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Predicting Chinese stock prices using convertible bond: an evidence-based neural network approach

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Abstract

Purpose – The primary objective of this study is to investigate whether the inclusion of convertible bond prices as important inputs into artificial neural networks can lead to improved accuracy in predicting Chinese stock prices. This novel approach aims to uncover the latent potential inherent in convertible bond dynamics, ultimately resulting in enhanced precision when forecasting stock prices.

Design/methodology/approach – The authors employed two machine learning models, namely the backpropagation neural network (BPNN) model and the extreme learning machine neural networks (ELMNN) model, on empirical Chinese financial time series data.

Findings – The results showed that the convertible bond price had a strong predictive power for low-market-value stocks but not for high-market-value stocks. The BPNN algorithm performed better than the ELMNN algorithm in predicting stock prices using the convertible bond price as an input indicator for low-market-value stocks. In contrast, ELMNN showed a significant decrease in prediction accuracy when the convertible bond price was added.

Originality/value – This study represents the initial endeavor to integrate convertible bond data into both the BPNN model and the ELMNN model for the purpose of predicting Chinese stock prices.

Keywords Chinese stock, Convertible bond, Predictive power, BPNN model, ELMNN model

Paper type Research paper

1. Introduction

Stock markets have become integral to the global economy, serving as a robust gauge of a nation's economic vitality. Notably, China has ascended to become the world's second-largest economy in recent decades, with its stock market mirroring this meteoric rise and offering burgeoning prospects for investors. Consequently, an expanding cohort of scholars and researchers has turned their scholarly gaze toward the Chinese stock market. In a notable contribution, Zhang (2018) conducted a comprehensive inquiry into the evolution of Chinese stock exchanges, shedding light on their pivotal role within the nation's economic landscape.

Researchers have always been interested in predicting future stock prices to increase their returns on investments. However, due to the nonlinear, nonstationary and high-dimensional

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nature of stock data, this is an extremely challenging task (Cai and Chen, 2011). A wide range of macro and microfactors, such as the macroeconomic environment, political policies, market news, earnings per share and total net asset value, can influence stock prices. Despite these challenges, scholars have proposed several models to describe stock prices and predict future trends. By improving our understanding of the market and identifying the best models, we can make more informed investment decisions and benefit from the promising opportunities in the Chinese stock market.

Price prediction models fall into two main categories: statistical models and machine learning models. Statistical models, including differential autoregressive moving average, exponential smoothing and multiple linear regression, are often used to understand and explain linear patterns in stock prices (Yu *et al.*, 2020).On the other hand, artificial neural networks (ANNs), a type of machine learning model, are widely recognized for their accuracy and versatility. ANNs are nonlinear and possess attributes like self-organization, data-driven learning and memory retention, similar to human thought processes. They are commonly applied in classification, prediction and pattern recognition tasks (Hu *et al.*, 2018). Additionally, ANNs are adept at uncovering hidden relationships among variables. Both statistical and ANN models can predict future Chinese stock prices, but their suitability depends on the data characteristics. Statistical models work well with linear data trends, while ANNs excel with nonlinear and changing data. It's also important to note that statistical models aim to understand variable relationships, whereas ANNs prioritize precise predictions.

The primary objective of this study is to perform a comparative analysis of two algorithms, backpropagation (BP) and extreme learning machine (ELM), for predicting stock prices. This analysis leverages the distinctive characteristics of stock data and harnesses the advantages offered by artificial neural networks (ANNs). Despite the numerous models and algorithms proposed in previous research for forecasting stock prices, there exists a notable gap in the literature pertaining to a direct comparison of the predictive capabilities of BP and ELM algorithms within the context of stock models. Furthermore, in addition to delving into various algorithms within the domain of ANNs, this study aligns with the research interest expressed by Rahman, Shamsuddin and Lee in 2019. As a specific focus of this study, we will use the price of convertible bonds (CBs) as an input variable in our analysis. The aim of this study is to identify the optimal model for predicting Chinese stock prices by leveraging the strengths of ANNs and incorporating a novel indicator, the price of CBs. It is assumed that both the ANNs model with the BP algorithm and the ELM algorithm can accurately predict future stock prices, but it is important to compare the outcomes to select the optimal model. There is significant evidence in the literature that the price of CBs has the predictive ability to forecast future stock returns using statistical methods (An *et al.*, 2014; Hubbard and Johnson, 1969; Pan and Poteshman, 2006; Yang *et al.*, 2018). However, it remains to be seen if the same holds true for the ANNs model. By including the price of CBs as an input indicator, we hope to gain further insight into its predictive power and potential value in stock price forecasting.

Moreover, we will categorize the selected stocks into high and low-market-value groups to examine the performance of the ANN model in each group. This division allows us to test the model's behavior with respect to varying market values, which is a crucial factor in predicting stock prices. We will use a dataset consisting of 10 selected stocks for testing, with an equal division of 5 stocks with high market values and 5 with low market values. Our ultimate goal is to provide strong empirical evidence to identify the optimal model for predicting Chinese stock prices, which can have significant implications for investors and financial analysts.

