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Forecasting the total market value of a shares traded in the Shenzhen stock exchange via the neural network

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Abstract

Stock total market value forecasting is a significant issue for policy makers and investors. This study explores usefulness of the nonlinear autoregressive neural network for this forecasting problem in a dataset of the daily total market value of A shares traded in the Shenzhen Stock Exchange during January 4, 2016 – August 23, 2021. Through examining various model settings across the algorithm, delay, hidden neuron, and data splitting ratio, the model leading to generally accurate and stable performance is reached. Usefulness of the machine learning technique for the total market value forecasting problem of the A shares is illustrated. Results here might be used on a standalone basis as technical forecasts or combined with fundamental forecasts to form perspectives of total market value trends and perform policy analysis.

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1. Introduction

Stock total market value forecasting is a significant issue for policy makers and investors. Because of irregular volatilities (Xu, 2017a, 2020), great influences on decision making processes, and hence on resource allocation and economic welfare (Xu, 2019a,c), significance of their forecasts to the society might need little motivation.

A great amount of previous studies (Arouri et al., 2012; Awokuse and Yang, 2003; Babula et al., 2004; Bessler, 1982, 1990; Bessler and Babula, 1987; Bessler and Brandt, 1981, 1992; Bessler and Chamberlain, 1988; Bessler and Hopkins, 1986; Bessler and Kling, 1986; Bessler et al., 2003; Brandt and Bessler, 1981, 1982, 1983, 1984; Chen and Bessler, 1987, 1990; Huang et al., 2018; Kling and Bessler, 1985; McIntosh and Bessler, 1988; Wang and Chen, 2013; Wang and Bessler, 2004; Xu, 2017c, 2018e, 2019a,c; Xu and Zhang, 2022b; Yang and Awokuse, 2003; Yang et al., 2001; Yang and Leatham, 1998; Yang et al., 2021, 2003; Zhang and Sun, 2017; Zhou et al., 2019) have concentrated on a wide variety of (time series) econometric models, expert forecasts, commercial services, and so forth for price forecasts. Econometric models often seen in the literature include the autoregressive moving average (Bessler, 1982, 1990; Bessler and Babula, 1987; Bessler and Brandt, 1981; Bessler and Chamberlain, 1988; Brandt and Bessler, 1981, 1982, 1983, 1984; Kling and Bessler, 1985; McIntosh and Bessler, 1988; Yang et al., 2001), vector autoregressive (Awokuse and Yang, 2003; Babula et al., 2004; Bessler, 1990; Bessler and Babula, 1987; Bessler and Brandt, 1992; Bessler and Hopkins, 1986; Bessler and Kling, 1986; Bessler et al., 2003; Brandt and Bessler, 1982, 1984; Chen and Bessler, 1987, 1990; Kling and Bessler, 1985; Wang and Bessler, 2004; Xu, 2019a,c; Yang et al., 2003), vector error correction (Bessler et al., 2003; Wang and Bessler, 2004; Xu, 2019a,c; Yang and Awokuse, 2003; Yang and Leatham, 1998; Yang et al., 2021), and a diverse variety of their variations. Recently, machine learning methods have shown their potential for stock price forecasting (Long et al., 2019; Lu and Li, 2017; Ning, 2020; Sun et al., 2015; Wang et al., 2016; Yang and Cheng, 2015; Yao et al., 2018). In addition to the price, another important aspect related to the stock total market value is the trading volume. In the line of research on forecasting trading volumes of financial indices and instruments, machine learning models have also proven themselves as promising tools (Alvim et al., 2010; Bordino et al., 2014; Brownlees et al., 2011; Chen et al., 2016, 2011; Gharehchopogh et al., 2013; Joseph et al., 2011; Kaastra and Boyd, 1995; Ma and Li, 2021; Nasir et al., 2019; Oliveira et al., 2017; Satish et al., 2014; Ye et al., 2014).

Among different machine learning methods, previous studies have shown that the neural network technique has great potential for forecasting economic and financial time series, which generally tend to be highly noised and chaotic (Karasu et al., 2020; Wang and Yang, 2010; Wegener et al., 2016; Xu, 2014b, 2015b, 2018a,b,d; Xu and Zhang, 2022j; Yang et al., 2010, 2008). Previous research has also shown that the neural network technique could lead to high accuracy under different forecast settings (Karasu et al., 2017a,b; Wang and Yang, 2010; Wegener et al., 2016; Yang et al., 2010, 2008). This can benefit from capabilities of self-learning of the neural network for forecasting (Karasu et al., 2020; Xu and Zhang, 2022g) and capturing nonlinearities (Altan et al., 2021; Xu and Zhang, 2022a) often inhabiting in economic and financial time series data (Xu and Zhang, 2022h). One greatest advantage of the neural network as compared to other nonlinear methods for time series data is that a class of multilayer neural networks could well approximate a large class of functions (Wang and Yang, 2010; Yang et al., 2010, 2008). The present study will concentrate on the neural network for forecasting the stock total market value.

To facilitate analysis, the forecasting problem in a dataset of the daily total market value of A shares traded in the Shenzhen Stock Exchange during January 4, 2016 – August 23, 2021 is investigated via the nonlinear autoregressive neural network. By examining various model

Table I
Summary statistics of the daily total market value of A shares traded in the Shenzhen Stock Exchange

Series	Minimum	Mean	Median	Maximum	Standard deviation	Skewness	Kurtosis	Jarque–Bera p–value
Market value	158693.0000	242102.9694	226620.5000	377627.0000	53772.3319	1.0236	3.0170	<0.001
First difference	−20350.0000	113.5834	264.0000	11157.0000	3487.0956	−0.7779	6.4596	<0.001

settings across the algorithm, delay, hidden neuron, and data splitting ratio, the model leading to generally accurate and stable performance is arrived at. Results here could be used on a standalone basis as technical forecasts or combined with fundamental forecasts to form perspectives of the total market value trend and perform policy analysis. The forecasting framework might also be generalized to related forecasting problems in other different economic sectors.

2. Data

A shares are stock shares of companies based in mainland China that are traded on the Shanghai Stock Exchange and Shenzhen Stock Exchange, as well as the National Equities Exchange and Quotations. A shares were only available to mainland citizens given China's restrictions on foreign investments until 2003 when selected foreign institutions were able to participate in trading through the Qualified Foreign Institutional Investor system. A shares have grown along with the Chinese economy. With substantially increased demand over the years, stock exchange regulators in China continue their efforts in making A shares more broadly available to international investors and have them recognized by the global investing community. The total market value of A shares was only about 0.5% of the Chinese gross domestic product back in 1991, which has grown to more than 80% as of 2021. There are more than 4,600 publicly traded companies covered by A shares in 2021.

The daily total market value (unit: one million RMB) of A shares traded in the Shenzhen Stock Exchange during January 4, 2016 – August 23, 2021 for analysis is sourced from Wind Information Co., Ltd. and plotted on the top panel of Figure 1, together with its first differences. The bottom panel of Figure 1 also visualizes the daily total market value and its first differences with histograms of fifty bins and kernel estimates to present the distributions. Table I reports summary statistics of the data, where one could see that they are not normally distributed, as generally expected for financial series (Xu, 2015a, 2017b, 2018c, 2019b; Xu and Zhang, 2021c,d, 2022e).

