast errors and thus better manage portfolio risk. One historic problem with neural networks has been a lack of model transparency that made it difficult to trace the steps linking data inputs and predictive outputs (Hawley et al. 1990). Recent advancements in estimation techniques have addressed this concern. It is now possible, with commercially-available software packages, to analyze the weights assigned to various variables and evaluate their impact on the predictive power of the ANN model. In all likelihood, ANN models are being used by investors who have incentives not to reveal advantageous proprietary information. Given the relative lack of information in emerging markets and the sometimes-questionable quality of the information that is available, ANN models offer the promise of enhanced predictive power to investors in developing countries. We hope that the results presented here will encourage further investigation into the use of neural network models to predict returns in emerging markets. Finally, we'd like to state that it is very easy for practitioners to adopt our methodology as a trading strategy even with limited knowledge of neural networks. In terms of implementation, the practitioners can purchase off-the-shelf neural network application software (no need for specific programming knowledge) such as NeuroShell© and then create a neural network application to solve their forecasting and pattern recognition problems. Users of NeuroShell© have created an impressive suite of applications including medical, financial, and business predictions. (For detailed applications of the software, please go to company website at http://www.wardsystems.com/apptalk.asp.) Tutorials are included in the NeuroShell© and users can find help anytime they use the software. Moreover, Ward Systems Group, which produces and sells the NeurShell© software, provides free technical support including assistance with how to build your particular application.

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