This study is organized into distinct sections. In Section 2, we offer an overview of the existing literature. Section 3 delves into the methodology and data employed in this research. The subsequent section, Section 4, showcases the outcomes derived from data analysis. This includes a juxtaposition of the predictive capabilities of the BP algorithm against the ELM algorithm in forecasting stock prices. Furthermore, it encompasses an assessment of the impact arising from incorporating CB prices as input variables. Conclusively, Section 5 encapsulates our findings and draws relevant conclusions from the study's results.

2. Literature review

Su and Fleisher (1998) conducted an extensive analysis of risk and return behaviors in the Chinese stock markets. The study findings unveiled that stock market return volatility was notably high, and risk-adjusted mean stock returns were comparably low when juxtaposed against developed markets. Furthermore, returns within the Chinese stock markets exhibited a significantly heightened degree of autocorrelation with market capitalization in comparison to their developed market counterparts. This scenario accentuated the imperative of precise stock price forecasting, given the overarching objective of capitalizing on market opportunities.

Contrary to the foundational concept of the efficient market hypothesis (EMH) that asserts stock prices follow unpredictable random paths (Malkiel and Fama, 1970), an increasing body of scholarly research has presented compelling evidence revealing a nuanced layer of predictability within stock prices. Lo (2004) offered a new perspective on market efficiency by highlighting its dependence on various factors such as competitive dynamics, profit potential and investor insight. This fresh viewpoint prompted a reevaluation of the extent to which stock markets can be predicted. Interestingly, Kim *et al.* (2011) consistently found significant results. In specific contexts, he demonstrated that there exists a quantifiable level of predictability in stock returns, albeit within a realm of measured uncertainty. This insight depended on the inherent volatility of the stock market and the strong economic fundamentals that drive it, providing a strong rationale for the emergence of recognizable patterns. Building on this discourse, Groenewald *et al.* (2003) discovered a noteworthy departure from the weak form of the EMH within the behavior of the Chinese stock market. This deviation manifested as returns that could be predicted based on historical values, a revelation that directly contradicted established EMH principles. By delving into the foundations of the weak EMH, this study presented counterevidence that urged a reevaluation of conventional beliefs. In alignment with these revelations, Chong *et al.* (2012) and Beltratti *et al.* (2016) expressed similar sentiments, both independently demonstrating an increase in efficiency within the Chinese stock market. This gradual evolution served as a strong testament to the adaptability and flexibility of market behaviors. Furthermore, it underscored the idea that as markets mature and integrate new dynamics, their efficiency can evolve, challenging the EMH's assumption of a static market equilibrium.

From the perspective of forecasting methodologies, vast body of research underscores its critical importance. Predicting stock prices is a pivotal task, prompting a thorough exploration of various methods. These methods can be broadly divided into two main categories: traditional statistical tools and supervised learning techniques. Traditional statistical tools encompass a range of proven techniques like regression analysis, exponential smoothing and the widely used autoregressive integrated moving averages (ARIMA). These methods have consistently demonstrated their effectiveness and are the cornerstone of stock market forecasting, empowering investors with reliable insights for decision-making. The ARIMA method holds prominence in the realm of time series forecasting. Researchers such as Balsara *et al.* (2007), Chung *et al.* (2009) and Jarrett and Kyper (2011) have extensively utilized ARIMA for forecasting Chinese stock prices, showcasing its efficacy in short-term curve prediction. However, it is noteworthy that Liao *et al.*, 2020 have highlighted a limitation of ARIMA. This method, which assumes linear correlation within the time series, struggles to adequately model nonlinear series. The effectiveness of ARIMA relies on the stability of the time series; it falters when faced with irregular or unstable data patterns. Consequently, the direct application of ARIMA to stock price forecasting is often deemed unsuitable, given the inherent instability of stock prices. The evolution of computational intelligence over the past few decades has led to heightened interest in alternative forecasting methods capable of accommodating nonlinear and unstable datasets.

In recent years, there has been a strong focus on using machine learning models to predict stock prices. A notable example of this is the use of ANNs. ANNs have gained attention because they can handle different types of information and network setups. Their popularity stems from their effectiveness in recognizing complex relationships and patterns in training data, which allows them to make accurate predictions using deep learning techniques (Liu *et al.*, 2022). The evidence supported the notion that ANNs are a valuable tool for predicting stock prices. The success of ANNs in predicting stock prices depends on carefully selecting input indicators and designing the neural network's structure. This viewpoint is also supported by Senol and Ozturan (2009) who suggested that combining well-chosen indicators with a strong neural network architecture is crucial for achieving reliable predictive performance. Furthermore, they emphasized that ANNs outperform traditional methods like logistic regression, particularly in predicting stock price trends. Comparative studies that contrast statistical models with ANN approaches have played a significant role in evaluating predictive methods. For example, Bou-Hamad and Jamali (2020) demonstrated that, especially for time sequences with moderate to high persistence, ANNs yield better results than the AR(1)-GARCH (1,1) model in dynamic forecasting contexts. The effectiveness of ANNs is further highlighted in Yu *et al.* (2020), where the hybrid LLE-BPNN (a fusion of dimension reduction and neural network) is proven to surpass statistical methods like ARIMA models. This superiority is evident in metrics such as root mean square error and mean absolute error. Collectively, these findings emphasize the potency of data-driven techniques in revealing hidden patterns, ultimately bolstering predictive accuracy.