3. Method

The nonlinear autoregressive neural network model is investigated here for forecasting the daily total market value of A shares traded in the Shenzhen Stock Exchange. The model can be expressed as $y_t = f(y_{t-1}, ..., y_{t-d})$, where y is the daily total market value to be forecasted, t indexes time, d is the number of delays, and f represents the function. The current study concentrates on one-day ahead forecasts. And the model based upon a two-layer feedforward network is employed.

The two-layer feedforward network contains a sigmoid transfer function for hidden layers and a linear transfer function for the output layer. It is worth noting that the output y_t is fed back through delays to the input of the network and model training would be in the form of open loops for efficiency, in which the true output is utilized rather than feeding back the one estimated. In particular, adopting the open loop could ensure that the input to the feedforward network is more accurate and the resultant network would possess an architecture that is pure

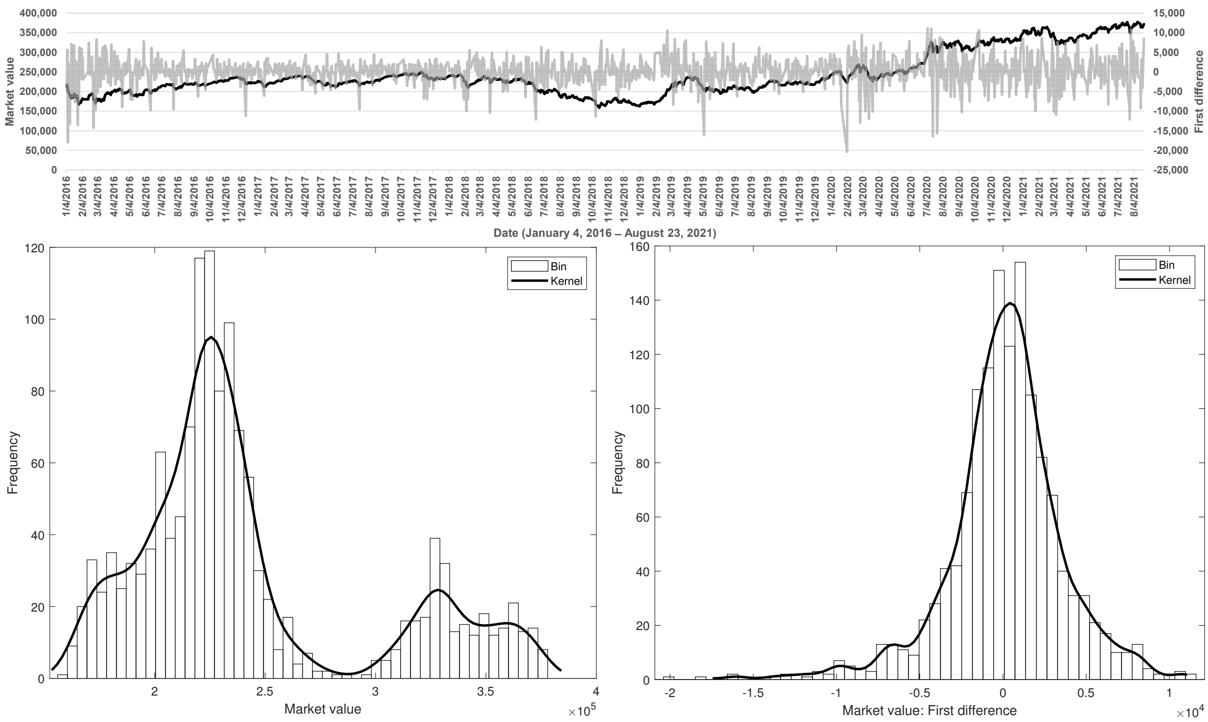


Figure 1: The daily total market value (black line) and its first differences (grey line) of A shares traded in the Shenzhen Stock Exchange (top panel) and histograms with fifty bins and kernel estimates of the daily total market value (bottom left panel) and its first differences (bottom right panel)

feedforward.

Different algorithms can be considered for model training. Here, the Levenberg-Marquardt (LM) algorithm (Levenberg, 1944; Marquardt, 1963) and scaled conjugate gradient (SCG) algorithm (Møller, 1993) are examined. These two algorithms have been adopted widely in different fields (Doan and Liong, 2004; Kayri, 2016; Khan et al., 2019; Selvamuthu et al., 2019; Xu and Zhang, 2021a,b,e,f, 2022c,k,l). Comparative research of these algorithms might be found from the literature (Al Bataineh and Kaur, 2018; Baghirli, 2015; Xu and Zhang, 2022d,i).

The LM algorithm approximates the second-order training speed for avoiding expensive computing of the Hessian matrix, $\boldsymbol{H}$ (Paluszek and Thomas, 2020). The approximation can be expressed as $\boldsymbol{H} = \boldsymbol{J}^T\boldsymbol{J}$, where $\boldsymbol{J} = \begin{bmatrix} \frac{\partial f}{\partial z_1} & \frac{\partial f}{\partial z_2} \end{bmatrix}$ for a nonlinear function $f\left(z_1, z_2\right)$ with $\boldsymbol{H} = \begin{bmatrix} \frac{\partial^2 f}{\partial z_1^2} & \frac{\partial^2 f}{\partial z_1 \partial z_2} \\ \frac{\partial^2 f}{\partial z_2 \partial z_1} & \frac{\partial^2 f}{\partial z_2^2} \end{bmatrix}$. $g = \boldsymbol{J}^T e$ reflects the gradient and e the error vector. The rule of $z_{k+1} = z_k - \left[\boldsymbol{J}^T\boldsymbol{J} + \mu \boldsymbol{I}\right]^{-1} \boldsymbol{J}^T e$ is adopted for updating weights and biases, where $\boldsymbol{I}$ is the identity matrix. The algorithm is similar to Newton's approach when $\mu = 0$ and it is gradient descent with small step sizes when μ is large. μ will be decreased if faster gradient descent is less needed after successful steps. The LM algorithm not only has desired attributes of steepest-descent algorithms and Gauss-Newton approaches but also avoids many of their limitations. Specifically, it is capable of efficiently dealing with the slow convergence problem (Hagan and Menhaj, 1994).

Backpropagation algorithms conduct adjustments of weights in the steepest descent as the performance function will rapidly decrease in the direction, which however, does not always represent the fastest convergence. Conjugate gradient algorithms conduct searches along the conjugate direction, which, in general, lead to faster convergence than the steepest descent.

Most algorithms utilize learning rates to determine the length of the updated weight step size. For conjugate gradient algorithms, step sizes are modified during iterations. Thus, the search is conducted along the conjugate gradient direction for determining the step size for reducing the performance function. Besides, for avoiding time-consuming line searches in conjugate gradient algorithms, the SCG algorithm could be used, which is fully-automated and supervised and is quicker than the LM backpropagation.

Finally, in arriving at our final model, different model settings over delays, hidden neurons, and data spitting ratios, in addition to algorithms, are examined. Specifically, delays of two, three, four, five, and six, hidden neurons of two, three, five, and ten, and data spitting ratios of 60% vs. 20% vs. 20%, 70% vs. 15% vs. 15%, and 80% vs. 10% vs. 10% for training, validation, and testing are explored. We note that the time series of the daily total market value of A shares is used directly and no particular data treatment has been made before applying neural network. Table II shows all investigated model settings, where the setting #117 is utilized to build our final chosen model. The setting #117 is based on five delays and ten hidden neurons and is constructed with the Levenberg-Marquardt algorithm (Levenberg, 1944; Marquardt, 1963) and a data splitting ratio of 80% vs. 10% vs. 10% for training, validation, and testing phases.

4. Result

All model settings listed in Table II are run for the daily total market value of A shares traded in the Shenzhen Stock Exchange. For a given model setting, the relative root mean square error (RRMSE) is calculated as the performance metric across training, validation, and testing phases, and the results are shown in Figure 2. Balancing model performance and stability, the setting #117 is chosen.

With the chosen setting, sensitivities of performance to different settings are analyzed by changing one setting each time and the results are presented in Figure 3, where RRMSEs for training, validation, and testing based on each setting are shown. The comparison between the settings #117 and #118 tests the sensitivity to the algorithm, between the setting #117 and settings #111, #113, #115, and #119 the sensitivity to the delay, between the setting #117 and settings #87, #97, and #107 the sensitivity to the hidden neuron, and between the setting #117 and settings #37 and #77 the sensitivity to the data splitting ratio. These results support the setting #117 as the final choice, leading to RRMSEs of 1.41%, 1.37%, and 1.38% for the training, validation, and testing phases, respectively, and the overall RRMSE of 1.40%.

Detailed visualization of forecasted results and forecast errors based on the chosen setting for the training, validation, and testing phases are shown in Figure 4. Overall, the chosen setting results in accurate and stable performance, suggesting usefulness of the neural network for forecasting the daily total market value of A shares traded in the Shenzhen Stock Exchange. One could also observe that forecast errors are relatively larger during several sub-periods with elevated price volatilities. This might not be surprising and the model generally still captures the trends during these sub-periods.

Table II

Explored model settings for the daily total market value of A shares traded in the Shenzhen Stock Exchange

Setting	Algorithm	Delay	Hidden neuron	Training vs. Validation vs. Testing	Setting	Algorithm	Delay	Hidden neuron	Training vs. Validation vs. Testing
#1	LM	2	2	70% vs. 15% vs. 15%	#61	LM	2	5	60% vs. 20% vs. 20%
#2	SCG	2	2	70% vs. 15% vs. 15%	#62	SCG	2	5	60% vs. 20% vs. 20%
#3	LM	3	2	70% vs. 15% vs. 15%	#63	LM	3	5	60% vs. 20% vs. 20%
#4	SCG	3	2	70% vs. 15% vs. 15%	#64	SCG	3	5	60% vs. 20% vs. 20%
#5	LM	4	2	70% vs. 15% vs. 15%	#65	LM	4	5	60% vs. 20% vs. 20%
#6	SCG	4	2	70% vs. 15% vs. 15%	#66	SCG	4	5	60% vs. 20% vs. 20%
#7	LM	5	2	70% vs. 15% vs. 15%	#67	LM	5	5	60% vs. 20% vs. 20%
#8	SCG	5	2	70% vs. 15% vs. 15%	#68	SCG	5	5	60% vs. 20% vs. 20%
#9	LM	6	2	70% vs. 15% vs. 15%	#69	LM	6	5	60% vs. 20% vs. 20%
#10	SCG	6	2	70% vs. 15% vs. 15%	#70	SCG	6	5	60% vs. 20% vs. 20%
#11	LM	2	3	70% vs. 15% vs. 15%	#71	LM	2	10	60% vs. 20% vs. 20%
#12	SCG	2	3	70% vs. 15% vs. 15%	#72	SCG	2	10	60% vs. 20% vs. 20%
#13	LM	3	3	70% vs. 15% vs. 15%	#73	LM	3	10	60% vs. 20% vs. 20%
#14	SCG	3	3	70% vs. 15% vs. 15%	#74	SCG	3	10	60% vs. 20% vs. 20%
#15	LM	4	3	70% vs. 15% vs. 15%	#75	LM	4	10	60% vs. 20% vs. 20%
#16	SCG	4	3	70% vs. 15% vs. 15%	#76	SCG	4	10	60% vs. 20% vs. 20%
#17	LM	5	3	70% vs. 15% vs. 15%	#77	LM	5	10	60% vs. 20% vs. 20%
#18	SCG	5	3	70% vs. 15% vs. 15%	#78	SCG	5	10	60% vs. 20% vs. 20%
#19	LM	6	3	70% vs. 15% vs. 15%	#79	LM	6	10	60% vs. 20% vs. 20%
#20	SCG	6	3	70% vs. 15% vs. 15%	#80	SCG	6	10	60% vs. 20% vs. 20%
#21	LM	2	5	70% vs. 15% vs. 15%	#81	LM	2	2	80% vs. 10% vs. 10%
#22	SCG	2	5	70% vs. 15% vs. 15%	#82	SCG	2	2	80% vs. 10% vs. 10%
#23	LM	3	5	70% vs. 15% vs. 15%	#83	LM	3	2	80% vs. 10% vs. 10%
#24	SCG	3	5	70% vs. 15% vs. 15%	#84	SCG	3	2	80% vs. 10% vs. 10%
#25	LM	4	5	70% vs. 15% vs. 15%	#85	LM	4	2	80% vs. 10% vs. 10%
#26	SCG	4	5	70% vs. 15% vs. 15%	#86	SCG	4	2	80% vs. 10% vs. 10%
#27	LM	5	5	70% vs. 15% vs. 15%	#87	LM	5	2	80% vs. 10% vs. 10%
#28	SCG	5	5	70% vs. 15% vs. 15%	#88	SCG	5	2	80% vs. 10% vs. 10%
#29	LM	6	5	70% vs. 15% vs. 15%	#89	LM	6	2	80% vs. 10% vs. 10%
#30	SCG	6	5	70% vs. 15% vs. 15%	#90	SCG	6	2	80% vs. 10% vs. 10%
#31	LM	2	10	70% vs. 15% vs. 15%	#91	LM	2	3	80% vs. 10% vs. 10%
#32	SCG	2	10	70% vs. 15% vs. 15%	#92	SCG	2	3	80% vs. 10% vs. 10%
#33	LM	3	10	70% vs. 15% vs. 15%	#93	LM	3	3	80% vs. 10% vs. 10%
#34	SCG	3	10	70% vs. 15% vs. 15%	#94	SCG	3	3	80% vs. 10% vs. 10%
#35	LM	4	10	70% vs. 15% vs. 15%	#95	LM	4	3	80% vs. 10% vs. 10%
#36	SCG	4	10	70% vs. 15% vs. 15%	#96	SCG	4	3	80% vs. 10% vs. 10%
#37	LM	5	10	70% vs. 15% vs. 15%	#97	LM	5	3	80% vs. 10% vs. 10%
#38	SCG	5	10	70% vs. 15% vs. 15%	#98	SCG	5	3	80% vs. 10% vs. 10%
#39	LM	6	10	70% vs. 15% vs. 15%	#99	LM	6	3	80% vs. 10% vs. 10%
#40	SCG	6	10	70% vs. 15% vs. 15%	#100	SCG	6	3	80% vs. 10% vs. 10%
#41	LM	2	2	60% vs. 20% vs. 20%	#101	LM	2	5	80% vs. 10% vs. 10%
#42	SCG	2	2	60% vs. 20% vs. 20%	#102	SCG	2	5	80% vs. 10% vs. 10%
#43	LM	3	2	60% vs. 20% vs. 20%	#103	LM	3	5	80% vs. 10% vs. 10%
#44	SCG	3	2	60% vs. 20% vs. 20%	#104	SCG	3	5	80% vs. 10% vs. 10%
#45	LM	4	2	60% vs. 20% vs. 20%	#105	LM	4	5	80% vs. 10% vs. 10%
#46	SCG	4	2	60% vs. 20% vs. 20%	#106	SCG	4	5	80% vs. 10% vs. 10%
#47	LM	5	2	60% vs. 20% vs. 20%	#107	LM	5	5	80% vs. 10% vs. 10%
#48	SCG	5	2	60% vs. 20% vs. 20%	#108	SCG	5	5	80% vs. 10% vs. 10%
#49	LM	6	2	60% vs. 20% vs. 20%	#109	LM	6	5	80% vs. 10% vs. 10%
#50	SCG	6	2	60% vs. 20% vs. 20%	#110	SCG	6	5	80% vs. 10% vs. 10%
#51	LM	2	3	60% vs. 20% vs. 20%	#111	LM	2	10	80% vs. 10% vs. 10%
#52	SCG	2	3	60% vs. 20% vs. 20%	#112	SCG	2	10	80% vs. 10% vs. 10%
#53	LM	3	3	60% vs. 20% vs. 20%	#113	LM	3	10	80% vs. 10% vs. 10%
#54	SCG	3	3	60% vs. 20% vs. 20%	#114	SCG	3	10	80% vs. 10% vs. 10%
#55	LM	4	3	60% vs. 20% vs. 20%	#115	LM	4	10	80% vs. 10% vs. 10%
#56	SCG	4	3	60% vs. 20% vs. 20%	#116	SCG	4	10	80% vs. 10% vs. 10%
#57	LM	5	3	60% vs. 20% vs. 20%	#117	LM	5	10	80% vs. 10% vs. 10%
#58	SCG	5	3	60% vs. 20% vs. 20%	#118	SCG	5	10	80% vs. 10% vs. 10%
#59	LM	6	3	60% vs. 20% vs. 20%	#119	LM	6	10	80% vs. 10% vs. 10%
#60	SCG	6	3	60% vs. 20% vs. 20%	#120	SCG	6	10	80% vs. 10% vs. 10%