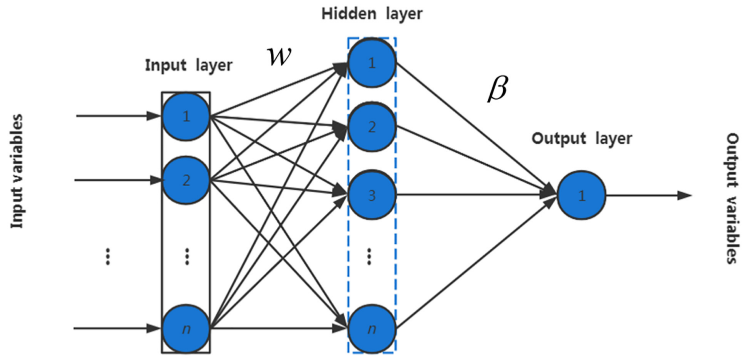
Numerous researchers have shown a strong interest in improving predictive models by incorporating various input indicators. These include factors like oil prices (Sim and Zhou, 2015), economic policy uncertainty (Chen *et al.*, 2023) and data from Google Trends (Saetia and Yokrattanasak, 2022). However, it's important to note that the use of bond-related predictors is relatively limited in the existing research. Specifically, the potential of bonds, especially CBs, to enhance the accuracy of predicting stock prices has not received much attention. CBs have untapped potential to make stock price forecasts more accurate. They can mirror market sentiment and give insights into investor expectations, creating a dynamic link that improves predictive models. CBs allow bondholders to convert them into stocks, creating a direct connection between bond values and stock prices. This acts as an indicator of market sentiment, where conversions indicate positive outlooks. Moreover, CBs can be used strategically for timing the market; higher conversions during periods of strong stock performance might push stock prices up. This unique behavior provides valuable insights into market dynamics, particularly during times of high market volatility. While previous studies have explored the relationship between stocks and bonds (Hubbard and Johnson, 1969; AN *et al.*, 2014; Pan and Poteshman, 2006), the use of ANNs for predictive purposes is notably absent.

To bridge this gap, the present study aims to incorporate CB prices as crucial inputs into ANNs. This innovative approach seeks to tap into the hidden potential within CB dynamics, thus improving the accuracy of stock price predictions.

3. Methodology and data

3.1 Artificial neural networks model (ANNs)

In the scope of machine learning, ANNs find extensive use among scholars and researchers for prediction tasks. Figure 1 illustrates the standard architecture of ANNs, featuring a single



Source(s): Modified fromManeejuk and Srichaikul (2021)

Figure 1. Overview of an artificial neural network (ANN) architecture

hidden layer. This diagram offers insights into the operational mechanics of the ANN model, comprised of three distinct layers: the input layer, the hidden layer and the output layer. Each layer contains multiple neurons, and the output of the previous layer serves as the input for the current layer. This sequential processing transforms initial inputs into meaningful output information within the output layer. By referring to Figure 1, we can formulate the ANN equation as follows: in the output layer. From Figure 1, we can write the ANN equation as

$$\mathbf{y}_j = \sum_{i=1}^{L} \beta_i g(\mathbf{w}_i \bullet \mathbf{x}_j + b_i), j = 1, \ldots, N \tag{1}$$

where $\mathbf{y}$ is output neuron, $\mathbf{x}_j = [x_{j1}, \ldots, x_{jN}]$ is the jth sample of input neuron i, $\mathbf{w}_i = [w_{i1}, \ldots, w_{iN}]$ is the weight vector connecting the ith hidden neuron and the input neurons, L is the number of the hidden neurons. β_i is the weight vector connecting the ith hidden neuron and the output neurons, and b_i is the bias of the ith hidden neuron. $g()$ is the sigmoid activation function.

It's important to note that the choice of activation function can have a significant impact on the performance of the ANN model (Yu *et al.*, 2020). The binary step function and linear activation function are typically used for binary classification tasks and linear regression, respectively. However, for nonlinear regression tasks such as stock price prediction, nonlinear activation functions are preferred as they can better capture complex patterns in the data. The logistic function is a popular choice as it maps any input value to a value between 0 and 1, which can be interpreted as a probability. Other activation functions like the Tanh function, ReLU function and leaky ReLU function have also been shown to be effective for different types of data and problems. The choice of activation function should be based on the specific characteristics of the data and the objective of the model (Yamaka *et al.*, 2021).

In a neural network model, the loss function plays a crucial role in quantifying the disparity between the anticipated output and the model's actual output. Subsequently, the model's weights are adjusted based on the gradients derived from this loss function, and the overall cost is determined by calculating the mean of all these individual losses. Several types of loss functions are at one's disposal, including the squared error function, mean square error loss function and logistic loss function. For the purposes of this study, the squared error function, as specified by Maneejuk and Srichaikul (2021), will serve as the chosen loss function.