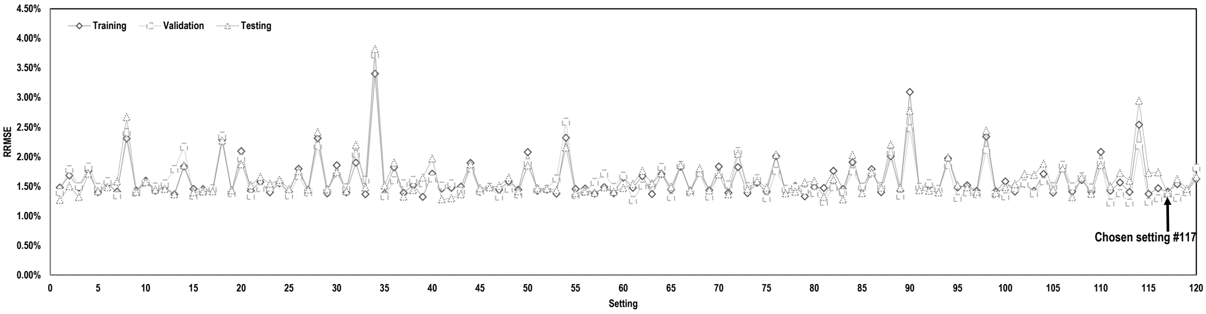
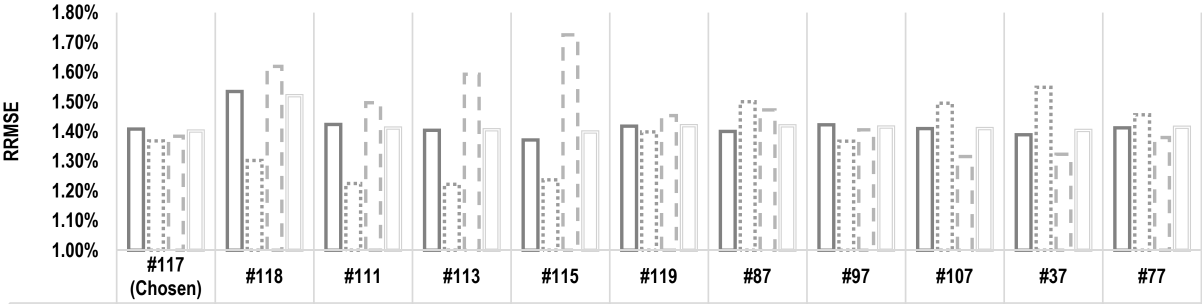


Figure 2: RRMSEs across all model settings for the daily total market value of A shares traded in the Shenzhen Stock Exchange



	#117 (Chosen)	#118	#111	#113	#115	#119	#87	#97	#107	#37	#77
Training	1.41%	1.53%	1.42%	1.40%	1.37%	1.42%	1.40%	1.42%	1.41%	1.39%	1.41%
Validation	1.37%	1.30%	1.22%	1.22%	1.24%	1.40%	1.50%	1.37%	1.49%	1.55%	1.46%
Testing	1.38%	1.62%	1.50%	1.59%	1.73%	1.45%	1.47%	1.41%	1.32%	1.32%	1.38%
Overall	1.40%	1.52%	1.41%	1.41%	1.40%	1.42%	1.42%	1.41%	1.41%	1.40%	1.41%

Setting

Figure 3: Sensitivities of model performance (the RRMSE) to different model settings for the daily total market value of A shares traded in the Shenzhen Stock Exchange

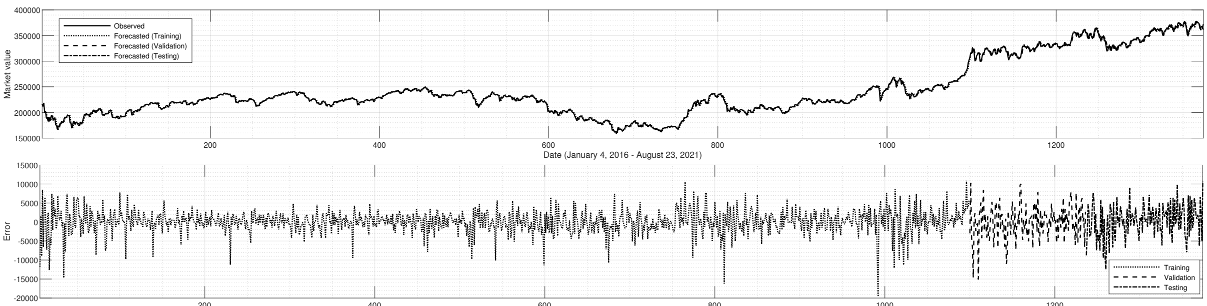


Figure 4: Forecasts (top) and forecast errors calculated as observations minus forecasts (bottom) for the daily total market value of A shares traded in the Shenzhen Stock Exchange