3.2 Backpropagation algorithm (BP)

BP is a widely embraced algorithm for training feedforward neural networks within the field of machine learning, as highlighted by Xiong and Lu in 2017. Its effectiveness stems from its capacity to efficiently calculate the gradient of the loss function concerning the network's weights for individual input–output instances as opposed to collectively calculating the gradient for all weights simultaneously. This efficiency allows for the utilization of gradient-based methods in training multilayer networks, thereby optimizing the weights to minimize the loss effectively. Once the BP-ANN completes its training, it offers an output corresponding to a given input, facilitating predictive applications across various domains. The BP algorithm leverages the chain rule of differentiation to systematically propagate errors through the network's layers. This, in turn, leads to weight updates by computing the gradients of the loss function concerning each weight. This iterative process can be executed using optimization techniques like stochastic gradient descent to attain convergence, as demonstrated by Ma, Wang, and Dong in 2010. The formulation of the loss function for this optimization task can be expressed as follows:

$$loss = \sum_{j=1}^{N}\left(\sum_{i=1}^{L}\beta_i g(\mathbf{w}_i \bullet \mathbf{x}_j + b_i) - \mathbf{y}_j\right)^2 \tag{2}$$

This study will set the learning rate to be $\eta = 0.01$ and the target error rate is set to 0.001, which means that the algorithm should aim to minimize the error such that it is equal to or less than 0.001. During the training process, the algorithm should continuously monitor the error and terminate the process once the error is equal to or less than the target error rate.

3.3 Extreme learning machine algorithm (ELM)

In contrast to the BP algorithm, the ELM does not utilize backward procedures to adjust the weights of the neurons. Instead, it randomly initializes the weights and only adjusts the output weights through a simple linear system of equations (Huang *et al.*, 2004). The mathematical model of ELM-ANN with N arbitrary distinct samples can be shown using a set of equations, where the weights are adjusted iteratively during the training process. To simplify the estimation of the model, these equations can be written compactly as a single equation.

$$\mathbf{Y} = \mathbf{H}\boldsymbol{\beta} \tag{3}$$

where

$$\mathbf{H} = \begin{bmatrix} g(\mathbf{w}_1 \bullet \mathbf{x}_1 + b_1) & \cdots & g(\mathbf{w}_L \bullet \mathbf{x}_N + b_L) \\ \vdots & \vdots & \vdots \\ g(\mathbf{w}_1 \bullet \mathbf{x}_N + b_1) & \cdots & g(\mathbf{w}_L \bullet \mathbf{x}_N + b_L) \end{bmatrix}_{N\times L}, \tag{4}$$

$$\boldsymbol{\beta} = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_L \end{bmatrix}_{L\times 1} \text{ and } \mathbf{Y} = \begin{bmatrix} \mathbf{y}_1 \\ \vdots \\ \mathbf{y}_N \end{bmatrix}_{N\times 1} \tag{5}$$

After arbitrarily assigning the weights for the input neurons and the biases for the hidden neurons, the output matrix of the hidden layer ($\mathbf{H}$) becomes uniquely determinate and can be calculated. To train an ELM is simply equivalent to finding a least-squares solution $\widehat{\boldsymbol{\beta}}$ of the linear system (Eq.3) and the smallest norm least-squares solution of this linear system is

$$\boldsymbol{\beta} = \mathbf{H}^{+}\mathbf{Y} \tag{6}$$

where H^{+} is the Moore–Penrose generalized inverse of matrix H. Finally, the smallest training error can be reached by

$$\widehat{\boldsymbol{\beta}} = \underset{\boldsymbol{\beta}}{Min}\|\mathbf{Y} - \mathbf{H}\boldsymbol{\beta}\| \tag{7}$$

3.4 Forecasting performance measures

In this study, we utilize two statistical metrics to rigorously assess and distinguish the performance of competing models. Specifically, we consider mean absolute error (MAE) and root mean square error (RMSE). MAE, founded on the absolute loss function, is represented as:

$$MAE = \frac{1}{M}\sum_{t=1}^{M}|\mathbf{Y}_t - true_t| \tag{8}$$

where $true_t$ the actual values at day t. The number of the testing dataset samples is denoted as "M". RMSE can be computed as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{M}(\mathbf{Y}_t - true_t)^2}{M}} \tag{9}$$

3.5 Data and data processing

In this study, we compile a comprehensive dataset comprising 10 Chinese stocks that have issued CBs. From this dataset, we choose the top five stocks with the highest market values, as well as the bottom five stocks with the lowest market values. This selection enables us to conduct a comparative analysis of the predictive capabilities of the CB premium for these two distinct market value groups. Notably, our analysis of delisting CBs reveals a significant trend, wherein approximately 70% of such bonds are repurchased by the issuing companies within a two-year timeframe. As a result, we limit our dataset to cover the period from June 1, 2020, to February 28, 2022. This timeframe spans 424 days for each of the ten selected stocks. Given the relatively short duration of this period, we can confidently exclude macroeconomic effects from our analysis. For reference, Table 1 lists the ten selected stocks, with the first five belonging to the high market value category and the remaining five categorized under low market values.

In this particular study, the ANNs model was trained using the daily closing price of a stock for the preceding five trading days and the current trading day's CB price as input variables. To ensure compatibility between the model's output values and actual values, normalization was deemed necessary, given that the selected activation function yields output values between 0 and 1. Therefore, to maintain consistency, a normalization procedure was applied to the data, which can be expressed as follows

$$NP_t = \frac{P_t - \min(P)}{\max(P) - \min(P)}, \tag{10}$$

where P_t is the daily close price of time t, max () and min () represent the highest and lowest functions, respectively. The same normalization approach was also applied to the CB price.

Stocks			Convertible bonds	
Symbol	Name	Market value (billion yuan)	Symbol	Name
600000	PUFAYINGHANG (PYH)	225.13	110059	PUFAZHUANZAI (PFZ)
601998	ZHONGXINYIHANG (ZXH)	222.16	113534	ZHONGXINZHUANZAI (ZXZ)
601818	GUANGDAYINHANG (GDH)	156.69	113011	GUANGDAZHUANZAI (GZZ)
300088	CHANGXINKEJI (CXK)	123.98	123022	CHANGXINZHUANZAI (CXZ)
600919	JIANGSUYINHANG (JYH)	100.43	110053	SUYINZHUANZAI (SZZ)
300539	HENGHEJINGMI(HHG)	2.06	123013	HENGHEZHUANZAI (HHZ)
002846	YINGLIANGUFEN (YLF)	1.96	128079	YINGLIANZHUANZAI (YLZ)
002787	HUAYUANKONGGU (HYG)	1.80	128049	HUAYUANZHUANZAI (WYZ)
603089	ZHENGYUGONGYE (ZGY)	1.80	113537	WENCHANZHUANZAI (WZZ)
603320	DIBEIDIANQI (DBQ)	1.56	113546	DIBEIZHUANZAI (DZZ)

Source(s): Compiled from Thomson Reuters Database

Table 1. Stocks and convertible bonds

This method ensures that the resulting values fall within the 0–1 range, as required by the selected activation function.

$$NB_t = \frac{B_t - \min(B)}{\max(B) - \min(B)}, \tag{11}$$

where B_t is the daily close price at time t.

Subsequently, we partitioned the empirical data into two distinct subsets: a training dataset utilized for developing the predictive model and a testing dataset employed to validate the trained model. Precisely, 70% of the total data constituted the training dataset, with the remaining 30% allocated to the testing dataset. Due to the time series nature of the stock data, the partitioning was conducted chronologically, with the samples ordered from day 1 to day 423. Consequently, the training dataset encompassed samples from day 1 to day 296, while the testing dataset comprised samples from day 297 to day 423.

4. Empirical results

This study conducted a comparison between two forecasting models: one that incorporated the CB price as an input variable (With_CB) and one that did not include it (Without_CB). The evaluation of each model's performance was conducted via in-sample and out-of-sample experiments, where the RMSE and MAE were used as performance metrics.

4.1 In-sample results

In the in-sample experiment, we employed the training dataset to construct the predictive models, which were subsequently applied to the same dataset to generate predicted prices. This methodology allowed us to evaluate the performance of the ANN models in terms of their fit to the training data. Essentially, our goal was to assess how effectively the models matched the observed data within the training set.

Tables 2 and 3 present the results of RMSE and MAE values for backpropagation neural network (BPNN) and extreme learning machine neural networks (ELMNN) models with and

Table 2.
In-sample comparison of RMSE between BPNN and ELMNN

	RMSE					
	BPNN			ELMNN		
Stock	With_CB	Without_CB	Percentage improvement	With_CB	Without_CB	Percentage improvement
PYH	0.0544	0.1067	48.9583%	0.0483	0.0477	−1.2712%
ZXH	0.0622	0.0620	−0.3257%	0.0525	0.0526	0.1919%
GDH	0.0718	0.0691	−3.9474%	0.0638	0.0625	−2.1002%
CXK	0.0435	0.0448	2.9279%	0.0425	0.0424	−0.2381%
JYH	0.0533	0.0540	1.3084%	0.0366	0.0371	1.3624%
HHG	0.0630	0.0564	−11.8280%	0.0478	0.0472	−1.2848%
YLF	0.0568	0.0526	−7.8695%	0.0430	0.0427	−0.7092%
HYG	0.0461	0.0462	0.0021%	0.0355	0.0352	−0.5731%
ZGY	0.0621	0.0612	−1.4851%	0.0505	0.0487	−3.7344%
DBQ	0.0482	0.0477	−1.0593%	0.0378	0.0376	−0.5376%

Note(s): The percentage improvement measures the degree to which the accuracy of the model with the convertible bond price as an input improves compared to the model without it
Source(s): Authors' computation

Table 3.
In-sample comparison of MAE between BPNN and ELMNN

	MAE					
	BPNN			ELMNN		
Stock	With_CB	Without_CB	Percentage improvement	With_CB	Without_CB	Percentage improvement
PYH	0.0364	0.0836	56.5217%	0.0331	0.0324	−2.1807%
ZXH	0.0429	0.0406	−5.7214%	0.0361	0.0364	0.8333%
GDH	0.0492	0.0471	−4.5064%	0.0436	0.0423	−3.1026%
CXK	0.0337	0.0346	2.6239%	0.0258	0.0257	−0.3937%
JYH	0.0410	0.0415	1.2165%	0.0306	0.0311	1.6234%
HHG	0.0456	0.0393	−15.9383%	0.0318	0.0316	−0.6390%
YLF	0.0361	0.0345	−4.3860%	0.0294	0.0291	−1.0417%
HYG	0.0327	0.0321	−1.8868%	0.0241	0.0238	−1.2712%
ZGY	0.0473	0.0449	−5.1685%	0.0362	0.0350	−3.1700%
DBQ	0.0360	0.0355	−1.4245%	0.0282	0.0281	−0.3597%