5. Benchmark analysis

We conduct benchmark analysis by comparing our final neural network model with the linear autoregressive model, in terms of forecast performance across the training, validation, and testing phases. The lag of the linear autoregressive model is determined by the Bayesian information criterion (Schwarz et al., 1978). We use a modified Diebold-Mariano (Diebold and Mariano, 1995) test (Harvey et al., 1997) to compare forecast performance, which helps mitigate several shortcomings in the original test, including the over-sized problem. The modified test is based on $d_t = \left(\text{error}_t^{M_1}\right)^2 - \left(\text{error}_t^{M_2}\right)^2$ for the horizon h ($h = 1$ for our case), where $error_t^{M_1}$ and $error_t^{M_2}$ are forecast errors from model M_1 and model M_2 indexed at time t. The forecast comparison test statistic is: $MDM = \left[\frac{T+1-2h+T^{-1}h(h-1)}{T}\right]^{1/2} \left[T^{-1}\left(\gamma_0 + 2\sum_{k=1}^{h-1}\gamma_k\right)\right]^{-1/2} \bar{d}$, where T is the length of the sample period, $\bar{d}$ the sample mean of d_t, $\gamma_0 = T^{-1}\sum_{t=1}^{T}\left(d_t - \bar{d}\right)^2$ is the variance of d_t, and $\gamma_k = T^{-1}\sum_{t=k+1}^{T}\left(d_t - \bar{d}\right)\left(d_{t-k} - \bar{d}\right)$ is the kth auto-covariance of d_t for $k = 1, \ldots, h-1$ and $h \geq 2$. Under the null hypothesis that mean squared errors generated by two models are equal, the MDM test follows a t – distribution with $T - 1$ degrees of freedom.

We find that, for the training, validation, and testing phases, our final neural network model leads to better performance, i.e. lower root mean square errors, than the linear autoregressive model. p-values of the MDM tests across the training, validation, and testing phases are all nearly 0, specifically, 0.0016, 0.0011, and 0.0008, respectively. Therefore, performance of our final neural network model is statistically significantly different from that of the linear autoregressive model.

It might be worth nothing that a model not performing as well than another model does not necessarily mean that it could not contribute to forecasting. Many forecast combination studies aim at weighting different forecasts for better and more stable performance. One interesting direction in forecast combinations is to combine linear models and nonlinear models for better results. Some previous studies (Blake and Kapetanios, 1999; Stock and Watson, 1998) provide good examples in this direction.

6. Conclusion

Stock total market value forecasting is a significant issue for policy makers and investors (Xu and Thurman, 2015a,b). In the present study, this forecasting problem is investigated in a dataset of the daily total market value of A shares traded in the Shenzhen Stock Exchange during January 4, 2016 – August 23, 2021. The nonlinear autoregressive neural network is considered as the forecasting tool and is explored over different model settings, leading to generally accurate and stable performance. In particular, the chosen model with five delays and ten hidden neurons is constructed with the Levenberg-Marquardt algorithm (Levenberg, 1944; Marquardt, 1963) and a data splitting ratio of 80% vs. 10% vs. 10% for training, validation, and testing phases. It leads to relative root mean square errors (RRMSEs) of 1.41%, 1.37%, and 1.38% for the training, validation, and testing phases, respectively, and the overall RRMSE of 1.40%. Results here might be used on a standalone basis as technical forecasts or combined with fundamental forecasts for forming perspectives of the total market value trend and conducting policy analysis. The forecasting framework here should not be difficult to implement, which is an important consideration to many decision makers (Brandt and Bessler, 1983; Xu, 2014a). Future research of interest might be investigating the potential of combining time series approaches and graph theory from machine learning for time series forecasting (Bessler and Wang, 2012; Kano et al., 2003; Shimizu et al., 2006, 2011; Shimizu and Kano, 2008; Xu and Zhang, 2022f). Investigating economic significance of adopting neural network modeling for forecasting might also be a worthwhile avenue for future research (Wang and Yang, 2010; Yang et al., 2010, 2008). It might be of interest to researchers to explore the forecasting problems based on B shares and H shares as well using the neural network. While there are previous studies finding that neural networks are capable of modeling seasonality directly and prior deseasonalization is not necessary, there is other research concluding just the opposite (Zhang and Qi, 2005). Empirical evidence tends to be mixed on this issue and future work taking detrending and/or deseasonalization into consideration might be worth pursuing.

Compliance with Ethical Standards

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References

Al Bataineh, A., Kaur, D., 2018. A comparative study of different curve fitting algorithms in artificial neural network using housing dataset, in: NAECON 2018-IEEE National Aerospace and Electronics Conference, IEEE. pp. 174–178. doi:10.1109/NAECON.2018.8556738.

Altan, A., Karasu, S., Zio, E., 2021. A new hybrid model for wind speed forecasting combining long short-term memory neural network, decomposition methods and grey wolf optimizer. Applied Soft Computing 100, 106996. doi:10.1016/j.asoc.2020.106996.

Alvim, L., dos Santos, C.N., Milidiu, R.L., 2010. Daily volume forecasting using high frequency predictors, in: Proceedings of the 10th IASTED International Conference, p. 248.

Arouri, M.E.H., Jawadi, F., Nguyen, D.K., 2012. Nonlinearities in carbon spot-futures price relationships during phase ii of the eu ets. Economic Modelling 29, 884–892. doi:10.1016/j.econmod.2011.11.003.

Awokuse, T.O., Yang, J., 2003. The informational role of commodity prices in formulating monetary policy: a reexamination. Economics Letters 79, 219–224. doi:10.1016/S0165-1765(02)00331-2.

Babula, R.A., Bessler, D.A., Reeder, J., Somwaru, A., 2004. Modeling us soy-based markets with directed acyclic graphs and bernanke structural var methods: The impacts of high soy meal and soybean prices. Journal of Food Distribution Research 35, 29–52. doi:10.22004/ag.econ.27559.

Baghirli, O., 2015. Comparison of lavenberg-marquardt, scaled conjugate gradient and bayesian regularization backpropagation algorithms for multistep ahead wind speed forecasting using multilayer perceptron feedforward neural network.

Bessler, D.A., 1982. Adaptive expectations, the exponentially weighted forecast, and optimal statistical predictors: A revisit. Agricultural Economics Research 34, 16–23. doi:10.22004/ag.econ.148819.

Bessler, D.A., 1990. Forecasting multiple time series with little prior information. American Journal of Agricultural Economics 72, 788–792. doi:10.2307/1243059.

Bessler, D.A., Babula, R.A., 1987. Forecasting wheat exports: do exchange rates matter? Journal of Business & Economic Statistics 5, 397–406. doi:10.2307/1391615.

Bessler, D.A., Brandt, J.A., 1981. Forecasting livestock prices with individual and composite methods. Applied Economics 13, 513–522. doi:10.1080/00036848100000016.

Bessler, D.A., Brandt, J.A., 1992. An analysis of forecasts of livestock prices. Journal of Economic Behavior & Organization 18, 249–263. doi:10.1016/0167-2681(92)90030-F.

Bessler, D.A., Chamberlain, P.J., 1988. Composite forecasting with dirichlet priors. Decision Sciences 19, 771–781. doi:10.1111/j.1540-5915.1988.tb00302.x.

Bessler, D.A., Hopkins, J.C., 1986. Forecasting an agricultural system with random walk priors. Agricultural Systems 21, 59–67. doi:10.1016/0308-521X(86)90029-6.

Bessler, D.A., Kling, J.L., 1986. Forecasting vector autoregressions with bayesian priors. American Journal of Agricultural Economics 68, 144–151. doi:10.2307/1241659.

Bessler, D.A., Wang, Z., 2012. D-separation, forecasting, and economic science: a conjecture. Theory and decision 73, 295–314. doi:10.1007/s11238-012-9305-8.

Bessler, D.A., Yang, J., Wongcharupan, M., 2003. Price dynamics in the international wheat market: modeling with error correction and directed acyclic graphs. Journal of Regional Science 43, 1–33.

Blake, A., Kapetanios, G., 1999. Forecast combination and leading indicators: combining artificial neural network and autoregressive forecasts. Manuscript, National Institute of Economic and Social Research .

Bordino, I., Kourtellis, N., Laptev, N., Billawala, Y., 2014. Stock trade volume prediction with yahoo finance user browsing behavior, in: 2014 IEEE 30th International Conference on Data Engineering, IEEE. pp. 1168–1173. doi:10.1109/ICDE.2014.6816733.

Brandt, J.A., Bessler, D.A., 1981. Composite forecasting: An application with us hog prices. American Journal of Agricultural Economics 63, 135–140. doi:10.2307/1239819.

Brandt, J.A., Bessler, D.A., 1982. Forecasting with a dynamic regression model: A heuristic approach. North Central Journal of Agricultural Economics , 27–33doi:10.2307/1349096.

Brandt, J.A., Bessler, D.A., 1983. Price forecasting and evaluation: An application in agriculture. Journal of Forecasting 2, 237–248. doi:10.1002/for.3980020306.

Brandt, J.A., Bessler, D.A., 1984. Forecasting with vector autoregressions versus a univariate arima process: An empirical example with us hog prices. North Central Journal of Agricultural Economics , 29–36doi:10.2307/1349248.

Brownlees, C.T., Cipollini, F., Gallo, G.M., 2011. Intra-daily volume modeling and prediction for algorithmic trading. Journal of Financial Econometrics 9, 489–518. doi:10.1093/jjfinec/nbq024.

Chen, D.T., Bessler, D.A., 1987. Forecasting the us cotton industry: Structural and time series approaches, in: Proceedings of the NCR-134 Conference on Applied Commodity Price Analysis. Forecasting, and Market Risk Management, Chicago Mercantile Exchange, Chicago. doi:10.22004/ag.econ.285463.

Chen, D.T., Bessler, D.A., 1990. Forecasting monthly cotton price: structural and time series approaches. International Journal of Forecasting 6, 103–113. doi:10.1016/0169-2070(90)90101-G.

Chen, R., Feng, Y., Palomar, D., 2016. Forecasting intraday trading volume: a kalman filter approach. Available at SSRN 3101695 .

Chen, S., Chen, R., Ardell, G., Lin, B., 2011. End-of-day stock trading volume prediction with a two-component hierarchical model. The Journal of Trading 6, 61–68. doi:10.3905/jot.2011.6.3.061.

Diebold, F.X., Mariano, R.S., 1995. Comparing predictive accuracy. Journal of Business & Economic Statistics 13, 253–263. doi:10.2307/1392185.

Doan, C.D., Liong, S.y., 2004. Generalization for multilayer neural network bayesian regularization or early stopping, in: Proceedings of Asia Pacific Association of Hydrology and Water Resources 2nd Conference, pp. 5–8.

Gharehchopogh, F.S., Bonab, T.H., Khaze, S.R., 2013. A linear regression approach to prediction of stock market trading volume: a case study. International Journal of Managing Value and Supply Chains 4, 25. doi:10.5121/ijmvsc.2013.4303.

Hagan, M.T., Menhaj, M.B., 1994. Training feedforward networks with the marquardt algorithm. IEEE transactions on Neural Networks 5, 989–993. doi:10.1109/72.329697.

Harvey, D., Leybourne, S., Newbold, P., 1997. Testing the equality of prediction mean squared errors. International Journal of Forecasting 13, 281–291. doi:10.1016/S0169-2070(96)00719-4.

Huang, W., Lai, P.C., Bessler, D.A., 2018. On the changing structure among chinese equity markets: Hong kong, shanghai, and shenzhen. European Journal of Operational Research 264, 1020–1032. doi:10.1016/j.ejor.2017.01.019.

Joseph, K., Wintoki, M.B., Zhang, Z., 2011. Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search. International Journal of Forecasting 27, 1116–1127. doi:10.1016/j.ijforecast.2010.11.001.

Kaastra, I., Boyd, M.S., 1995. Forecasting futures trading volume using neural networks. The Journal of Futures Markets 15, 953. doi:10.1002/fut.3990150806.

Kano, Y., Shimizu, S., et al., 2003. Causal inference using nonnormality, in: Proceedings of the international symposium on science of modeling, the 30th anniversary of the information criterion, pp. 261–270.

Karasu, S., Altan, A., Bekiros, S., Ahmad, W., 2020. A new forecasting model with wrapper-based feature selection approach using multi-objective optimization technique for chaotic crude oil time series. Energy 212, 118750. doi:10.1016/j.energy.2020.118750.

Karasu, S., Altan, A., Saraç, Z., Hacioğlu, R., 2017a. Estimation of fast varied wind speed based on narx neural network by using curve fitting. International Journal of Energy Applications and Technologies 4, 137–146.

Karasu, S., Altan, A., Saraç, Z., Hacioğlu, R., 2017b. Prediction of wind speed with non-linear autoregressive (nar) neural networks, in: 2017 25th Signal Processing and Communications Applications Conference (SIU), IEEE. pp. 1–4. doi:10.1109/SIU.2017.7960507.

Kayri, M., 2016. Predictive abilities of bayesian regularization and levenberg–marquardt algorithms in artificial neural networks: a comparative empirical study on social data. Mathematical and Computational Applications 21, 20. doi:10.3390/mca21020020.

Khan, T.A., Alam, M., Shahid, Z., Mazliham, M., 2019. Comparative performance analysis of levenberg-marquardt, bayesian regularization and scaled conjugate gradient for the prediction of flash floods. Journal of Information Communication Technologies and Robotic Applications , 52–58.

Kling, J.L., Bessler, D.A., 1985. A comparison of multivariate forecasting procedures for economic time series. International Journal of Forecasting 1, 5–24. doi:10.1016/S0169-2070(85)80067-4.

Levenberg, K., 1944. A method for the solution of certain non-linear problems in least squares. Quarterly of Applied Mathematics 2, 164–168. doi:10.1090/qam/10666.