Note(s): The percentage improvement measures the degree to which the accuracy of the model with the convertible bond price as an input improves compared to the model without it
Source(s): Authors' computation

without the convertible bond price (CB) as input for ten different stocks. The tables also show the percentage improvement in model performance with CB input compared to without CB input. A positive percentage indicates an improvement, while a negative percentage indicates a decrease in performance.

Regarding the BPNN model, the results show that using CB as input improves the forecasting accuracy for most stocks. For instance, for "PUFA YINGHANG" stock, the BPNN model with CB input has a percentage improvement of 48.9583% and 1756.52% in RMSE and MAE, respectively. However, for "HUAYUAN KONGGU" stock, the percentage improvement is only −0.0021% and −1.8868% in RMSE and MAE, indicating that CB input does not significantly improve the model's performance for this stock. In contrast, for the ELMNN model, using CB as input only improves the forecasting accuracy for two out of ten stocks. The most significant improvement is observed for "JIANGSU YINHANG" stock, with a percentage improvement of 1.3624% for RMSE and 1.6234% for MAE. This suggests that the inclusion of CB prices as input improves the ELMNN model's ability to capture the complex relationships between stock prices and CB prices for this stock.

Overall, the results suggest that including the CB price as an input can enhance the forecasting accuracy of both models for some stocks. However, the effectiveness of this approach depends on the specific characteristics of each stock.

4.2 Out-of-sample results

In the out-of-sample experiment, we employed a training approach for the BPNN model using a batch size of 32, running for a total of 10,000 iterations. In each iteration, 32 samples were randomly selected. During the testing phase, the model sequentially predicted daily data, ensuring that the previous day's data was always incorporated into the model. Before forecasting the closing price for the next day, the model underwent retraining using data from the preceding 32 trading days. We initialized the weights and biases with random values and set a fixed learning rate of 0.1. For example, to evaluate the model's performance on sample day 298, the model was trained using the 32 samples from sample day 266 to sample day 297. Likewise, the training set for testing day 299 comprised data from sample days 267–298. In the case of the ELMNN model, we adopted a larger batch size of 256 to enhance model accuracy. The testing procedure closely resembled that of the BPNN model.

Analyzing the RMSE results presented in Table 4, it becomes apparent that the ELMNN model exhibits superior performance compared to the BPNN model as indicated by the lower RMSE values for many stocks. However, it's noteworthy that the incorporation of CB leads to enhanced forecasting accuracy for most of the stocks within the BPNN model. This improvement is evident through positive percentage improvements in most cases for BPNN. Nevertheless, it's interesting to note that there are a few exceptional cases where the inclusion of CB results in a decrease in forecast accuracy within the ELMNN model.

Interestingly, from the results in Table 5, we can see that the inclusion of CB does not improve the forecast accuracy for the ELMNN model in many cases. This could be due to the fact that the ELMNN model is already capable of capturing the underlying patterns in the stock data without the need for additional information from the CB. In fact, this is supported by the finding that the ELMNN model generally outperforms the BPNN model, even without the inclusion of CB.

Furthermore, the fact that the BPNN model shows significant improvement in forecast accuracy with the inclusion of CB while the ELMNN model does not suggests that the BPNN

	RMSE					
	BPNN			ELMNN		
Stock	With_CB	Without_CB	Percentage improvement	With_CB	Without_CB	Percentage improvement
PYH	0.0781	0.0797	2.0279%	0.0538	0.0410	−31.2808%
ZXH	0.0907	0.0929	2.3913%	0.0404	0.0352	−14.6132%
GDH	0.0763	0.0752	−1.3423%	0.0311	0.0314	0.9646%
CXK	0.2176	0.2081	−4.5631%	0.0650	0.0612	−6.2706%
JYH	0.1509	0.1531	1.4512%	0.0473	0.0457	−3.5398%
HHG	0.1193	0.1211	1.5013%	0.0363	0.0361	−0.5602%
YLF	0.0516	0.0519	0.5837%	0.0196	0.0231	15.2838%
HYG	0.0800	0.0811	1.3699%	0.0293	0.0258	−13.7255%
ZGY	0.1025	0.1029	0.3925%	0.0465	0.0342	−35.6932%
DBQ	0.1546	0.1560	0.9061%	0.0741	0.0681	−8.9021%

Note(s): The percentage improvement measures the degree to which the accuracy of the model with the convertible bond price as an input improves compared to the model without it