Long, W., Lu, Z., Cui, L., 2019. Deep learning-based feature engineering for stock price movement prediction. Knowledge-Based Systems 164, 163–173. doi:10.1016/j.knosys.2018.10.034.

Lu, T., Li, Z., 2017. Forecasting csi 300 index using a hybrid functional link artificial neural network and particle swarm optimization with improved wavelet mutation, in: 2017 International Conference on Computer Network, Electronic and Automation (ICCNEA), IEEE. pp. 241–246. doi:10.1109/ICCNEA.2017.55.

Ma, S., Li, P., 2021. Predicting daily trading volume via various hidden states. arXiv preprint arXiv:2107.07678 .

Marquardt, D.W., 1963. An algorithm for least-squares estimation of nonlinear parameters. Journal of the Society for Industrial and Applied Mathematics 11, 431–441. doi:10.1137/0111030.

McIntosh, C.S., Bessler, D.A., 1988. Forecasting agricultural prices using a bayesian composite approach. Journal of Agricultural and Applied Economics 20, 73–80. doi:10.1017/S0081305200017611.

Møller, M.F., 1993. A scaled conjugate gradient algorithm for fast supervised learning. Neural Networks 6, 525–533. doi:10.1016/S0893-6080(05)80056-5.

Nasir, M.A., Huynh, T.L.D., Nguyen, S.P., Duong, D., 2019. Forecasting cryptocurrency returns and volume using search engines. Financial Innovation 5, 1–13. doi:10.1186/s40854-018-0119-8.

Ning, S., 2020. Short-term prediction of the csi 300 based on the bp neural network model, in: Journal of Physics: Conference Series, IOP Publishing. p. 012054. doi:10.1088/1742-6596/1437/1/012054.

Oliveira, N., Cortez, P., Areal, N., 2017. The impact of microblogging data for stock market prediction: Using twitter to predict returns, volatility, trading volume and survey sentiment indices. Expert Systems with applications 73, 125–144. doi:10.1016/j.eswa.2016.12.036.

Paluszek, M., Thomas, S., 2020. Practical MATLAB Deep Learning: A Project-Based Approach. Apress.

Satish, V., Saxena, A., Palmer, M., 2014. Predicting intraday trading volume and volume percentages. The Journal of Trading 9, 15–25. doi:10.3905/jot.2014.9.3.015.

Schwarz, G., et al., 1978. Estimating the dimension of a model. Annals of Statistics 6, 461–464. doi:10.1214/aos/1176344136.

Selvamuthu, D., Kumar, V., Mishra, A., 2019. Indian stock market prediction using artificial neural networks on tick data. Financial Innovation 5, 16. doi:10.1186/s40854-019-0131-7.

Shimizu, S., Hoyer, P.O., Hyvärinen, A., Kerminen, A., Jordan, M., 2006. A linear non-gaussian acyclic model for causal discovery. Journal of Machine Learning Research 7.

Shimizu, S., Inazumi, T., Sogawa, Y., Hyvärinen, A., Kawahara, Y., Washio, T., Hoyer, P.O., Bollen, K., 2011. Directlingam: A direct method for learning a linear non-gaussian structural equation model. The Journal of Machine Learning Research 12, 1225–1248.

Shimizu, S., Kano, Y., 2008. Use of non-normality in structural equation modeling: Application to direction of causation. Journal of Statistical Planning and Inference 138, 3483–3491. doi:10.1016/j.jspi.2006.01.017.

Stock, J.H., Watson, M.W., 1998. A comparison of linear and nonlinear univariate models for forecasting macroeconomic time series. Technical Report. National Bureau of Economic Research.

Sun, B., Guo, H., Karimi, H.R., Ge, Y., Xiong, S., 2015. Prediction of stock index futures prices based on fuzzy sets and multivariate fuzzy time series. Neurocomputing 151, 1528–1536. doi:10.1016/j.neucom.2014.09.018.

Wang, C., Chen, R., 2013. Forecasting csi 300 volatility: The role of persistence, asymmetry,

and distributional assumption in garch models, in: 2013 Sixth International Conference on Business Intelligence and Financial Engineering, IEEE. pp. 355–358. doi:10.1109/BIFE.2013.74.
Wang, J., Hou, R., Wang, C., Shen, L., 2016. Improved v-support vector regression model based on variable selection and brain storm optimization for stock price forecasting. Applied Soft Computing 49, 164–178. doi:10.1016/j.asoc.2016.07.024.
Wang, T., Yang, J., 2010. Nonlinearity and intraday efficiency tests on energy futures markets. Energy Economics 32, 496–503. doi:10.1016/j.eneco.2009.08.001.
Wang, Z., Bessler, D.A., 2004. Forecasting performance of multivariate time series models with full and reduced rank: An empirical examination. International Journal of Forecasting 20, 683–695. doi:10.1016/j.ijforecast.2004.01.002.
Wegener, C., von Spreckelsen, C., Basse, T., von Mettenheim, H.J., 2016. Forecasting government bond yields with neural networks considering cointegration. Journal of Forecasting 35, 86–92. doi:10.1002/for.2385.
Xu, X., 2014a. Causality and price discovery in us corn markets: An application of error correction modeling and directed acyclic graphs doi:10.22004/ag.econ.169806.
Xu, X., 2014b. Price discovery in us corn cash and futures markets: The role of cash market selection doi:10.22004/ag.econ.169809.
Xu, X., 2015a. Causality, price discovery, and price forecasts: Evidence from us corn cash and futures markets .
Xu, X., 2015b. Cointegration among regional corn cash prices. Economics Bulletin 35, 2581–2594. URL: http://www.accessecon.com/Pubs/EB/2015/Volume35/EB-15-V35-I4-P259.pdf.
Xu, X., 2017a. Contemporaneous causal orderings of us corn cash prices through directed acyclic graphs. Empirical Economics 52, 731–758. doi:10.1007/s00181-016-1094-4.
Xu, X., 2017b. The rolling causal structure between the chinese stock index and futures. Financial Markets and Portfolio Management 31, 491–509. doi:10.1007/s11408-017-0299-7.
Xu, X., 2017c. Short-run price forecast performance of individual and composite models for 496 corn cash markets. Journal of Applied Statistics 44, 2593–2620. doi:10.1080/02664763.2016.1259399.
Xu, X., 2018a. Causal structure among us corn futures and regional cash prices in the time and frequency domain. Journal of Applied Statistics 45, 2455–2480. doi:10.1080/02664763.2017.1423044.
Xu, X., 2018b. Cointegration and price discovery in us corn cash and futures markets. Empirical Economics 55, 1889–1923. doi:10.1007/s00181-017-1322-6.
Xu, X., 2018c. Intraday price information flows between the csi300 and futures market: an application of wavelet analysis. Empirical Economics 54, 1267–1295. doi:10.1007/s00181-017-1245-2.
Xu, X., 2018d. Linear and nonlinear causality between corn cash and futures prices. Journal of Agricultural & Food Industrial Organization 16, 20160006. doi:10.1515/jafio-2016-0006.
Xu, X., 2018e. Using local information to improve short-run corn price forecasts. Journal of Agricultural & Food Industrial Organization 16. doi:10.1515/jafio-2017-0018.
Xu, X., 2019a. Contemporaneous and granger causality among us corn cash and futures prices. European Review of Agricultural Economics 46, 663–695. doi:10.1093/erae/jby036.
Xu, X., 2019b. Contemporaneous causal orderings of csi300 and futures prices through directed acyclic graphs. Economics Bulletin 39, 2052–2077. URL: http://www.accessecon.com/Pubs/EB/2019/Volume39/EB-19-V39-I3-P192.pdf.
Xu, X., 2019c. Price dynamics in corn cash and futures markets: cointegration, causality, and forecasting through a rolling window approach. Financial Markets and Portfolio Management 33, 155–181. doi:10.1007/s11408-019-00330-7.
Xu, X., 2020. Corn cash price forecasting. American Journal of Agricultural Economics 102, 1297–1320. doi:10.1002/ajae.12041.
Xu, X., Thurman, W., 2015a. Forecasting local grain prices: An evaluation of composite models in 500 corn cash markets doi:10.22004/ag.econ.205332.
Xu, X., Thurman, W.N., 2015b. Using local information to improve short-run corn cash price forecasts doi:10.22004/ag.econ.285845.
Xu, X., Zhang, Y., 2021a. Corn cash price forecasting with neural networks. Computers and

Electronics in Agriculture 184, 106120. doi:10.1016/j.compag.2021.106120.
Xu, X., Zhang, Y., 2021b. House price forecasting with neural networks. Intelligent Systems with Applications 12, 200052. doi:10.1016/j.iswa.2021.200052.
Xu, X., Zhang, Y., 2021c. Individual time series and composite forecasting of the chinese stock index. Machine Learning with Applications 5, 100035. doi:10.1016/j.mlwa.2021.100035.
Xu, X., Zhang, Y., 2021d. Network analysis of corn cash price comovements. Machine Learning with Applications 6, 100140. doi:10.1016/j.mlwa.2021.100140.
Xu, X., Zhang, Y., 2021e. Rent index forecasting through neural networks. Journal of Economic Studies doi:10.1108/JES-06-2021-0316.
Xu, X., Zhang, Y., 2021f. Second-hand house price index forecasting with neural networks. Journal of Property Research doi:10.1080/09599916.2021.1996446.
Xu, X., Zhang, Y., 2022a. Canola and soybean oil price forecasts via neural networks. Advances in Computational Intelligence .
Xu, X., Zhang, Y., 2022b. Cointegration between housing prices: evidence from one hundred chinese cities. Journal of Property Research .
Xu, X., Zhang, Y., 2022c. Coking coal futures price index forecasting with the neural network. Mineral Economics doi:10.1007/s13563-022-00311-9.
Xu, X., Zhang, Y., 2022d. Commodity price forecasting via neural networks for coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat. Intelligent Systems in Accounting, Finance and Management doi:10.1002/isaf.1519.
Xu, X., Zhang, Y., 2022e. Contemporaneous causality among one hundred chinese cities. Empirical Economics doi:10.1007/s00181-021-02190-5.
Xu, X., Zhang, Y., 2022f. Contemporaneous causality among residential housing prices of ten major chinese cities. International Journal of Housing Markets and Analysis doi:10.1108/IJHMA-03-2022-0039.
Xu, X., Zhang, Y., 2022g. Network analysis of housing price comovements of a hundred chinese cities. National Institute Economic Review doi:10.1017/nie.2021.34.
Xu, X., Zhang, Y., 2022h. Network analysis of price comovements among corn futures and cash prices. Journal of Agricultural & Food Industrial Organization .
Xu, X., Zhang, Y., 2022i. Residential housing price index forecasting via neural networks. Neural Computing and Applications doi:10.1007/s00521-022-07309-y.
Xu, X., Zhang, Y., 2022j. Retail property price index forecasting through neural networks. Journal of Real Estate Portfolio Management .
Xu, X., Zhang, Y., 2022k. Soybean and soybean oil price forecasting through the nonlinear autoregressive neural network (narnn) and narnn with exogenous inputs (narnn–x). Intelligent Systems with Applications 13, 200061. doi:10.1016/j.iswa.2022.200061.
Xu, X., Zhang, Y., 2022l. Thermal coal price forecasting via the neural network. Intelligent Systems with Applications 14, 200084. doi:10.1016/j.iswa.2022.200084.
Yang, J., Awokuse, T.O., 2003. Asset storability and hedging effectiveness in commodity futures markets. Applied Economics Letters 10, 487–491. doi:10.1080/1350485032000095366.
Yang, J., Cabrera, J., Wang, T., 2010. Nonlinearity, data-snooping, and stock index etf return predictability. European Journal of Operational Research 200, 498–507. doi:10.1016/j.ejor.2009.01.009.
Yang, J., Haigh, M.S., Leatham, D.J., 2001. Agricultural liberalization policy and commodity price volatility: a garch application. Applied Economics Letters 8, 593–598. doi:10.1080/13504850010018734.
Yang, J., Leatham, D.J., 1998. Market efficiency of us grain markets: application of cointegration tests. Agribusiness: An International Journal 14, 107–112. doi:10.1002/(SICI)1520-6297(199803/04)14:2<107::AID-AGR3>3.0.CO;2-6.
Yang, J., Li, Z., Wang, T., 2021. Price discovery in chinese agricultural futures markets: A comprehensive look. Journal of Futures Markets 41, 536–555. doi:10.1002/fut.22179.
Yang, J., Su, X., Kolari, J.W., 2008. Do euro exchange rates follow a martingale? some out-of-sample evidence. Journal of Banking & Finance 32, 729–740. doi:10.1016/j.jbankfin.2007.05.009.
Yang, J., Zhang, J., Leatham, D.J., 2003. Price and volatility transmission in international wheat futures markets. Annals of Economics and Finance 4, 37–50.
Yang, L., Cheng, X., 2015. Predictive analytics on csi 300 index based on arima and rbf-ann

combined model. Journal of Mathematical Finance 5, 393. doi:10.4236/jmf.2015.54033.
Yao, S., Luo, L., Peng, H., 2018. High-frequency stock trend forecast using lstm model, in: 2018 13th International Conference on Computer Science & Education (ICCSE), IEEE. pp. 1–4. doi:10.1109/ICCSE.2018.8468703.
Ye, X., Yan, R., Li, H., 2014. Forecasting trading volume in the chinese stock market based on the dynamic vwap. Studies in Nonlinear Dynamics & Econometrics 18, 125–144. doi:10.1515/snde-2013-0023.
Zhang, G.P., Qi, M., 2005. Neural network forecasting for seasonal and trend time series. European Journal of Operational Research 160, 501–514. doi:10.1016/j.ejor.2003.08.037.
Zhang, Y.T., Sun, B., 2017. Analysis of csi 300 stock index futures price trend based on arima model. DEStech Transactions on Social Science, Education and Human Science doi:10.12783/dtssehs/seme2017/18022.
Zhou, J., Huo, X., Xu, X., Li, Y., 2019. Forecasting the carbon price using extreme-point symmetric mode decomposition and extreme learning machine optimized by the grey wolf optimizer algorithm. Energies 12, 950. doi:10.3390/en12050950.