Source(s): Authors' computation

Table 4. Out-of-sample comparison of RMSE between BPNN and ELMNN

	MAE					
	BPNN			ELMNN		
Stock	With_CB	Without_CB	Percentage improvement	With_CB	Without_CB	Percentage improvement
PYH	0.0571	0.0579	1.3962%	0.0358	0.0321	−11.3208%
ZXH	0.0755	0.0782	3.3592%	0.0297	0.0269	−10.5263%
GDH	0.0606	0.0598	−1.3514%	0.0233	0.0243	4.1494%
CXK	0.1698	0.1621	−4.7352%	0.0459	0.0417	−9.9274%
JYH	0.1206	0.1232	2.1311%	0.0365	0.0345	−5.5556%
HHG	0.0986	0.1003	1.7120%	0.0283	0.0277	−2.1898%
YLF	0.0449	0.0450	0.2242%	0.0150	0.0176	14.3678%
HYG	0.0692	0.0698	0.8683%	0.0227	0.0199	−14.2132%
ZGY	0.0859	0.0866	0.8168%	0.0310	0.0251	−23.2932%
DBQ	0.1193	0.1202	0.7563%	0.0550	0.0520	−5.8252%

Note(s): The percentage improvement measures the degree to which the accuracy of the model with the convertible bond price as an input improves compared to the model without it
Source(s): Authors' computation

Table 5.
Out-of-sample comparison of MAE in BPNN and ELMNN

model may be more sensitive to the additional information provided by the CB. On the other hand, the ELMNN model's superior performance may be attributed to its ability to capture more complex nonlinear patterns in the data without the need for explicit feature engineering or preprocessing. Overall, these findings suggest that the choice of model architecture can play an important role in determining the effectiveness of including additional information such as CB in stock price forecasting.

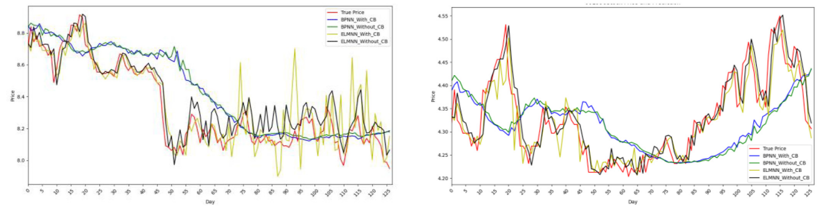
We compared the performance of CB on stocks with high and low market values, and we've summarized the results in Table 6. This table provides the averages, lowest and highest values of RMSE and MAE based on the outcomes presented in Tables 4 and 5. Our findings reveal that CB exhibits robust predictive capabilities for low-market-value stocks, as evidenced by the lower average RMSE and MAE values for BPNN. However, this improvement is not as pronounced for high-market-value stocks, where the impact of CB on predictive accuracy is not significant. Interestingly, for the ELMNN models, the results suggest that ELMNN tends to decrease prediction accuracy for both high and low-market-value stock groups.

To delve deeper into the performance of these models, we visually represent both the actual prices and the predicted prices of all 10 stocks in Figure 2.

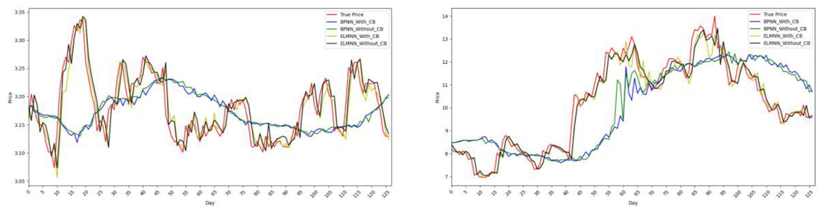
	RMSE				MAE			
	With_CB		Without_CB		With_CB		Without_CB	
BPNN	*LMV*	*HMV*	*LMV*	*HMV*	*LMV*	*HMV*	*LMV*	*HMV*
Average	0.5131	0.6196	0.5132	0.6090	0.0835	0.0968	0.0843	0.0963
Highest	0.0521	0.0771	0.0519	0.0752	0.0449	0.0571	0.0450	0.0579
Lowest	0.1561	0.2198	0.1560	0.2081	0.1193	0.1698	0.1202	0.1621
ELMNN	*LMV*	*HMV*	*LMV*	*HMV*	*LMV*	*HMV*	*LMV*	*HMV*
Average	0.0411	0.0476	0.0375	0.0429	0.0304	0.0342	0.0285	0.0319
Highest	0.0196	0.0311	0.0231	0.0314	0.0150	0.0233	0.0176	0.0243
Lowest	0.0741	0.0650	0.0681	0.0612	0.0550	0.0459	0.0520	0.0417

Note(s): The HMV and LMV denote the high market value group and low market value group, respectively
Source(s): Authors' computation

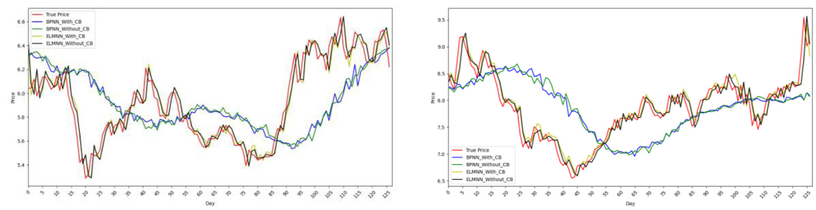
Table 6.
Comparison of out-of-sample for high and low-value market stocks between BPNN and ELMNN models



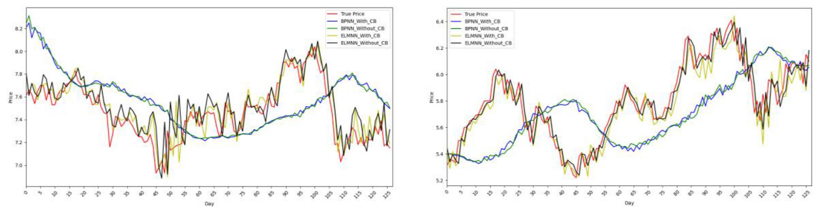
PYHZXH



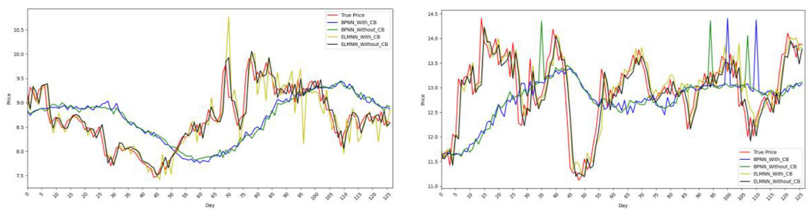
GDHCXK



JYHHHG



YLFHYG



ZGY DBQ

Source(s): Author's Computation

Figure 2.
Comparison between actual stock prices and predicted prices

In Figure 2, we can see that the BPNN models capture the general price trends, while the ELMNN models closely follow the actual price movements. Notably, their performance remains consistent whether CBs are present or not, with the exception of some noticeable predictive bias in PYH, ZGY and DBQ during certain time periods. In essence, the ANN models provide effective forecasts for future prices and trends of all the studied stocks in the Chinese stock markets.

4.3 Predictive power of convertible bond analysis

To evaluate the predictive influence of CBs on the stock price, we then employ the regression model to validate the forecasting results. The model utilized in this subsection is as follows:

$$lnP_t = \alpha + \beta lnB_{t-1} + \beta^* lnB_{t-1}M + \varepsilon_t, \tag{12}$$

where lnP_t represents the logarithm of the stock price at time t, and B_{t-1} signifies the logarithm of the CB price at time t-1. Additionally, we gather market indexes from the Shangzheng and Shenzheng stock exchanges within the same timeframe. These indexes contribute to establishing the value of market indicator $M_{t\text{-}1}$, which equals one when the cumulative market return over three days is negative, and zero otherwise.

Table 7 presents ten regression models. Our analysis reveals that all the coefficients related to lnB_{t-1} are statistically noteworthy. This suggests a strong predictive capability of the CB price at time *t-1* for the stock price at time *t*. Moreover, we observed that β^* holds significance in many stocks, thereby allowing us to reject the null hypothesis $\beta^* = 0$. This outcome underscores the statistical dissimilarity in the predictive strength of economic/market conditions. To be specific, the ability of the Chinese market to predict stock prices varies significantly during the economic slowdown, recovery and in down- and up-market scenarios.

5. Conclusion

In this study, the performance of two algorithms, BPNN and ELMNN, in predicting stock prices in the Chinese market using the CB price as a predictor variable was investigated.

	PYH	*ZGY*	*GDH*	*CXK*	*JYH*
β	−1.329***	−0.069***	1.464***	0.847***	1.791***
	(0.227)	(0.003)	(0.041)	(0.015)	(0.085)
β*	−0.008***	0.001	0.002***	−0.014***	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
R-squared	0.242	0.576	0.826	0.898	0.676
	HHG	*YLF*	*HYG*	*ZGY*	*DBQ*
β	−0.055***	1.161***	1.252***	−0.127***	1.374***
	(0.032)	0.084	0.068	0.032	0.036
β*	0.000	−0.023***	−0.022***	−0.005	−0.014***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.001)
R-squared	0.007	0.378	0.602	0.101	0.779

Note(s): ***indicates statistical significance at the 1% level. The parenthesis indicates the standard error
Source(s): Authors' computation

Table 7.
Regression results

The results revealed that the CB has strong predictive power for low-market-value stocks but not for high-market-value stocks. This finding indicates that CB may be a useful input indicator for investors interested in low-market-value stocks, but may not be as effective for high-market-value stocks. Moreover, the study found that the BPNN algorithm outperformed the ELMNN algorithm in predicting stock prices using CB as an input indicator. This result suggests that investors may achieve better predictive accuracy by using the BPNN algorithm when incorporating CB prices as an input for stock price prediction. However, the ELMNN algorithm showed a significant decrease in prediction accuracy when CB was added.

These findings have practical implications for investors interested in the Chinese stock market, particularly those who seek to invest in low-market-value stocks. The study recommends that investors consider using CB prices as an input indicator when predicting the future prices of low-market-value stocks. Additionally, it suggests that the BPNN model may be a better choice than the ELMNN model when using CB prices as an input for low-market-value stocks.

However, investors should exercise caution when using CB prices as an input indicator for high-market-value stocks, as the results show that the CB does not significantly improve the predictive power of the models for this group. Moreover, investors should be aware of the limitations of the models used in this study and exercise caution when making investment decisions based solely on predictions generated by these models.

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